Computers in Industry 123 (2020) 103316

Contents lists available at ScienceDirect

Computers in Industry

journal homepage: www.elsevier.com/locate/compind

Digital Twin for maintenance: A literature review

Itxaro Errandonea[a,b,*], Sergio Beltrán[a,b], Saioa Arrizabalaga[a,b]

[a] CEIT-Basque Research and Technology Alliance (BRTA), Manuel Lardizabal 15, 20018, Donostia/San Sebastián, Spain
[b] Universidad de Navarra, Tecnun, Manuel Lardizabal 13, 20018, Donostia/San Sebastián, Spain

ARTICLE INFO

Article history:
Received 2 March 2020
Received in revised form 2 September 2020
Accepted 3 September 2020

Keywords:
Decision support systems
Digital twin
Information system
Knowledge support system
Smart maintenance

ABSTRACT

In recent years, Digital Twins (DT) have been implemented in different industrial sectors, in several applications areas such as design, production, manufacturing, and maintenance. In particular, maintenance is one of the most researched applications, as the impact of the execution of maintenance task may have a great impact in the business of the companies. For example, in sector such as energy or manufacturing, a maintenance activity can cause the shutdown of an entire production line, or in the case of a wind turbine inspection, may face the safety of an operator to measure a simple indicator. Hence, the application of more intelligent maintenance strategies can offer huge benefits. In this context, this paper focuses on the review of DT applications for maintenance, as no previous work has been found with this aim. For instance, both "Digital Twin" and "maintenance" concepts and strategies are described in detail, and then a literature review is carried out where these two concepts are involved. In addition to identifying and analyzing how DTs are currently being applied for maintenance, this paper also highlights future research lines and open issues.

© 2020 Elsevier B.V. All rights reserved.

Contents

* Corresponding author at: Manuel Lardizabal 15, 20018, Donostia/San Sebastián, Spain.
E-mail address: ierrandonea@ceit.es (I. Errandonea).

https://doi.org/10.1016/j.compind.2020.103316
0166-3615/© 2020 Elsevier B.V. All rights reserved.

1. Introduction

In recent decades technological progresses in several areas like the Internet of Things (IoT), Artificial Intelligence or Cloud computing have enabled the digitalization of the different assets, systems, and processes in different industrial sectors (Mabkhot et al., 2018).

Sensors and intelligent data acquisition are helping to improve the life cycle of any asset, starting from design, manufacturing, distribution, maintenance, until recycling. These new technologies provide the necessary basis to enable the research on different areas such as fault prognostics and production efficiency among others. DT concept also relies in the aforementioned technologies and enables the possibility of integrating a virtual object with a physical through the life cycle (Qi and Tao, 2018).

Given the interest related to DT concept, several researches have been carried out related to its application in different sectors of industry (Tao et al., 2019; Kritzinger et al., 2018). In this article, a review of the use of DTs is offered for the specific application of maintenance in the different sectors of industry. For this purpose, a specific search including both “Digital Twin” and “maintenance” concepts has been performed in two databases: Šcopusänd Ẅeb of Science. In total, 167 results have been collected, categorized and analyzed, until December 2019. Among these results, there are journal articles, conference articles, book chapters, reviews, and business articles (see in Fig. 1).

Fig. 1 shows that the research or application of DT for the maintenance has become more popular in the last few years. The number of articles published by 2019 is promising to next year with probably more results than in 2019, by following the increasing trend in the last three years. It can also be seen that between 2014 and 2015 no results have been obtained. This may be caused because previous steps such as digitalization, incorporation of IoT technologies or collected data exploitation through machine learning algorithms, were being matured before incorporating DT technologies for maintenance.

No previous work has been identified focused on researching the relationship between these two terms: Ďigital Twinänd Ṁaintenance. In this paper, the different uses given to DTs in different industrial sectors are shown, focusing more on analyzing the maintenance application and its different strategies.

The rest of the article is organized as follows: Section 2 describes the DT paradigm, followed by a description of the evolution of the different maintenance strategies in Section 3. Section 4 reviews all the results of the research identifying the application areas and the different industrial sectors. Then, Section 5 is focused on the maintenance case studies and an analysis of maintenance strategy is detailed. Finally, some open issues are highlighted in Section 6 and conclusions are drawn in Section 7.

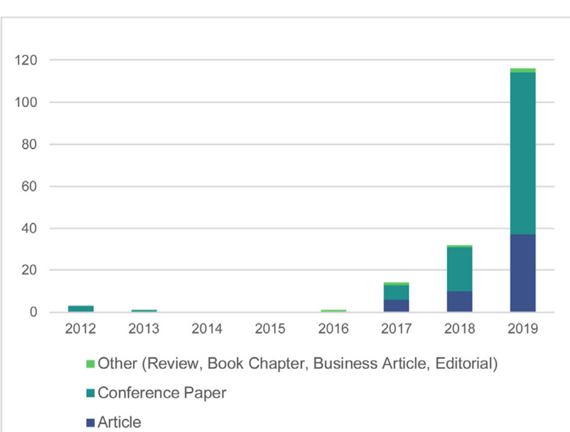


Fig. 1. Search result per year.

2. Digital Twin, the paradigm

The concept of DT has evolved since its first appearance in 2002. Given the complexity of the concept, a variety of definitions can be found in the literature. For instance, the definition varies so much (Autiosalo et al., 2020; Kritzinger et al., 2018; Tao et al., 2018a; Lee et al., 2013), even that it is sometimes incorrect.

The first definition of the concept of DT was made in 2012 by Grieves. Years later, he defined it as follows: P̈hysical product in real space, virtual product in virtual space and the connection of data and information that ties the two spaces together.G̈rieves pointed out that he was referring to a set of information that describes an asset completely, from its most general geometry, to the most concrete behavior (Grieves and Vickers, 2017). Rosen says the concept as two identical spaces, physical and virtual, which allows the mirroring between them to analyze the conditions that occur in all phases of the life cycle of the object (Rosen et al., 2015). Shortly thereafter, Boschert and Rosen detail that a DT covers all the physical and functional information that can be useful from a component, product or system (Boschert and Rosen, 2016). Both authors agree that DTs are not only data, but also algorithms that describe behavior and come to decide on actions in production.

The most common definition of DT was postulated by Glaessgen and Stargel. They dictate that a DT consists of three parts: the physical product, virtual product and the communication between them and define it as follows: “An integrated multi-physics, multiscale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, and so forth, to mirror the life of its flying twin” (Glaessgen and Stargel, 2012).

Recently, it could be said, ẗhat the digital twin of a real distributed product is a virtual mirror, which can describe the comprehensive physical and functional properties of the product throughout its life cycle and can deliver and receive product information(̈Tharma et al., 2018). The term DT define like the replica of a physical asset, process or system used for control and decision making (Vatn, 2018). And in the latest publications the idea and concept of DT, “which contains mainly real-time data acquisition technology, data mapping technology and data-based prediction technology, can make the convergence between the physical product and virtual space a reality(̈Liu et al., 2019a).

In (Schleich et al., 2017) it is described that one of the capabilities of the DT is to predict the response of the system to an unexpected event, before it occurs. Predictions of this type can be made by comparing the analysis of these events and the current response with the predictions of behavior that were made. Depending on the data collection and exchange capabilities and the completeness of the simulations used, a sufficiently complete DT instance can be obtained. Even for advanced living models of this type, (Liu et al., 2018; Booyse et al., 2020) a combination of physics-based models and data-based analysis is recommended. R̈ealistic models of the current state of the process and their own behaviors in interacting with their environment in the real world is called the DT” (Liu et al., 2019a). In short, “the vision of the DT describes the vision of a two-way relationship between a physical artifact and the set of its virtual models.(̈Schleich et al., 2017).

There are several concepts that are closely related to DT such as simulations, Cyber physical systems (CPSs) and Internet of things (IoT). This may lead to confusion between the concepts, however they are different in concept, core element and application (Lu et al., 2020). In many cases, the confusion is caused by the fact that the concept is among the components of a DT. In (Rosen et al.,

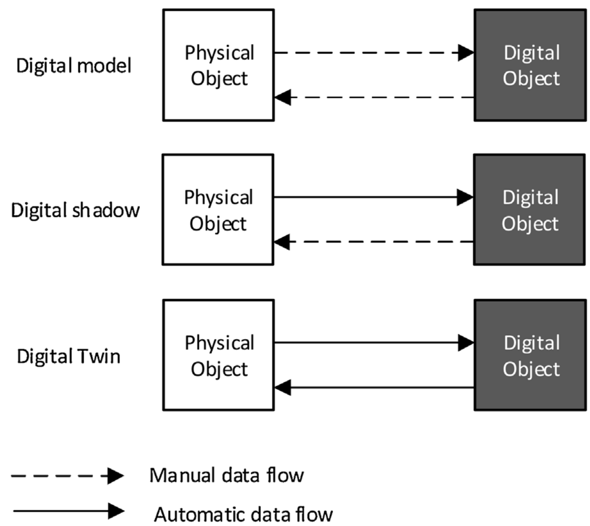


Fig. 2. Flow on different integration modes (Kritzinger et al., 2018).

2015) comment that DT is the next wave on modelling, simulation and optimization. This happens in the case of concepts such as MBD (Model-base definition). In this case, the integration of several model-base models would be part of the DT (Miller et al., 2018). The same is true for the concepts of CAD or BIM (Madni et al., 2019; Boje et al., 2020).

In recent years, several analyses of the concept have been carried out by adding features with the aim of defining the DT. Some common characteristics are identified (Talkhestani et al., 2019; Tao et al., 2018a). A DT should be the most realistic representation of a physical asset, incorporating models and all available information. It should contain all process information, and acquire operational, organizational and technical information. Of course, it is always synchronized with the physical asset. It must be able to run simulations of physical asset behavior. Another feature is the self-evolution of DT. A DT is something alive that changes, improves and evolves while maintaining the comparison between physical and virtual space. Interaction and convergence are two key aspects of the DT. Based on the described characteristics, the s̈ystem thinkingäpproach could assist in the detection of DTs.

All the information about the physical element as well as the process and the service of it must be in contact with each other. The same applies to the interaction and convergence between historical and real-time information. In addition, most importantly, the interaction between virtual and physical space. In this interaction, DTs can have different levels of integration depending on the data flow involved (Kritzinger et al., 2018). In the first level, the Digital Model can be found, in second place the Digital shadow and in third place the DT (see Fig. 2).

Clearly, the difference between these three integrations focuses on the way in which the physical object interacts with the digital object. In the case of the Digital Model, the interaction between the physical object and the digital model is manual in both directions.

In the case of the Digital shadow, the direction of the data from the physical object to the digital object is automatic, but we could not say the same in the other direction. For example, when the digital model is fed from the data of the inspections carried out on the physical object, or from the data coming from sensors.

Finally, the interaction between the two objects, physical and digital, is automatic and bidirectional in a DT. The flow of data goes from the physical object to the digital, as well as from digital to physical. In this case, in addition to including the information from sensors or enhanced inspections, the digital model should result in the action to be performed on the physical object, such as the maintenance activity relevant to the state received from it.

3. Maintenance

This section describes the different maintenance strategies that might be followed when making decisions about when (and what) maintenance activities need to be carried out. The strategies analyzed are the following:

- Reactive maintenance
- Preventive maintenance
- Condition-based maintenance
- Predictive maintenance
- Prescriptive maintenance.

3.1. *Reactive maintenance*

This first strategy is also known as corrective maintenance or failure base maintenance. It applies to any activity that could be called an emergency, which has been caused by breakage or breakdown. These activities have not been previously planned (Swanson, 2001).

This type of strategy is only suitable for assets or systems that may not cause a big impact in the business. If not, these types of strategies lead to high costs in maintenance, as the maintenance activity is focused in the renewal of the asset that has been broken or damaged. This is obviously more expensive than activities related to enhancing the asset, without replacing it. Furthermore, it can additionally incur in higher costs due to the fact of the interruption of the service that this asset is providing: penalties due to service interruption, delays in production, etc. (Gallimore and Penlesky, 1988)

3.2. *Preventive maintenance*

In order to try to mitigate the consequences of reactive maintenance, a preventive maintenance strategy can be followed. It is also known by other terms such as time-base maintenance. Is a proactive approach carried out to prevent or reduce failures in assets (Shafiee, 2015). This type of strategy is based on the experience of the plant/infrastructure/asset manager, who plans different maintenance activities with different frequencies over time, with the aim of avoiding service interruption, or if it is mandatory, minimize the impact of it by planning it beforehand (Bashiri et al., 2011).

Although this level is substantially better than the reactive, it is far from optimal: In this type of strategy, the trend is to ensure safety and service maintenance by over-maintaining the asset, thus causing a high economic cost.

3.3. *Condition-based maintenance*

Condition-based maintenance (CBM) consists of anticipating a maintenance activity based on evidence of degradation and deviation from the normal behavior of the asset (Nikolaev et al., 2019). It is also known as diagnosis based maintenance. These anomalies are detected thanks to the maturity of technologies such as IoT and cloud computing, which are applied to monitor the condition of the asset.

Condition-based approaches can be enhanced by artificial intelligence algorithms to diagnose and acquire detailed status data (Mabkhot et al., 2018).

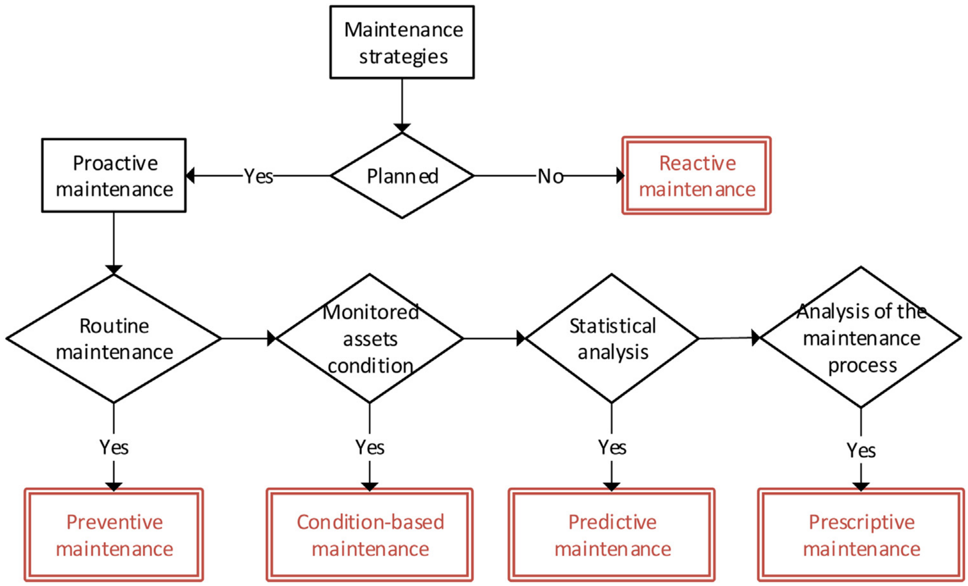


Fig. 3. Maintenance strategies diagram.

3.4. Predictive maintenance

Predictive maintenance or prognosis maintenance consists of using all the information that composes and surrounds a system, and using it to be able to predict its remaining life. It can lead to more complex architectures when different assets are simultaneously involved.

Different techniques can be used to merge all available information for performing maintenance predictions to be as accurate as possible (Fang et al., 2017; Animah and Shafiee, 2018; Rajesh et al., 2019; Werner et al., 2019). There might be data-driven or model driven approaches. On the one hand, the data-driven approach is a Big data-oriented technique where a large volume of data on the state of the asset is required, which can be obtained with the appropriate sensor deployment. Based on the information available, a data analysis algorithm is developed. It provides results on the trends observed before the behavior of the asset (Liu et al., 2018).

On the other hand, the model-driven approach requires the development of a model that describes the asset in a mathematical way. Models can be analytical, physical or numerical models. These models describe the way in which the component is degraded with a high level of reliability (Sivalingam et al., 2018). The advances made in computing techniques have made this type of models improve their viability since it has a very high cost computationally speaking. As stated in (Zenisek et al., 2019), “Predictive Maintenance is one of the most intensively investigated topics in the current Industry 4.0 movement”.

3.5. Prescriptive maintenance

The last of the strategies is the prescriptive maintenance or knowledge-based maintenance (Ansari et al., 2019). It refers to optimizing maintenance based on predictions. In addition to using historical and real-time data analysis to predict the status of required asset, it is also committed to prescribe an action plan (Consilvio et al., 2019). This results in a change from the preventive maintenance plan to a proactive and intelligent plan (Matyas et al., 2017; Setrag and Rostetter, 2015). The impact on service, cost and safety is expected to be optimal.

Gartner performs a description of the path to obtain a prescriptive analysis. For each maintenance strategy, he associates a specific question. For preventive maintenance, he associates the question ẅhat happened?”; for CBM, ẅhy did it happen?; for predictive maintenance, ẅhat will happen?; and for prescriptive maintenance, ḧow can we make it happens?(̈Nikolaev et al., 2019; Ansari et al., 2019).

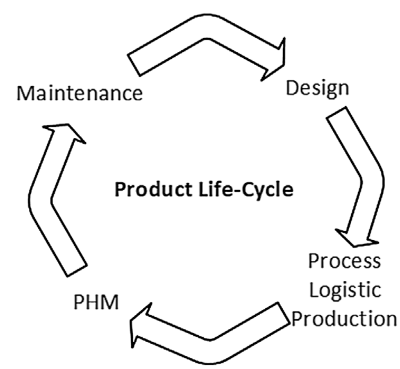


Fig. 4. Product life cycle.

The following diagram (see Fig. 3) shows the knowledge and information that needs to be collected to obtain intelligent maintenance. At the beginning, the difference between adopting a reactive or proactive strategy is the need to have planned maintenance activities. The preventive plan avoids failures, and thus detects the weakest points of the system. By monitoring the asset, it is possible to obtain information in real time and thus be able to analyze the behavior of this, and to diagnose when the failure occurred. Now, using historical and real-time data analysis of predictive models, the failure can be predicted. Then, the established maintenance processes have to be obtained and analyzed to be able to define some rules of performance in case of predicting a failure.

These last two maintenance strategies provide the highest potential in current digitization trends. These approaches to maintenance are applicable to different sectors, given that great advantages can be appreciated, such as:

- Reduced production downtime
- Reduced breakdowns
- Cost savings
- Improved productivity
- Eliminate ambiguity in maintenance tasks

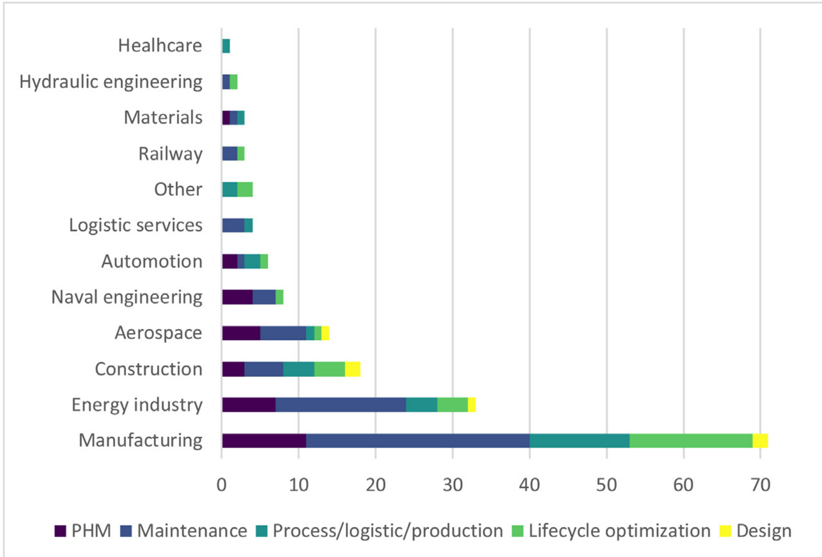


Fig. 5. Digital Twin in industrial sectors.

- Expended equipment life
- Improved customer service and reputation
- Reduced energy waste
- Improved facility security

4. Application of digital twins

For years, the different industries have adopted the paradigm of the DT, in order to reduce the risks identified in the assets and to improve traceability, maintenance and analytical improving its life cycle (Hlady et al., 2018). In fact, DT technology may come to play in several different aspects in the life of an asset (see in Fig. 4). DT can be related to an asset and its performance, or more complex systems like a production or a service where there are more than one component with different behavior (Shubenkova et al., 2018).

In Fig. 5, it can be seen that the manufacturing industry is the sector in which most research on the implementation of DTs is concentrated. Secondly, there are industries related to the extraction of gas and oil, management of wind turbines, industries usually with offshore infrastructure. And thirdly, of course, construction and aeronautics. It remains to be clarified that all case studies such as buildings and bridges fall into the construction category. As it can be seen, the three of them are industries that traditionally invest on R&D. In addition, there might be safety requirements on them that makes it necessary to incur in high costs for maintenance activity.

Although the search was carried out by including the concept of "Maintenance", when analyzing one by one all the results it has been detected that they might be focused in some similar but complementary applications (see Fig. 6). In fact, only 68 out of 167 are focused on the application of DTs in the different maintenance strategies already described, which will be analyzed more in detail in Section 5. Hence, it has been found of interest to perform another categorization of all the results within the following five groups:

- Design: results in which the application of DTs focuses on analyzing state failures so that, in a second interaction, the design of the asset can be improved.
- Process/logistic/production: all the results related to the use of the DT for the optimization of the process that is carried out or in cases of improvement of the logistics or improvement of the production, are in this category.

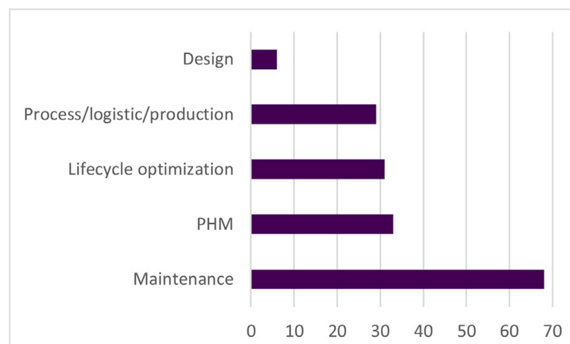


Fig. 6. Digital Twin applications.

- Prognostic Health Management (PHM): all the cases in which they focus on the prognosis of the state of the asset, are in this section.
- Maintenance: the analyzed cases that have relation with the improvement of the maintenance process, optimization of the proposed strategy, calculation of the costs and of course, with the prediction of the state of the component and the RUL to predict the maintenance, are in this category.
- Life cycle in general: the results that propose various uses of the DTs to improve different aspects, previously mentioned, during the entire life of an object, are in this category.

4.1. Design

Among the 167 results obtained, 6 are more focused on the design phase. As said in (Raman and Hassanaly, 2019), the use of simulations for design optimization is something that has been used until now. However, given its high computational cost, other data-oriented approaches or hybrid approaches have being selected lately. Same needs are highlighted in (Day et al., 2019; Yan et al., 2019) related to the construction sector.

In the manufacturing industry, the results in this field are focused more on the production lines. For example, in (Zhang et al., 2017; Garrido and Sáez, 2019; Martinelli et al., 2019) new methodologies using DTs for the design of production lines are described. Using approaches based on systems modeling based on physics and real-time process data, it achieves the capacity for analysis and assists in design decision making.

4.2. Process, logistic and production

Another possible application of the DTs is the optimization of processes, logistics or production. At first glance, it may seem that this type of application would only occur in the manufacturing industry, but this is not the case. Among the results of the search, articles have been found in the aeronautical sector, automotive, energy industry, naval, health and of course, manufacturing industry.

In most of the results obtained, the application focuses on the optimization of the production process or operation (van Kruijsdijk, 2018; Hatano, 2018; Landolfi et al., 2018; Peeters, 2018; Vachalek et al., 2017; Wantia and Roßmann, 2017; Yerra and Pilla, 2017; Cao, 2017). In these articles, the application of DTs focuses on optimizing the production process, improving line availability and optimizing operations (by detecting fluctuation in demand) to improve production throughput.

Among the results, some methodologies can be highlighted (Centomo et al., 2018; Kupetz et al., 2017; Zipper et al., 2018; Lin and Low, 2019; Zhang et al., 2019a; Szabo et al., 2019; Campos et al., 2019; Guerreiro et al., 2019; Laborie et al., 2019; Devold and Fjellheim, 2019; Schwingenschloegl, 2019; Boikov et al., 2019; Settemsdal, 2019a; Törmä et al., 2019; Weyer et al., 2019), where the form of integration of the sensorized part of the production line with the simulations of the line itself is defined. Another of the methodologies proposed in the search results is the one proposed in the article (Waschull et al., 2018), which attempts to improve the manufacturing process using DTs. There are other examples where the application of the DT is to improve the existing process as in (Antonino et al., 2019; Corneli et al., 2019; Gobeawan et al., 2019).

In (Tao and Zhang, 2017) different ways of creating a DT of the entire production plant itself are described.

4.3. Prognostic health management

The results within the category of Prognostic Health Management (PHM) are mostly found in the manufacturing sector, followed by the following sectors: Energy, Aerospace, and Automotive.

The manufacturing sector, together with materials, is the one that goes one step further and is committed to develop new methodologies. Starting from complex cases of forecasting such as the objects described in (Reifsnider and Majumdar, 2013), to more directed methodologies of forecasting with semantic models, such as the one described in (Riemer, 2018). The most recent article describes methodologies more oriented to the creation of DTs for the process of monitoring and diagnosis of the state (Olivotti et al., 2019; He et al., 2019).

The rest of the results provide a description of the different case studies, to predict the failures of different equipment's (Xu et al., 2019; Luo et al., 2019; Schirmann et al., 2018; Mars et al., 2018; Tao et al., 2018b; Zaccaria et al., 2018; Stojanovic et al., 2018). A clear example is that of (Mars et al., 2018) where advances in simulation-based fatigue prediction are applied to gain control over vehicle reliability. In (Tygesen et al., 2019) future directions are reviewed for predictive modelling.

The detection and identification of faults in the components are mandatory steps in this category. There are more different examples for the different sectors: Aerospace (Ezhilarasu et al., 2019; Chowdhury et al., 2019; Wantia and Roßmann, 2017), in manufacturing (Ghoshal et al., 2019; Qiao et al., 2019; Cattaneo and MacChi, 2019; Parri et al., 2019; Keserovic et al., 2019; Bellavista and Mora, 2019; Misrudin and Foong, 2019), Naval engineering (Johansen and Nejad, 2019; Bhalla et al., 2019; Osnabrugge and Van Den Berg, 2019), in energy industry (Oñederra et al., 2019; Settemsdal, 2019b; Nixon and Pena, 2019; Singh et al., 2019; Mnasri et al., 2019) and construction (Tahmasebinia et al., 2019; Andersen and Rex, 2019).

Sectors such as aeronautics, demand the reduction of the cost of maintenance and an increase on availability, for which this step is necessary (Zaccaria et al., 2018)

4.4. Maintenance

Finally, 68 out of 197 results are directly related to the application of maintenance strategies. As described in Section 3, there are several maintenance strategies, starting from the simplest process such as corrective maintenance to the most intelligent maintenance which is prescriptive. The use of DTs provides the possibility to switch to more advanced strategies such as the one mentioned above.

As mentioned before, in different sectors such as aeronautics, naval, or windfarm, given their rigorous environment and complex equipment, maintenance costs are very high (Tao et al., 2018b), which justifies the investment on creating DTs with the aim of optimizing maintenance activities. This is due sometimes to the difficulty in getting access to the physical asset (as in offshore platforms). In this scenario, the DT hosted in the cloud can be accessed from anywhere and thus can provide information on the status of this, such as data in the publication (Tang et al., 2018; Pivano et al., 2019; Liew et al., 2019).

In most of the results, DTs are used to predict the state of the asset, in order to consequently predict the corresponding maintenance plan: (Tjønn, 2019; Zenisek et al., 2019; Eckhart and Ekelhart, 2018; Boschert and Rosen, 2018; Dufour et al., 2018; Patnaik and Wu, 2018; Shubenkova et al., 2018; Moyne and Iskandar, 2017; Ocampo et al., 2017; Tuegel, 2012; Aivaliotis et al., 2019a). Prognosis is the main process of maintenance prediction. Therefore, in these case studies, part of the development presented would be based on PHM but with the objective of predicting maintenance activity. Therefore, apart from PHM, more analyses and processes are carried out. There are several examples from different sectors: in aerospace (Liu et al., 2019b), in automotion (Rajesh et al., 2019), in construction (Shim et al., 2019; Kaewunruen and Xu, 2018), in energy industry (Shokooh and Nordvik, 2019; Marwaha and Kohn, 2019; Botz et al., 2019; Burrafato et al., 2019; Gitelman et al., 2019; Settemsdal, 2019c; Joy and Smith, 2019), in hydraulic engineering (Bhowmik, 2019), in logistics (Szpytko and Duarte, 2019), in manufacturing (Aivaliotis et al., 2019b; Altun and Tavli, 2019; Barthelmey et al., 2019; Lermer and Reich, 2019; Ladwig et al., 2019; Short and Twiddle, 2019; Khalil et al., 2019; Ding et al., 2019; Aivaliotis et al., 2019c; Tugengol'd et al., 2019; Cho et al., 2019; Cahyati et al., 2019; Werner et al., 2019) and naval engineering (Fotland et al., 2020; Coraddu et al., 2019)

Some additional references include the use of technologies such as Augmented reality (AR) in order to show future failures in components to determine maintenance (Rabah et al. (2018); Sivalingam et al. (2018); Luo et al. (2018); Strohmeier et al., 2018; Utzig et al., 2019; Yashin et al., 2019).

DT has also application in preventive strategies, where they are used for the prediction of the state of the asset to reduce the number of preventive maintenance activities and remove unnecessary maintenance activities, providing longer time intervals between them (Longo et al., 2019; Lammer and Lanzenberger, 2018; Tang et al., 2018; Vatn, 2018; Vathoopan et al., 2018; Myers, 2017; Boutrot et al., 2017; Felsberger et al., 2019; Kim, 2019). There are also more general approaches: a methodology to improve the maintenance plan can be found in (Hlady et al., 2018), and how to get a good production is detailed in (Liu et al., 2018).

In some other cases, DTs are only used to help the operator to perform the specific maintenance task (Pairet et al., 2019; Rødseth

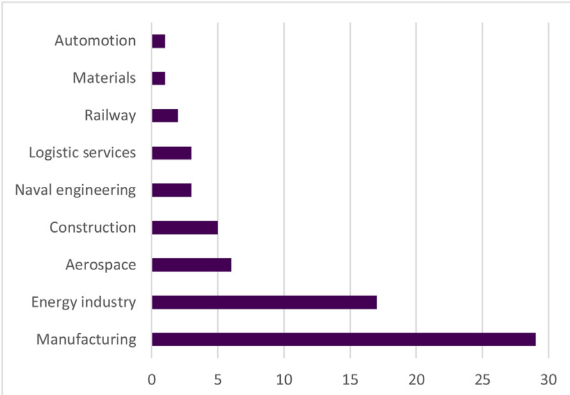


Fig. 7. Maintenance application of Digital twin on sectors.

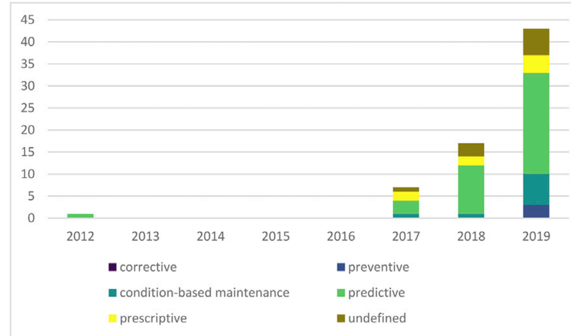


Fig. 8. Maintenance strategies evolution.

et al., 2019; Longo et al., 2019; Venables, 2017; Omer et al., 2019; Anderson et al., 2019). Others do not even predict failure, but they detect and diagnose the fault that has occurred and hence the subsequent maintenance activity can be more directed (Barbosa et al., 2018).

Finally, DTs have been also found useful for cost-related applications (Kraft and Kuntzagk, 2017; Harvey, 2017). In (Kaewunruen and Xu, 2018) DTs are used specifically to calculate the cost of the maintenance activity.

4.5. Life cycle in general

This category gathers those results that do not fit in previous categories, as their scope is more general. These papers describe the different options for improvement that are enabled by the application of DTs in all the categories mentioned above.

Some publications perform a literature review (Mabkhot et al., 2018; Qi and Tao, 2018; Kritzinger et al., 2018; La Grange, 2018; Cimino et al., 2019; Cohen et al., 2019a; Cohen et al., 2019b; Oliveira and Afonso, 2019; Khajavi et al., 2019; Zhang et al., 2019b; Novack, 2019). They describe the different improvements that the application of DTs has in any of the final objectives mentioned in the different sections.

The rest of the publications that fit in this category describe the optimization of the life cycle management of different types of applications (Kaewunruen and Lian, 2019; Schueller et al., 2019; Shi et al., 2019; Madni et al., 2019; Gockel et al., 2012; Boschert and Rosen, 2016; Love and Matthews, 2019; Talkhestani et al., 2019; Borth et al., 2019; Zhu et al., 2019; Tchana et al., 2019; LaGrange, 2019; Mondoro and Grisso, 2019; Mudassar et al., 2019; Grosse, 2019; Hiraoka et al., 2019).

There are other proposals for new methodologies (Zhang et al., 2019c) of DTs and for risk control (Lehmann and Jones, 2019; Baskaran et al., 2019).

5. Digital twins for maintenance

This section provides a comprehensive analysis of the sectors and trends over time of the results focused on the application of DTs in maintenance. From the initial 167 collected results, 68 articles are included in the analysis of this section.

Fig. 7 shows the sectors where DTs are being applied in maintenance: manufacturing, energy industry and aerospace are the top three sectors.

In addition, the results have been categorized within the different maintenance strategies that were introduced in Section 3: reactive, preventive, condition-based, predictive or prescriptive. If the integration levels of DTs presented in Section 2 are taken into account, the reactive and preventive maintenance strategies are using a digital model, given that the flow of data on both cases is manual. In condition-based and predictive maintenance strategies, digital shadow integration is present, given that the digital model automatically obtains information on the state of the physical asset.

Finally, the integration level defined as DT is used on prescriptive maintenance strategies, where the final step of proposing a maintenance action is provided.

Tables 1 and 2show the details of the 68 results focused on maintenance optimization. Regarding the maintenance strategy, predictive maintenance is the one used most. Predictive maintenance is corrective maintenance planned for convenience, taking primarily into account the performance of this (Vathoopan et al., 2018). For those results where the strategy is not clearly stated, the category is filled in as Ündefined. The details of the evolution of publications from the strategies point of view is detailed in Fig. 8. It can be seen that research areas where DT can be used is mainly oriented to predictive and prescriptive maintenance strategies. It is also remarkable that although the first publication in this topic was published in 2012, no activity has been detected between 2013 and 2016.

If the analysis is more focused towards the sectors, similar conclusions might be drawn (see Fig. 9). Predictive maintenance strategy is the dominant in the top three sectors (manufacturing, energy industry and aerospace), and additionally prescriptive maintenance examples based on DT can only be found in manufacturing and energy industry.

6. Open issues and future perspectives

Throughout the manuscript it has been observed that the terms Ďigital Twinänd Ňaintenanceȟave aroused the interest of researchers in recent years. The year 2018 shows a considerable increase in the number of publications. In the case of journal publications, the number of publications in 2019 has exceeded the number of publications in the previous year.

Tables 1 and 2, show that most publications are congress and conference articles. As mainly preliminary results are being published, it can be said that there is still plenty of work to be carried out. This paper identifies the benefits of applying DTs, the gaps between existing work and the expected future, and the issues to achieve this in the future.

During the analysis carried out, examples of the use of DT in all industrial sectors were found. Although the term sought was Ňaintenance, examples of other applications such as Design, Process/logistic/production, Prognostic Health management (PHM) or Life cycle in general have also been observed. Clearly, the most common application was maintenance. The sectors that most apply DTs for maintenance are manufacturing, the energy industry (wind turbines, oil, solar panels ...), construction and the aeronautics

Table 1
Categorical review of maintenance case studies (part I).

	Ref.	Doc. Type	Industry	Maintenance
1	(Yashin et al., 2019)	Conference	Construction	Condition-based
2	(Fotland et al., 2020)	Article	Naval engineering	predictive
3	(Aivaliotis et al., 2019b)	Article	Manufacturing	Predictive
4	(Altun and Tavli, 2019)	Conference	Manufacturing	Predictive
5	(Felsberger et al., 2019)	Conference	Manufacturing	Preventive
6	(Shim et al., 2019)	Article	Construction	Predictive
7	(Omer et al., 2019)	Article	Construction	Condition-based
8	(Barthelmey et al., 2019)	Conference	Manufacturing	Predictive
9	(Lermer and Reich, 2019)	Conference	Manufacturing	Predictive
10	(Ladwig et al., 2019)	Conference	Manufacturing	Undefined
11	(Short and Twiddle, 2019)	Article	Manufacturing	Predictive
12	(Coraddu et al., 2019)	Article	Naval engineering	Condition-based
13	(Khalil et al., 2019)	Conference	Manufacturing	Predictive
14	(Prajapat et al., 2019)	Conference	Manufacturing	Undefined
15	(Ding et al., 2019)	Article	Manufacturing	Predictive
16	(Aivaliotis et al., 2019c)	Conference	Manufacturing	Predictive
17	(Tugengol'd et al., 2019)	Article	Manufacturing	Prescriptive
18	(Shokooh and Nordvik, 2019)	Conference	Energy industry	Predictive
19	(Cho et al., 2019)	Conference	Manufacturing	Predictive
20	(Cahyati et al., 2019)	Article	Manufacturing	Undefined
21	(Utzig et al., 2019)	Conference	aerospace	Undefined
22	(Werner et al., 2019)	Conference	Manufacturing	Prescriptive
23	(Liu et al., 2019b)	Article	Aerospace	Predictive
24	(Szpytko and Duarte, 2019)	Article	Logistic	Predictive
25	(Bhowmik, 2019)	Conference	Hydraulic	Predictive
26	(Marwaha and Kohn, 2019)	Conference	Energy industry	Predictive
27	(Botz et al., 2019)	Conference	Energy industry	Undefined
28	(Pivano et al., 2019)	Conference	Naval engineering	Predictive
29	(Burrafato et al., 2019)	Conference	Energy industry	Condition-based
30	(Nikolaev et al., 2019)	Conference	Energy industry	Prescriptive
31	(Gitelman et al., 2019)	Article	Energy industry	Condition-based
32	(Settemsdal, 2019c)	Conference	Energy industry	Predictive
33	(Kim, 2019)	Conference	Logistic	Preventive
34	(Joy and Smith, 2019)	Conference	Energy industry	Predictive
35	(Anderson et al., 2019)	Conference	Manufacturing	Condition-based

Table 2
Categorical review of maintenance case studies (part II).

	Ref.	Type	Industry	Maintenance
36	(Liew et al., 2019)	Article	Construction	Condition-based
37	(Rajesh et al., 2019)	Conference	Automotion	Predictive
38	(Aivaliotis et al., 2019a)	Conference	Manufacturing	Predictive
39	(Pairet et al., 2019)	Conference	Energy industry	Preventive
40	(Tjønn, 2019)	Conference	Energy industry	Predictive
41	(Zenisek et al., 2019)	Conference	Manufacturing	Predictive
42	(Rødseth et al., 2019)	Conference	Manufacturing	Undefined
43	(Longo et al., 2019)	Article	Manufacturing	Prescriptive
44	(Sivalingam et al., 2018)	Conference	Energy industry	Predictive
45	(Eckhart and Ekelhart, 2018)	Conference	Manufacturing	Undefined
46	(Lammer and Lanzenberger, 2018)	Conference	Manufacturing	Prescriptive
47	(Hlady et al., 2018)	Conference	Energy industry	Undefined
48	(Tang et al., 2018)	Conference	Energy industry	Predictive
49	(Kaewunruen and Xu, 2018)	Article	Construction	Predictive
50	(Luo et al., 2018)	Conference	Manufacturing	Prescriptive
51	(Boschert and Rosen, 2018)	Article	Railway	Predictive
52	(Dufour et al., 2018)	Conference	Naval engineering	Undefined
53	(Strohmeier et al., 2018)	Article	Manufacturing	Predictive
54	(Vatn, 2018)	Conference	Railway	Predictive
55	(Patnaik and Wu, 2018)	Conference	Materials	Predictive
56	(Vathoopan et al., 2018)	Article	Manufacturing	Predictive
57	(Shubenkova et al., 2018)	Conference	Logistic Services	Predictive
58	(Liu et al., 2018)	Conference	Aerospace	Predictive
59	(Rabah et al., 2018)	Conference	Manufacturing	Predictive
60	(Barbosa et al., 2018)	Conference	Manufacturing	Condition-based
61	(Moyne and Iskandar, 2017)	Article	Manufacturing	Predictive
62	(Myers, 2017)	Article	Energy industry	Prescriptive
63	(Kraft and Kuntzagk, 2017)	Conference	Aerospace	Predictive
64	(Venables, 2017)	Article	Manufacturing	Condition-based
65	(Ocampo et al., 2017)	Conference	Aerospace	Undefined
66	(Boutrot et al., 2017)	Conference	Energy industry	Prescriptive
67	(Harvey, 2017)	Business	Energy industry	Predictive
68	(Tuegel, 2012)	Conference	Aerospace	Predictive

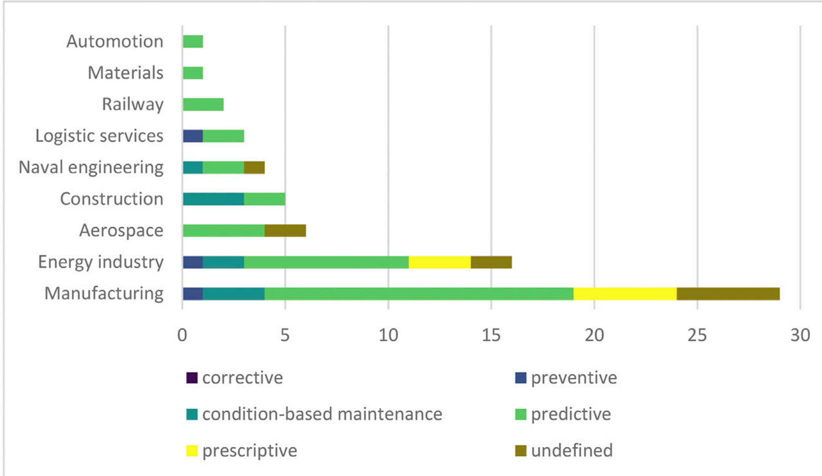


Fig. 9. Maintenance strategies per sector.

industry. On the other hand, in sectors such as health, hydraulics, or materials, interesting examples can also be found, although not as often. The creation of a DT can be costly. Therefore, in most cases, its application is because the maintenance of the asset itself is very expensive. In this way, a DT brings efficiency to maintenance strategies.

DTs are not used in reactive maintenance strategies. This type of strategy consists of repairing the asset once it has already broken down. In this case, DTs could be used to determine the cause of the breakage by means of models. However, in reality, once DTs are applied, another type of strategy is chosen.

In any of the abovementioned sectors, it has been observed that DTs are used for the improvement of different proactive maintenance strategies. Starting with preventive maintenance, the application of DT can help improving the preventive maintenance plan established in the company. Until now, preventive maintenance plans have been developed with the years of experience of the people in charge of maintenance or the manufacturer of the asset. Most companies often carry out an abusive preventive maintenance, also called over-maintenance, for the sake of security, safety or productivity. In this scenario, DTs could be applied in order to design a more effective preventive maintenance plan. However, it is also important to highlight that the accuracy of the DT is highly relevant, as it might be the only criteria for establishing the periodicity of the maintenance activities and the application of non-validated DTs could be generate undesired results. Moreover, regulatory and legislation obligations may be applied, mainly in critical assets and services.

For a maintenance strategy that follows a CBM strategy, the results obtained by sensors help improving the decision making. DTs bring an integrated communication from the physical asset to the virtual model through a complete sensorization. The integration of the data coming from sensors as input information to the physical/statistical/analytical models, results in the knowledge of the need for maintenance. In this way, more complex or costly parameters can be obtained from the physical asset, which better represent the condition of the asset.

From the point of view of one of the most studied strategies in the works analyzed here, predictive maintenance, the use of DTs is essential. DT can incorporate predictive models that evaluate the current state and after, analyze its behavior and predict the degradation of the component. This prediction improves when the DT includes more information about physical characteristics, characteristics of the process being carried out or characteristics of the operation. It must be highlighted that for the generation of predictive models it is necessary to have historical data for their calibration and validation. In the case that the model includes the information of how the asset improves after the maintenance activities, this information would also be necessary for the validation of the models. This historical data can be real, or it can be generated in a synthetic way.

Finally, for prescriptive maintenance the use of DTs is essential; however, in this case, it is complemented with information on maintenance processes and optimization models. By allowing this information to interact with the information from the sensory part and the predictive model part, it allows the DT to be part of a recommendation system, where it describes the activity and the process to be carried out by the maintainer.

After having analyzed the benefits of DT for maintenance for the different strategies, it can be stated that the future expected is related to the application of prescriptive strategies, where the integration of DT will be mandatory. However, it is not realistic to move directly from corrective strategies to prescriptive strategies, so the progress in the strategies and hence, in the application of DTs, will be necessarily gradual.

There might be some limitations in this evolution to the future. Prescriptive strategies only make sense in critical assets' maintenance. If the asset is non-critical and does not interfere in the production/service nor the safety of humans, it is still reasonable that the most efficient maintenance strategy is to repair the asset when it breaks. It might be the most simple and cost-effective solution.

For those assets that are critical, or when the application of DTs would have a great impact, some barriers may exist for the future evolution of the maintenance strategies. First, there might be regulatory issues that make maintainers follow strict preventive activities, although they might be over-maintained. There might be also human barriers. The reluctance to new changes may see new strategies as interferences on the traditional way of performing maintenance. In this sense, the demonstration by the scientific community of the benefits of the new technologies, the integration of these advances by technological solution providers and the open-minded board of directors that support the changes, will be the key for the success of prescriptive strategies in the future.

The remaining outstanding issues focus more on maintenance activities, and more specifically on the need to define the maintenance process in detail (Barbosa et al., 2018). The correct classification of activities is essential to strengthen a decision-making system.

Several scientific challenges are identified so that basic maintenance strategies could evolve to prescriptive maintenance strategies. One of the most repeated open issues is the importance of having an improvement in data availability. The need arises when integrating information from different sources such as asset information, operational information, historical maintenance activity and historical assets evolution information. This requires Big Data platforms that enable scalability and ubiquity. Most of them insist on the importance of optimizing the use of the data in order to improve the data fusion and consequently get an improvement on the models. Some authors even highlight the need to include Cybersecurity aspects and mention Blockchain technology as an option for improving security (Longo et al., 2019).There are technological gaps to be carried out. They are related to the generation or application of DTs in the different maintenance strategies. In preventive strategies, DTs might be used when designing the preventive scheduling plans. To move from this strategy to the CBM, the assets need to be monitored in real time, and DTs can help providing additional features describing the health of the asset in that moment. In this case, DT should be usable in near real-time. In order to move to a predictive strategy, the asset monitoring needs also to be integrated with DTs. In addition, DTs need to be able to predict the evolution of the degradation based on the operational information that affects to the degradation. At this stage, the need of data from different sources is evident, not only in relation to the asset itself, but also to the operation where it is involved. Unfortunately, data silos exist and efforts in collecting and integrating all the information in data warehouses are yet missing.

The unavailability of the required data may be due to several reasons. One of the causes is that it does not exist, for which different alternatives are proposed to mitigate the consequences. For example, one option is applying asset-monitoring systems with technologies such as IoT/IIoT. In some sectors, the need of integrating sensors in the components is demanded in order to be able to choose predictive models in real-time or to define methodologies that provide an alternative to the absence of these (Kraft and Kuntzagk, 2017).

Another proposal made to avoid the unavailability of data is the use of FEM (Finite element method) and BIM (Building information modeling) as a source of data. Historically, this type of technology is used in the design part. However, the possibility of using these technologies for maintenance proposes a challenge for experts. In these cases, the use of computationally efficient methods such as ROM (reduced order models) can be a key factor for the real-time implementation of DTs.

Another way to counteract the unavailability of data is to generate synthetic data through simulation. However, this type of strategy raises other problems, such as the need to establish a good methodology for defining the scenarios to be simulated (Animah and Shafiee, 2018).

Another challenge to overcome is assuring the quality of the collected data. Algorithms can be used to improve data quality by checking data integrity. In some sectors, errors in data collection might be due to monitoring systems themselves. In other occasions, if the infrastructure to be monitored is large and continuous (roads, rails...), there may be cases of misaligned data, as the position related to monitored data may accumulate incremental errors. Again, algorithms for data preprocessing will be of high interest to enhance the quality of the monitored data.

Finally, implementing prescriptive strategies should include the following tasks: a) risk analysis, which take into account the risk the maintainer is ready to admit related to the current state of the asset. b) Cost analysis, which involve a maintenance execution cost, a service unavailability penalization cost and an asset life-cycle. Moreover c) making optimized decisions for the maintenance of the assets, by taking into account holistic cost analysis.

To carry out this type of analysis there are several steps to be carried out. It starts with the analysis of the asset's life cycle. It must also be made of the calculation of the moment in which it is more cost-effective to replace the asset than keeping maintaining it. The need of correctly calculating the impact that maintenance activities have on the asset analyzed is also highlighted (Patnaik and Wu, 2018), so that it can consequently improve the optimization of these activities and correctly calculate the cost of maintenance actions (Tao et al., 2018b).

Another point to address is the possible cost due to unavailability of service/process operation. Penalizing the unavailability of the service is very common in transport sectors, for example, and it is immediate in manufacturing processes as the production is stopped. Finally, a risk analysis should be carried out. The goal of the different sectors would be to keep their assets in operation and be economically sustainable without taking risks (or at least assuming controlled risks).

To sum up, in order to make potential users aware of the benefits of implementing DTs, gradual incremental deployment is fundamental, together with the evolution of the maintenance strategy. When moving forward towards the generation of more complex and intelligent DTs, the integration of different advanced technologies will be necessary, including IoT/IIoT, data processing algorithms for enhancing data quality, complementary reliable alternatives to overcome data gaps (e.g. simulation processes), data warehouses, reduced data models, remote communications and cybersecurity. As additional help in the generation of DT's, the definition of methodologies for the different cases of the different sectors will also benefit the implementation of DTs in a more agile way (Aivaliotis et al., 2019c).

7. Conclusions

The work carried out consisted of performing a combined concurrent search of “Digital Twin” and “Maintenance” terms in order to analyze the outcomes, understand the relationship between both terms and provide a deeper insight of the synergies between both concepts.

As conclusion, it is indisputable that DT and maintenance are two concepts on which the world of research has been focusing in recent years. The number of 2018 results exceeds by far the number of 2017 results. Both conference articles and journal articles have grown considerably. Considering the number of results obtained in 2019, it can be seen that the number of works related to the concepts has grown exponentially.

Focusing the analysis on the industrial sectors confirms that those who invest the most in this research can obtain clear benefits. The sectors that are betting for it are the sectors where higher costs are assumed in the maintenance. This might be motivated by different reasons: high costs of the activity itself, safety aspects related to the operators performing the maintenance activities (which needs to provide costly mitigation approaches to minimize the risk) and/or unavailability of components (which may cause service unavailability costs).

The literature review shows that although the search has been oriented to the maintenance, some other applications also arise, such as Design, Process/logistic/production, PHM or Life cycle in general. However, all of these publications do mention the benefits that could be obtained in the maintenance or the direct repercussion they have in maintenance.

Related to maintenance strategies, the top three sectors (manufacturing, energy and aeronautic industries) opt for a more intelligent strategy in the last two years. They are investing their efforts in prediction and even in going for prescriptive maintenance. They opt for complete integration, where all interactions between the physical and digital object are automated.

To conclude, in order to perform advances in maintenance strategies from prediction to prescription, there are two big research areas to be resolved. First of all, lack of data availability needs to be solved by means of IoT/IIoT technologies and model integration as enablers, also for enhancing data quality. Second, the need to ensure a well-detailed maintenance procedure is the key to move forward that direction. Thanks to progresses in the calculation of the maintenance impact and a well-defined process, the optimization of activities would be more reliable and thus, a stable and reliable recommendation system would be obtained.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was supported by the "Ayudas Cervera para Centros Tecnológicos 2019Ërogramme of CDTI (Centre for the Development of Industrial Technology) under the Ministry of Science and Innovation, within the research project MIRAGED (CER-20190001).

References

Aivaliotis, P., Georgoulias, K., Arkouli, Z., Makris, S., 2019a]. Methodology for enabling digital twin using advanced physics-based modelling in predictive maintenance. Procedia CIRP 81, 417–422.
Aivaliotis, P., Georgoulias, K., Chryssolouris, G., 2019b. The use of Digital Twin for predictive maintenance in manufacturing. Int. J. Comput. Integr. Manuf. 32 (11), 1067–1080.
Aivaliotis, P., Georgoulias, K., Alexopoulos, K., 2019c]. Using digital twin for maintenance applications in manufacturing: State of the art and gap analysis. 2019 IEEE international conference on engineering, technology and innovation (ICE/ITMC).
Altun, C., Tavli, B., 2019]. Social internet of digital twins via distributed ledger technologies: application of predictive maintenance. TELFOR In: 27th Telecommunications Forum, 2019.
Andersen, J.E., Rex, S., 2019]. Structural health monitoring of henry Hudson I89. In: 20th Congress of IABSE, New York City 2019, The Evolving Metropolis - Report.
Anderson, S., Barvik, S., Rabitoy, C., 2019. Innovative digital inspection methods. Proceedings of the Annual Offshore Technology Conference, 2019, May.
Animah, I., Shafiee, M., 2018]. Condition assessment, remaining useful life prediction and life extension decision making for offshore oil and gas assets. J. Loss Prev. Process Ind. 53 (May), 17–28.
Ansari, F., Glawar, R., Nemeth, T., 2019. PriMa: a prescriptive maintenance model for cyber-physical production systems. Int. J. Comput. Integr. Manuf. 32 (May 4–5), 482–503.
Antonino, M., Nicola, M., Claudio, D.M., Luciano, B., Fulvio, R.C., 2019. Office building occupancy monitoring through image recognition sensors. Int. J. Saf. Secur. Eng.
Autiosalo, J., Vepsalainen, J., Viitala, R., Tammi, K., 2020]. A feature-based framework for structuring industrial digital twins. IEEE Access 8, 1193–1208.
Barbosa, A.S., Silva, F.P., Crestani, L.R.S., Otto, R.B., 2018]. Virtual assistant to real time training on industrial environment. Adv. Trans. Discip. Eng. 7, 33–42.
Barthelmey, A., Lee, E., Hana, R., Deuse, J., 2019. Dynamic digital twin for predictive maintenance in flexible production systems. IECON Proceedings (Industrial Electronics Conference).
Bashiri, M., Badri, H., Hejazi, T.H., 2011]. Selecting optimum maintenance strategy by fuzzy interactive linear assignment method. Appl. Math. Model. 35 (January 1), 152–164.
Baskaran, V., Singh, S., Reddy, V., Mohandas, S., 2019]. Digital assurance for oil and gas 4.0: role, implementation and case studies. APOG In: Society of Petroleum Engineers - SPE/IATMI Asia Pacific Oil and Gas Conference and Exhibition 2019, 2019.
Bellavista, P., Mora, A., 2019]. Edge cloud as an enabler for distributed AI in industrial IoT applications: the experience of the iotwins project. CEUR Workshop Proceedings.
Bhalla, K., Fisher, K.J., Waligura, J.E., 2019. Digital initiatives for condition based maintenance using monitoring solutions with data analytics. OE In: Society of Petroleum Engineers - SPE Offshore Europe Conference and Exhibition 2019, 2019.
Bhowmik, S., 2019]. Digital twin of subsea pipelines: conceptual design integrating IoT, machine learning and data analytics. Proceedings of the Annual Offshore Technology Conference.
Boikov, A.V., Savelev, R.V., Payor, V.A., Erokhina, O.O., 2019. The control method concept of the bulk material behavior in the pelletizing drum for improving the results of DEM-modeling. CIS Iron Steel Rev.
Boje, C., Guerriero, A., Kubicki, S., Rezgui, Y., 2020]. Towards a semantic construction digital twin: directions for future research. Automation in Construction, 114. Elsevier B.V., pp. 103179, 01-Jun-.
Booyse, W., Wilke, D.N., Heyns, S., 2020. Deep digital twins for detection, diagnostics and prognostics. Mech. Syst. Signal Process 140, 106612, June.
Borth, M., Verriet, J., Muller, G., 2019. Digital twin strategies for SoS: 4 challenges and 4 architecture setups for digital twins of SoS. SoSE In: 2019 14th Annual Conference System of Systems Engineering, 2019.
Boschert, S., Rosen, R., 2016]. Digital twin—the simulation aspect. In: Mechatronic Futures. Springer International Publishing, Cham, pp. 59–74.
Boschert, S., Rosen, R., 2018]. Digital Twin: a Second Life for Engineering Models. ERCIM NEWS, 115, pp. 8–9, Oct.
Botz, M., Raith, M., Emiroglu, A., Wondra, B., Grosse, C.U., 2019]. Structural health monitoring as a tool for smart maintenance of wind turbines. Advances in Engineering Materials, Structures and Systems: Innovations, Mechanics and Applications - Proceedings of the 7th International Conference on Structural Engineering, Mechanics and Computation, 2019.
Boutrot, J., Giorgiutti, Y., Rezende, F., Barras, S., 2017]. Reliable and accurate determination of life extension for offshore units. 22nd Offshore Symposium 2017 - Redefining Offshore Development: Technologies and Solutions, 282–295.
Burrafato, S., Maliardi, A., Ferrara, P., Grasso, T., De Marchi, E., Campaci, R., 2019. Virtual reality in D&C: New approaches towards well digital twins. OMC In: Offshore Mediterranean Conference and Exhibition 2019, 2019.
Cahyati, S., Syaifudin, Achdianto, 2019]. A prototyping of additive manufacturing cell in cyber physical system for maintenance 4.0 preparation. Int. J. Adv. Sci. Technol.
Campos, J.G., López, J.S., Quiroga, J.I.A., Seoane, A.M.E., 2019. Automatic generation of digital twin industrial system from a high level specification. Procedia Manufacturing.
Cao, J., 2017]. Research on operation and maintenance management of equipment under intelligent manufacturing. Proceedings - 2017 Chinese Automation Congress, CAC 2017, 2017., pp. 5188–5191, Janua.
Cattaneo, L., MacChi, M., 2019]. A digital twin proof of concept to support machine prognostics with low availability of run-to-failure data. IFAC-PapersOnLine.
Centomo, S., Panato, M., Fummi, F., 2018]. Cyber-physical systems integration in a production line simulator. 2018 IFIP/IEEE International Conference on Very Large Scale Integration (VLSI-SoC), 237–242.
Cho, S., May, G., Kiritsis, D., 2019]. A semantic-driven approach for industry 4.0. DCOSS In: Proceedings - 15th Annual International Conference on Distributed Computing in Sensor Systems, 2019.
Chowdhury, S.H., Ali, F., Jennions, I.K., 2019. A methodology for the experimental validation of an aircraft ecs digital twin targeting system level diagnostics. Proceedings of the Annual Conference of the Prognostics and Health Management Society, PHM.
Cimino, C., Negri, E., Fumagalli, L., 2019]. Review of digital twin applications in manufacturing. Comput. Ind.
Cohen, Y., Faccio, M., Pilati, F., Yao, X., 2019a]. Design and management of digital manufacturing and assembly systems in the Industry 4.0 era. Int. J. Adv. Manuf. Technol.
Cohen, Y., Naseraldin, H., Chaudhuri, A., Pilati, F., 2019b]. Assembly systems in Industry 4.0 era: a road map to understand Assembly 4.0. Int. J. Adv. Manuf. Technol. 105 (December 9), 4037–4054, SI.
Consilvio, A., et al., 2019]. Prescriptive maintenance of railway infrastructure: from data analytics to decision support. MT-ITS 2019 - 6th International Conference on Models and Technologies for Intelligent Transportation Systems.
Coraddu, A., Oneto, L., Baldi, F., Cipollini, F., Atlar, M., Savio, S., 2019. Data-driven ship digital twin for estimating the speed loss caused by the marine fouling. Ocean Eng.
Corneli, A., Naticchia, B., Carbonari, A., Bosché, F., 2019. Augmented reality and deep learning towards the management of secondary building assets. ISARC In: Proceedings of the 36th International Symposium on Automation and Robotics in Construction, 2019.
Day, G., Gasparri, E., Aitchison, M., 2019]. Knowledge-based design in industrialised house building: a case-study for prefabricated timber walls. Lect. Notes Civ. Eng. 24, 989–1016.
Devold, H., Fjellheim, R., 2019]. Artificial intelligence in autonomous operation of oil and gas facilities. ADIP In: Society of Petroleum Engineers - Abu Dhabi International Petroleum Exhibition and Conference 2019, 2019.
Ding, H., Yang, L., Yang, Z., 2019]. A predictive maintenance method for shearer key parts based on qualitative and quantitative analysis of monitoring data. IEEE Access 7 (August), 108684–108702.
Dufour, C., Soghomonian, Z., Li, W., 2018]. Hardware-in-the-loop testing of modern on-board power systems using digital twins. In: SPEEDAM 2018 - Proc. Int. Symp. Power Electron. Electr. Drives, Autom. Motion, pp. 118–123.
Eckhart, M., Ekelhart, A., 2018]. A specification-based State replication approach for digital twins. Proceedings of the 2018 Workshop on Cyber-Physical Systems Security and PrivaCy - CPS-SPC' 18, 36–47.
Ezhilarasu, C.M., Skaf, Z., Jennions, I.K., 2019]. Understanding the role of a digital twin in integrated vehicle health management (IVHM). Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics.
Fang, X., Gebraeel, N.Z., Paynabar, K., 2017]. Scalable prognostic models for large-scale condition monitoring applications. IISE Trans. 49 (July 7), 698–710.

Felsberger, L., Todd, B., Kranzlmuller, D., 2019]. Power converter maintenance optimization using a model-based digital reliability twin paradigm. ICSRS In: 2019 4th International Conference on System Reliability and Safety, 2019, pp. 213–217.

Fotland, G., Haskins, C., Rølvåg, T., 2020. Trade study to select best alternative for cable and pulley simulation for cranes on offshore vessels. Syst. Eng. 23 (March 2), 177–188.

Gallimore, K.F., Penlesky, R.J., 1988]. Framework for developing maintenance strategies. Prod. Invent. Manag. J. 29 (1), 16–22.

Garrido, J., Sáez, J., 2019. Integration of Automatic Generated Simulation Models, Machine Control Projects and Management Tools to Support Whole Life Cycle of Industrial Digital Twins. IFAC-PapersOnLine.

Ghoshal, S., Deb, S., Haste, D., Hess, A., Zahiri, F., Sutton, G., 2019. An integrated model-based approach for fmeca development for smart manufacturing applications. Proceedings of the Annual Conference of the Prognostics and Health Management Society, PHM.

Gitelman, L.D., Kozhevnikov, M.V., Kaplin, D.D., 2019]. Asset management in grid companies using integrated diagnostic devices. Int. J. Energy Prod. Manag.

Glaessgen, E., Stargel, D., 2012]. The digital twin paradigm for future NASA and U.S. air force vehicles. 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference&BR&20th AIAA/ASME/AHS Adaptive Structures Conference&BR&14th AIAA.

Gobeawan, L., et al., 2019]. Convenient tree species modeling for virtual cities. LNCS In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 11542, pp. 304–315.

Gockel, B.T., Tudor, A.W., Brandyberry, M.D., Penmetsa, R.C., Tuegel, E.J., 2012. Challenges with structural life forecasting using realistic mission profiles. Collection of Technical Papers - AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference.

Grieves, M., Vickers, J., 2017]. Digital twin: mitigating unpredictable, undesirable emergent behavior in complex systems. In: Transdisciplinary Perspectives on Complex Systems. Springer International Publishing, Cham, pp. 85–113.

Grosse, C.U., 2019]. Monitoring and inspection techniques supporting a digital twin concept in civil engineering. Sustain. Construct. Mater. and Technol.

Guerreiro, G., et al., 2019. A digital twin for intra-logistics process planning for the automotive sector supported by big data analytics. ASME International Mechanical Engineering Congress and Exposition, Proceedings (IMECE).

Harvey, A.L., 2017]. Solar power's golden opportunity: connected tech. Power 161 (12).

Hatano, K., 2018]. Fog in the smart factory: optimizing production for perishable goods manufacturing. Cut. Bus. Technol. J. 31 (6), 11–16.

He, R., Chen, G., Dong, C., Sun, S., Shen, X., 2019]. Data-driven digital twin technology for optimized control in process systems. ISA Trans. (May).

Hiraoka, H., Nagahata, T., Saito, H., Tanigawa, T., 2019]. Estimation of prospective states of mechanical parts for lifecycle support by part agents. IFIP Adv. Inf. Commun. Technol.

Hlady, J., Glanzer, M., Fugate, L., 2018]. Automated creation of the pipeline digital twin during construction - improvement to construction quality and pipeline integrity. Proceedings of the Biennial International Pipeline Conference, IPC, 2.

Johansen, S.S., Nejad, A.R., 2019]. On digital twin condition monitoring approach for drivetrains in marine applications. Proceedings of the International Conference on Offshore Mechanics and Arctic Engineering - OMAE, 10.

Joy, D., Smith, D., 2019]. Processing asset data at the intelligent edge: implementation of an industrial IoT architecture to drive business value. Proceedings - SPE Annual Technical Conference and Exhibition.

Kaewunruen, S., Lian, Q., 2019. Digital twin aided sustainability-based lifecycle management for railway turnout systems. J. Clean. Prod. 228 (August), 1537–1551.

Kaewunruen, S., Xu, N., 2018]. Digital twin for sustainability evaluation of railway station buildings. Front. Built Environ. 4 (December), 77.

Keserovic, A., Fosselie, T., Lilleengen, J.I., Wiggen, F., Sivertsen, K., Eriksson, K.E., 2019]. From joint industry project to digital business - the CuI risk manager. NACE - Int. Corros. Conf. Ser. 2019, March.

Khajavi, S.H., Motlagh, N.H., Jaribion, A., Werner, L.C., Holmstrom, J., 2019]. Digital Twin: vision, benefits, boundaries, and creation for buildings. IEEE Access.

Khalil, M., Bergs, C., Papadopoulos, T., Wuchner, R., Bletzinger, K.-U., Heizmann, M., 2019]. IIoT-based fatigue life indication using augmented reality. IEEE International Conference on Industrial Informatics (INDIN).

Kim, H.W., 2019]. Study on virtual crane simulation for monitoring and prevent maintenance of launching and recovery system. Proceedings of the World Congress on Mechanical, Chemical, and Material Engineering.

Kraft, J., Kuntzagk, S., 2017]. Engine fleet-management - the use of digital twins from a mro perspective. Proceedings of the ASME Turbo Expo 1.

Kritzinger, W., Karner, M., Traar, G., Henjes, J., Sihn, W., 2018]. Digital Twin in manufacturing: a categorical literature review and classification. IFAC- PapersOnLine 51 (11), 1016–1022.

Kupetz, A., Schluse, M., Rossmann, J., 2017. Novel development methodologies using a holistic virtual testbed for modular satellites. Proceedings of the International Astronautical Congress, IAC 14, 9525–9533.

La Grange, E., 2018. A roadmap for adopting a digital lifecycle approach to offshore oil and gas production. Proceedings of the Annual Offshore Technology Conference 2, 865–879.

Laborie, F., Røed, O.C., Engdahl, G., Camp, A., 2019. Extracting value from data using an industrial data platform to provide a foundational digital twin. Proceedings of the Annual Offshore Technology Conference.

Ladwig, P., Dewitz, B., Preu, H., Säger, M., 2019. Remote guidance for machine maintenance supported by physical LEDs and virtual reality. ACM International Conference Proceeding Series.

LaGrange, E., 2019]. Developing a digital twin: the roadmap for oil and gas optimization. OE In: Society of Petroleum Engineers - SPE Offshore Europe Conference and Exhibition 2019, 2019.

Lammer, G., Lanzenberger, R., 2018. APO - automated process optimization. AISTech - Iron and Steel Technology Conference Proceedings, 2018., pp. 3297–3302, May.

Landolfi, G., et al., 2018. Intelligent value chain management framework for customized assistive healthcare devices. Procedia CIRP 67, 583–588.

Lee, J., Lapira, E., Bagheri, B., an Kao, H., 2013]. Recent advances and trends in predictive manufacturing systems in big data environment. Manuf. Lett. 1 (1), 38–41.

Lehmann, S., Jones, S., 2019]. Bringing it all together: the emergence of operational risk management digital twins - Two case studies. 53rd Annual Loss Prevention Symposium 2019, LPS 2019 - Topical Conference at the 2019 AIChE Spring Meeting and 15th Global Congress on Process Safety.

Lermer, M., Reich, C., 2019]. Creation of digital twins by combining fuzzy rules with artificial neural networks. IECON Proceedings (Industrial Electronics Conference).

Liew, J.X., Bin, J., Liu, Z., 2019]. Software as a service: the future of NDI data analysis in the cloud. Insight Non-Destructive Test. Cond. Monit.

Lin, W.D., Low, M.Y.H., 2019]. Concept and implementation of a cyber-pbysical digital twin for a SMT line. IEEE International Conference on Industrial Engineering and Engineering Management, 1455–1459.

Liu, Z., Meyendorf, N., Mrad, N., 2018]. The role of data fusion in predictive maintenance using digital twin. AIP Conference Proceedings 1949 (1), 020023.

Liu, J., et al., 2019a]. Dynamic evaluation method of machining process planning based on digital twin. IEEE Access 7, 19312–19323.

Liu, Z., Chen, W., Zhang, C., Yang, C., Chu, H., 2019b]. Data super-network fault prediction model and maintenance strategy for mechanical product based on digital twin. IEEE Access.

Longo, F., Nicoletti, L., Padovano, A., 2019]. Ubiquitous knowledge empowers the smart factory: the impacts of a service-oriented digital twin on enterprises' performance. Annu. Rev. Control (February).

Love, P.E.D., Matthews, J., 2019]. The 'how' of benefits management for digital technology: from engineering to asset management. Autom. Constr.

Lu, Y., Liu, C., Wang, K.I.-K., Huang, H., Xu, X., 2020]. Digital twin-driven smart manufacturing: connotation, reference model, applications and research issues. Robot. Comput. Integr. Manuf. 61.

Luo, W., Hu, T., Zhang, C., Wei, Y., 2019. Digital twin for CNC machine tool: modeling and using strategy. J. Ambient Intell. Humaniz. Comput. 10 (March 3), 1129–1140.

Luo, W., Hu, T., Zhu, W., Tao, F., 2018. Digital twin modeling method for CNC machine tool. ICNSC 2018 - 15th IEEE Int. Conf. Networking, Sens. Control, 1–4, 51405270.

Mabkhot, M.M., Al-Ahmari, A.M., Salah, B., Alkhalefah, H., 2018]. Requirements of the smart factory system: a survey and perspective. Machines 6 (June 2).

Madni, A., Madni, C., Lucero, S., 2019]. Leveraging digital twin technology in model-based systems engineering. Systems 7 (January 1), 7.

Mars, W.V., Suter, J.D., Bauman, M., 2018]. Computing remaining fatigue life under incrementally updated loading histories. SAE Tech. Pap. 2018 (April).

Martinelli, I., et al., 2019]. Cost estimation method for gas turbine in conceptual design phase. Procedia CIRP.

Marwaha, G., Kohn, J., 2019. Predictive maintenance of gas turbine air inlet systems for enhanced profitability as a function of environmental conditions. ADIP In: Society of Petroleum Engineers - Abu Dhabi International Petroleum Exhibition and Conference 2019, 2019.

Matyas, K., Nemeth, T., Kovacs, K., Glawar, R., 2017]. A procedural approach for realizing prescriptive maintenance planning in manufacturing industries. CIRP Ann. Manuf. Technol. 66 (January 1), 461–464.

Miller, A.M., Alvarez, R., Hartman, N., 2018]. Towards an extended model-based definition for the digital twin. Comput. Des. Appl. 15 (6), 880–891.

Misrudin, F., Foong, L.C., 2019]. Digitalization in semiconductor manufacturing-simulation forecaster approach in managing manufacturing line performance. Procedia Manufacturing.

Mnasri, H., Wassar, T., Franchek, M.A., Marotta, E., 2019. Data-driven modeling of carbon dioxide corrosion for integrity management application. SPE Prod. Oper.

Mondoro, A., Grisso, B., 2019]. On the integration of SHM and digital twin for the fatigue assessment of naval surface ships. Structural Health Monitoring 2019: Enabling Intelligent Life-Cycle Health Management for Industry Internet of Things (IIOT) - Proceedings of the 12th International Workshop on Structural Health Monitoring, 1., pp. 918–925.

Moyne, J., Iskandar, J., 2017]. Big data analytics for smart manufacturing: case studies in semiconductor manufacturing. Processes 5 (3), 39.

Mudassar, R., Zailin, G., Jabir, M., Lei, Y., Hao, W., 2019]. Digital twin-based smart manufacturing system for project-based organizations: a conceptual framework. Proceedings of International Conference on Computers and Industrial Engineering, CIE.

Myers, G., 2017]. Digital twin for marine drilling risers. Offshore Eng. 42 (5), 58–63.

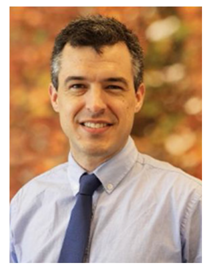
Nikolaev, S., Belov, S., Gusev, M., Uzhinsky, I., 2019]. Hybrid data-driven and physics-based modelling for prescriptive maintenance of gas-turbine power plant. IFIP In: IFIP Advances in Information and Communication Technology, 565, pp. 379–388.

Nixon, J., Pena, E., 2019]. The evolution of asset management: harnessing digitalization and data analytics. Proceedings of the Annual Offshore Technology Conference.

Novack, J., 2019]. Digital twins and industry 4.0: videogamers will staff and manage industrial projects in the near future. ADIP In: Society of Petroleum Engineers - Abu Dhabi International Petroleum Exhibition and Conference 2019, 2019.
Ocampo, J.D., et al., 2017]. Probabilistic damage tolerance for aviation fleets using a kriging surrogate model. 19th AIAA Non-Deterministic Approaches Conference 2017.
Oliveira, M., Afonso, D., 2019]. Industry focused in data collection: how industry 4.0 is handled by big data. ACM International Conference Proceeding Series.
Olivotti, D., Dreyer, S., Lebek, B., Breitner, M.H., 2019. Creating the foundation for digital twins in the manufacturing industry: an integrated installed base management system. Inf. Syst. E-bus. Manag. 17 (March 1), 89–116.
Omer, M., Margetts, L., Hadi Mosleh, M., Hewitt, S., Parwaiz, M., 2019]. Use of gaming technology to bring bridge inspection to the office. Struct. Infrastruct. Eng.
Oñederra, O., Asensio, F.J., Eguia, P., Perea, E., Pujana, A., Martinez, L., 2019]. MV cable modeling for application in the digital twin of a windfarm. ICCEP 2019 - 7th International Conference on Clean Electrical Power: Renewable Energy Resources Impact.
Osnabrugge, J., Van Den Berg, B., 2019. Increasing uptime and performance by using digital twins in dredging diagnostics. WODCON In: 22nd World Dredging Congress, 2019.
Pairet, È., Ardón, P., Liu, X., Lopes, J., Hastie, H., Lohan, K.S., 2019]. A digital twin for human-robot interaction. ACM/IEEE Int. Conf. Human-Robot Interact. 2019, 372, March.
Parri, J., Patara, F., Sampietro, S., Vicario, E., 2019]. JARVIS, a hardware/software framework for resilient industry 4.0 systems. Lect. Notes Comput. Sci. (Including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics).
Patnaik, P., Wu, X., 2018. Linking MRO to prognosis based health management through physics-of-failures understanding. Proceedings of the ASME Turbo Expo 6.
Peeters, E., 2018]. The Netherlands Organisation for Applied Scientific Research Works With Digital Twin in Real Life. ERCIM NEWS, 115, p. 41, Oct.
Pivano, L., Nguyen, D.T., Ludvigsen, K.B., 2019]. Digital twin for drilling operations - towards cloud-based operational planning. Proceedings of the Annual Offshore Technology Conference.
Prajapat, N., Tiwari, A., Tiwari, D., Turner, C., Hutabarat, W., 2019]. A framework for next generation interactive and immersive des models. IEEE International Conference on Industrial Informatics (INDIN).
Qi, Q., Tao, F., 2018]. Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. IEEE Access 6, 3585–3593.
Qiao, Q., Wang, J., Ye, L., Gao, R.X., 2019]. Digital twin for machining tool condition prediction. Procedia CIRP.
Rabah, S., et al., 2018. Towards improving the future of manufacturing through digital twin and augmented reality technologies. Procedia Manuf. 17 (January), 460–467.
Rajesh, P.K., Manikandan, N., Ramshankar, C.S., Vishwanathan, T., Sathishkumar, C., 2019]. Digital twin of an automotive brake pad for predictive maintenance. Procedia Comput. Sci. 165, 18–24.
Raman, V., Hassanaly, M., 2019]. Emerging trends in numerical simulations of combustion systems. Proc. Combust. Inst. 37 (January 2), 2073–2089.
Reifsnider, K., Majumdar, P., 2013]. Multiphysics stimulated simulation digital twin methods for fleet management. Collection of Technical Papers - AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference.
Riemer, D., 2018]. Feeding the digital twin: basics, models and lessons learned from building an IoT analytics toolbox (Invited Talk). 2018 IEEE International Conference on Big Data (Big Data), pp. 4212–4212.
Rødseth, H., Eleftheriadis, R., Lodgaard, E., Fordal, J.M., 2019]. Operator 4.0 – emerging job categories in manufacturing. Lect. Notes Electr. Eng. 484, 114–121.
Rosen, R., Von Wichert, G., Lo, G., Bettenhausen, K.D., 2015. About the importance of autonomy and digital twins for the future of manufacturing. IFAC-PapersOnLine 28 (3), 567–572.
Schirmann, M., Collette, M., Gose, J., 2018]. Ship motion and fatigue damage estimation via a digital twin. IALCCE In: Life-Cycle Analysis and Assessment in Civil Engineering: Towards an Integrated Vision - Proceedings of the 6th International Symposium on Life-Cycle Civil Engineering, 2019, pp. 2075–2082.
Schleich, B., Anwer, N., Mathieu, L., Wartzack, S., 2017. Shaping the digital twin for design and production engineering. CIRP Ann. 66 (January 1), 141–144.
Schueller, A., Modersohn, A., Kawohl, M., Wrede, J., 2019]. Digital twins in the process industry - Information management as an enabler of digitalization. ATP Ed. (1–2), 70–81.
Schwingenschloegl, C., 2019]. 3D vise simulation of a complete processing line. ESSC and DUPLEX 2019 - 10th European Stainless Steel Conference - Science and Market, 6th European Duplex Stainless Steel Conference and Exhibition.
Setrag, K., Rostetter, C., 2015]. Digital prescriptive maintenance. In: Internet Things, Process Everything, BPM Everywhere., pp. 1–20.
Settemsdal, S., 2019a]. Updated case study: the pursuit of an ultra-low manned platform pays dividends in the North Sea. Proceedings of the Annual Offshore Technology Conference.
Settemsdal, S., 2019b. Machine learning and artificial intelligence as a complement to condition monitoring in a predictive maintenance setting. OGIC In: Society of Petroleum Engineers - SPE Oil and Gas India Conference and Exhibition 2019, 2019.
Settemsdal, S.O., 2019c. Highly scalable digitalization platform for oil and gas operations enables total asset visibility for predictive, condition-based fleet management across single and multiple sites. ADIP In: Society of Petroleum Engineers - Abu Dhabi International Petroleum Exhibition and Conference 2019, 2019.
Shafiee, M., 2015]. Maintenance strategy selection problem: an MCDM overview. J. Qual. Maint. Eng. 21 (October 4), 378–402.
Shi, Y., Xu, J., Du, W., 2019]. Discussion on the new operation management mode of hydraulic engineering based on the digital twin technique. J. Phys. Conf. Ser. 1168 (February 2), 022044.
Shim, C.-S., Dang, N.-S., Lon, S., Jeon, C.-H., 2019]. Development of a bridge maintenance system for prestressed concrete bridges using 3D digital twin model. Struct. Infrastruct. Eng.
Shokooh, S., Nordvik, G., 2019]. A model-driven approach for situational intelligence & operational awareness. Petroleum and Chemical Industry Conference Europe Conference Proceedings, PCIC EUROPE.
Short, M., Twiddle, J., 2019. An industrial digitalization platform for condition monitoring and predictive maintenance of pumping equipment. Sensors (Switzerland).
Shubenkova, K., Valiev, A., Mukhametdinov, E., Shepelev, V., Tsiulin, S., Reinau, K.H., 2018]. Possibility of digital twins technology for improving efficiency of the branded service system. Proceedings - 2018 Global Smart Industry Conference, GloSIC 2018.
Singh, A., Sankaran, S., Ambre, S., Srikonda, R., Houston, Z., 2019]. Improving deepwater facility uptime using machine learning approach. Proceedings - SPE Annual Technical Conference and Exhibition.
Sivalingam, K., Sepulveda, M., Spring, M., Davies, P., 2018. A review and methodology development for remaining useful life prediction of offshore fixed and floating wind turbine power converter with digital twin technology perspective. Proc. - 2018 2nd Int. Conf. Green Energy Appl. ICGEA 2018, 197–204.
Stojanovic, V., Trapp, M., Richter, R., Hagedorn, B., Döllner, J., 2018. Towards the generation of digital twins for facility management based on 3D point clouds. ARCOM In: Proceeding of the 34th Annual ARCOM Conference, 2018, pp. 270–279.
Strohmeier, F., Schranz, C., Guentner, G., 2018]. i-Maintenance: A Digital Twin for Smart Maintenance. ERCIM NEWS, 115, pp. 12–14, Oct.
Swanson, L., 2001. Linking maintenance strategies to performance. Int. J. Prod. Econ. 70 (April 3), 237–244.
Szabo, G., Racz, S., Reider, N., Munz, H.A., Peto, J., 2019]. Digital twin: network provisioning of mission critical communication in cyber physical production systems. IAICT In: Proceedings - 2019 IEEE International Conference on Industry 4.0, Artificial Intelligence, and Communications Technology, 2019.
Szpytko, J., Duarte, Y.S., 2019]. Digital twins model for cranes operating in container terminal. IFAC-PapersOnLine.
Tahmasebinia, F., et al., 2019]. Numerical analysis of the creep and shrinkage experienced in the Sydney Opera House and the rise of digital twin as future monitoring technology. Buildings.
Talkhestani, B.A., et al., 2019]. An architecture of an intelligent digital twin in a cyber-physical production system. Autom. 67 (9), 762–782.
Tang, S., Wang, R., Zhao, X., Nie, X., 2018]. Building cloud services for monitoring offshore equipment and operators. Proceedings of the Annual Offshore Technology Conference 2, 852–864.
Tao, F., Zhang, H., Liu, A., Nee, A.Y.C., 2019]. Digital twin in industry: state-of-the-Art. IEEE Trans. Ind. Informatics 15 (April 4), 2405–2415.
Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H., Sui, F., 2018a. Digital twin-driven product design, manufacturing and service with big data. Int. J. Adv. Manuf. Technol. 94 (February 9–12), 3563–3576.
Tao, F., Zhang, M., Liu, Y., Nee, A.Y.C., 2018b. Digital twin driven prognostics and health management for complex equipment. CIRP Ann. 67 (1), 169–172.
Tao, F., Zhang, M., 2017]. Digital twin shop-floor: a new shop-floor paradigm towards smart manufacturing. IEEE Access 5, 20418–20427.
Tchana, Y., Ducellier, G., Remy, S., 2019]. Designing a unique Digital Twin for linear infrastructures lifecycle management. Procedia CIRP.
Tharma, R., Winter, R., Eigner, M., 2018]. An approach for the implementation of the digital twin in the automotive wiring harness field. Proceedings of International Design Conference, DESIGN, 6., pp. 3023–3032.
Tjønn, A.F., 2019. Digital twin through the life of a field. ADIPEC In: Society of Petroleum Engineers - Abu Dhabi International Petroleum Exhibition and Conference 2018, 2018.
Törmä, S., Toivola, P., Kiviniemi, M., Puntila, P., Lampi, M., Mätäsniemi, T., 2019. Ontology-based sharing of structural health monitoring data. 20th Congress of IABSE, New York City 2019: The Evolving Metropolis - Report.
Tuegel, E.J., 2012]. The airframe digital twin: some challenges to realization. Collection of Technical Papers - AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference.
Tugengol'd, A.K., Dimitrov, V.P., Borisova, L.V., Grankov, M.V., Voloshin, R.N., 2019]. Autonomous maintenance of digital equipment. Russ. Eng. Res.
Tygesen, U.T., Worden, K., Rogers, T., Manson, G., Cross, E.J., 2019]. State-of-the-art and future directions for predictive modelling of offshore structure dynamics using machine learning. Conference Proceedings of the Society for Experimental Mechanics Series, 223–233.
Utzig, S., Kaps, R., Azeem, S.M., Gerndt, A., 2019]. Augmented reality for remote collaboration in aircraft maintenance tasks. IEEE Aerospace Conference Proceedings.
Vachalek, J., Bartalsky, L., Rovny, O., Sismisova, D., Morhac, M., Loksik, M., 2017]. The digital twin of an industrial production line within the industry 4.0 concept. Proc. 2017 21st Int. Conf. Process Control. PC 2017, 258–262.
van Kruijsdijk, C., 2018]. Digital Twins As R&D Accelerators - the Case for an Open Source Ecosystem. ERCIM NEWS, pp. 14–15, 115, October.

Vathoopan, M., Johny, M., Zoitl, A., Knoll, A., 2018]. Modular fault ascription and corrective maintenance using a digital twin. IFAC-PapersOnLine 51 (11), 1041–1046.
Vatn, J., 2018]. Industry 4.0 and real-time synchronization of operation and maintenance. In: Safety and Reliability - Safe Societies in a Changing World - Proceedings of the 28th International European Safety and Reliability Conference, ESREL 2018, pp. 681–686.
Venables, M., 2017]. Future maintenance: transitioning from digitalisation to industry 4.0. Plant Eng. 2017 (May-June), 10–12.
Wantia, N., Roßmann, J., 2017]. An online task planning framework reducing execution times in industrial environments. ICIEA In: 2017 4th International Conference on Industrial Engineering and Applications, 2017, pp. 90–94.
Waschull, S., Wortmann, J.C., Bokhorst, J.A.C., 2018]. Manufacturing execution systems: the next level of automated control or of shop-floor support? IFIP Adv. Inf. Commun. Technol. 536, 386–393.
Werner, A., Zimmermann, N., Lentes, J., 2019]. Approach for a holistic predictive maintenance strategy by incorporating a digital twin. Procedia Manuf. 39, 1743–1751.
Weyer, S., et al., 2019]. Digital solutions for modern and efficient ironmaking. AISTech - Iron and Steel Technology Conference Proceedings.
Xu, Y., Sun, Y., Liu, X., Zheng, Y., 2019]. A digital-twin-assisted fault diagnosis using deep transfer learning. IEEE Access 7, 19990–19999.
Yan, J., Zlatanova, S., Aleksandrov, M., Diakite, A.A., Pettit, C., 2019]. Integration of 3D objects and terrain for 3D modelling supporting the digital twin. In: ISPRS Annals of the Photogrammetry. Remote Sensing and Spatial Information Sciences.
Yashin, G.A., Trinitatova, D., Agishev, R.T., Ibrahimov, R., Tsetserukou, D., 2019]. AeroVr: virtual reality-based teleoperation with tactile feedback for aerial manipulation. ICAR In: 2019 19th International Conference on Advanced Robotics, 2019.
Yerra, V.A., Pilla, S., 2017]. IIoT-enabled production system for composite intensive vehicle manufacturing. SAE Int. J. Engines 10 (April 2), 209–214.
Zaccaria, V., Stenfelt, M., Aslanidou, I., Kyprianidis, K.G., 2018. Fleet monitoring and diagnostics framework based on digital twin of aero-engines. Proceedings of the ASME Turbo Expo 6.
Zenisek, J., Wolfartsberger, J., Sievi, C., Affenzeller, M., 2019]. Modeling sensor networks for predictive maintenance. LNCS In: Lect. Notes Comput. Sci. (Including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), 11231, pp. 184–188.
Zhang, H., Liu, Q., Chen, X., Zhang, D., Leng, J., 2017]. A digital twin-based approach for designing and multi-objective optimization of hollow glass production line. IEEE Access 5, 26901–26911.
Zhang, T., Liu, X., Luo, Z., Dong, F., Jiang, Y., 2019a]. Time series behavior modeling with digital twin for Internet of Vehicles. EURASIP J. Wirel. Commun. Netw.
Zhang, H., Ma, L., Sun, J., Lin, H., Thürer, M., 2019b]. Digital twin in services and industrial product service systems: review and analysis. Procedia CIRP.
Zhang, H., Zhang, G., Yan, Q., 2019c. Digital twin-driven cyber-physical production system towards smart shop-floor. J. Ambient Intell. Humaniz. Comput. 10 (November 11), 4439–4453.
Zhu, Z., Liu, C., Xu, X., 2019]. Visualisation of the digital twin data in manufacturing by using augmented reality. Procedia CIRP.
Zipper, H., Auris, F., Strahilov, A., Paul, M., 2018]. Keeping the digital twin up-to-date - process monitoring to identify changes in a plant. Proceedings of the IEEE International Conference on Industrial Technology, 2018., pp. 1592–1597, Februry.

ITXARO ERRANDONEA received her M.Sc. degree in Computer Science from the Faculty of Informatics in San Sebastián (University of the Basque Country) in 2017. She joined the Ceit Research Center in San Sebastián, in 2017, where is currently a Research Assistant with the Information and Communication Technologies area (ICT). Her research activity lies in the field of data analysis and information management.



SERGIO BELTRÁN received the B.Sc and Ph.D. degree in industrial engineering from the University of Navarra, Spain, in 2006 and 2013, respectively. He is currently an Associate Professor of Tecnun (University of Navarra). He has published papers in international journals, conferences, and book chapters. Since 2006, he has been working at Ceit research center carrying out applied R&D projects and technical studies in data analysis and information management. His main areas of research are applied data intelligence, mathematical modeling, simulation, optimization, system identification and control and automation techniques.

SAIOA ARRIZABALAGA received her M.Sc. degree in Telecommunication Engineering from the Faculty of Engineering in Bilbao (University of the Basque Country) in 2003, and her Ph.D. degree in Engineering from TECNUN in 2009. She is a lecturer at TECNUN (University of Navarra), and a researcher at Ceit. She is the Head of Data Analytics and Information management Research group and has been involved in the participation of 30 national and international research projects, direction of 8 doctoral theses and 56 scientific and technical publications in national and international journals and conferences.