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# Digital Twin for the Oil and Gas Industry: Overview, Research Trends, Opportunities, and Challenges

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**ABSTRACT** With the emergence of industry 4.0, the oil and gas (O&G) industry is now considering a range of digital technologies to enhance productivity, efficiency, and safety of their operations while minimizing capital and operating costs, health and environment risks, and variability in the O&G project life cycles. The deployment of emerging technologies allows O&G companies to construct digital twins (DT) of their assets. Considering DT adoption, the O&G industry is still at an early stage with implementations limited to isolated and selective applications instead of industry-wide implementation, limiting the benefits from DT implementation. To gain the full potential of DT and related technological adoption, a comprehensive understanding of DT technology, the current status of O&G-related DT research activities, and the opportunities and challenges associated with the deployment of DT in the O&G industry are of paramount importance. In order to develop this understanding, this paper presents a literature review of DT within the context of the O&G industry. The paper follows a systematic approach to select articles for the literature review. First, a keywords-based publication search was performed on the scientific databases such as Elsevier, IEEE Xplore, OnePetro, Scopus, and Springer. The filtered articles were then analyzed using online text analytic software (Voyant Tools) followed by a manual review of the abstract, introduction and conclusion sections to select the most relevant articles for our study. These articles and the industrial publications cited by them were thoroughly reviewed to present a comprehensive overview of DT technology and to identify current research status, opportunities and challenges of DT deployment in the O&G industry. From this literature review, it was found that asset integrity monitoring, project planning, and life cycle management are the key application areas of digital twin in the O&G industry while cyber security, lack of standardization, and uncertainty in scope and focus are the key challenges of DT deployment in the O&G industry. When considering the geographical distribution for the DT related research in the O&G industry, the United States (US) is the leading country, followed by Norway, United Kingdom (UK), Canada, China, Italy, Netherland, Brazil, Germany, and Saudi Arabia. The overall publication rate was less than ten articles (approximately) per year until 2017, and a significant increase occurred in 2018 and 2019. The number of journal publications was noticeably lower than the number of conference publications, and the majority of the publications presented theoretical concepts rather than the industrial implementations. Both these observations suggest that the DT implementation in the O&G industry is still at an early stage.

**INDEX TERMS** Digitalization, digital twin (DT), industry 4.0, extended reality, industrial Internet of Things (IIoT), oil and gas.

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## I. INTRODUCTION

The oil and gas (O&G) industry is a highly regulated industry due to the inherent health, safety and environmental (HSE) risk associated with the exploration, drilling, production, processing and distribution activities. These regulatory requirements, in addition to an emerging skill gap due to retirement of experienced employees, and low oil prices for a longer period have driven O&G companies to be innovative and disruptive to enhance productivity and efficiency, reduce HSE risk, minimize the capital and operating costs, increase revenues, and improve regulatory compliance.

Over the past decade, the rapid pace of technological innovation and industry-wide technological adoption have shifted not only the fundamental business models, but also entire industrial, economic and socioeconomic landscapes. Recent advancements in information and communication technologies, including cloud computing, high-performance processors, high dimensional visualization capabilities, internet of things (IoT), wearable technologies, additive manufacturing, big data analytics, artificial intelligence, autonomous robotic systems, drones, and blockchain technology, have catalyzed digital adoption across industries. These technologies have facilitated cyber-physical integration by which data can be collected, analyzed, and visualized in order to make more informed decisions and to serve as a basis for simulations to optimize operations. This concept of cyber-physical interaction and simulation is generally referred to as a Digital Twin (DT) [1]–[4]. The Gartner Group, a leading research and advisory company, identified DT as one of the top ten recent strategic technology trends [5]–[8]. There is a range of industries, such as manufacturing [9]–[12], automotive [13], [14], healthcare [15]–[20], aviation [21]–[25] and terrestrial exploration [21], [26], where the DT concept has been successfully deployed.

The O&G industry has started to leverage digital technologies to change their business and operation models while providing new revenue and value-producing opportunities [27]–[33]. The adoption of digital technologies and moving to a digital business is typically known as digitalization [34]. With the adoption of emerging digital technologies, the O&G industry is also now considering how to implement DT technology [35]. Current digital technology adoption in the O&G industry typically follows a bottom-up approach, where technologies are unsymmetrically implemented [36]. As a result, companies are not realizing the full potential of digitalization and DT. To gain the full potential of DT and related technological adoption, a comprehensive understanding in DT technology, the current status of O&G-related DT research activities, and the opportunities and challenges associated with implementing DT in the O&G industry are important. In order to develop this understanding, we conducted a literature review of DT within the context of the O&G industry.

From this literature review, asset integrity monitoring, project planning, and life cycle management, were found to be key application areas of DT in the O&G industry, while cyber security, lack of standardization, and uncertainty in scope and focus are the key challenges for DT deployment in the O&G industry. When considering the geographical distribution of the DT related research in the O&G industry, the United States (US) is the leading country, followed by Norway, United Kingdom (UK), Canada, China, Italy, Netherland, Brazil, Germany, and Saudi Arabia. The overall publication rate was less than ten articles (approximately) per year until 2017, with a significant increase occurred in 2018 and 2019. The number of journal publications were noticeably lower than the number of conference publications. Additionally, the majority of the publications presented theoretical concepts rather than the industrial implementations. Both of these observations suggest that DT implementations in the O&G industry is still at an early stage.

**TABLE 1. Article screening criteria.**

| Searching index | Specific content |
|---|---|
| Database | Elsevier, IEEE Xplore, OnePetro, Scopus, Springer, |
| Article types | Scientific articles published in books, journals and conferences |
| Search string | ("digital twin" OR "digital twins" OR "digital model" OR "digital models" OR "digital environment" OR "digital environments" OR "virtual twin" OR "virtual twins" OR "virtual model" OR "virtual models" OR "virtual environment" OR "virtual environments") AND ("oil" AND "gas") |
| Search period | From January 2003 to April 2020 |
| Screening procedure | The relevance of the DT application to O&G was selected based on the number of occurrences of key terms followed by the manual review of the contents of the abstract, introduction and conclusion. |
| Classification scheme | The literature is classified based on the type of the study (review, concept, case-study), application areas, enabling technologies and researchers' affiliations (academic or industrial). |
| Other information | Opportunities and challenges related to DT applications are identified from the filtered articles. |

The remainder of this article is organized as follows. Section II outlines the methodology of the literature survey. An overview of DT and the current status of the research into DT deployment in the O&G industry are presented in Section III and Section IV, respectively. The opportunities and challenges of deploying DT are discussed in Section V. The paper concludes with a summary of the literature review.

## II. METHODOLOGY

Although data acquisition, simulation and physical twins have been around for several decades, the concept currently referred to as DT was first introduced in 2002 [37]. Since then, there have been numerous research and industrial implementations across many industrial sectors [38]. The scope of the literature review presented in this article, however, is limited to the O&G industry and follows a similar approach to that presented in [11], [38]–[42]. TABLE 1 and FIGURE 1 outline the article selection criteria for this study.

The paper selection was started by conducting a keyword-based paper search on digital libraries of scientific publications. This initial keyword-based article filtering

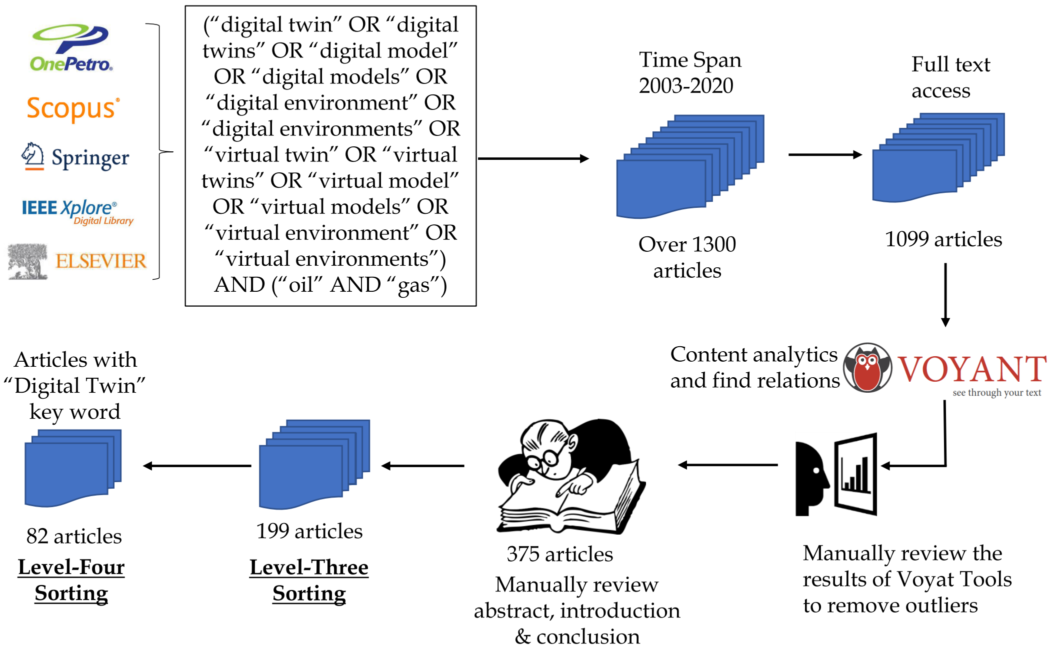


**FIGURE 1.** Overview of article selection criteria.

identified over 1300 articles. Among these articles, it was possible to obtain full access to 1099 articles through various means, including subscriptions to the particular sections of digital libraries, Google Scholar, and contacting authors via Academia.edu and ResearchGate networks. Since this includes more than 84% of the articles found through the keyword-based search, it is felt that the articles are representative of current status of the research into DT deployment in the O&G industry. Note that, this was a keyword-based database search, an article with keyword "digital twin" does not necessarily discuss DT implementation or research but may included the keyword only in passing reference within the article. It is important to identify such articles and remove them from the subsequent analysis. This further filtering was achieved by feeding the 1099 articles into the web-based text analysis software, "Voyant Tools" [43], [44]. This software performs automated text analysis and generates comprehensive information about unique terms, number of occurrences of these terms, their correlations and links, the context in which the term appears, and the spread of them across each article. The results of Voyant Tools were examined manually to select the articles that potentially related to our study using the following requirements,

- paper must have "oil (and) gas" key term more than five times,
- paper must contain at least one technical key term in the search string given in Table 1 more than five times, and
- key terms must spread across the paper instead of concentrating at the beginning ('Introduction' section) and/or end ('Conclusion' section).

There were 375 articles out of 1099 that satisfied all three requirements. The abstract, introduction and conclusion sections of these 375 articles were reviewed manually to identify articles which are more related to DT implementations in the O&G industry. This further analysis allowed us to narrow down the number of relevant articles to 199. Out of these 199 articles, 82 articles containing the term "digital twin" [1]–[3], [35], [36], [41], [45]–[120] were published during the last three years (2017-2019) and the first quarter of 2020. The selected 199 articles were reviewed comprehensively to answer the following research questions.

RQ1: What is a DT?
RQ2: What does the publication pattern tell about the current status of DT deployment in the O&G industry?
RQ3: What are the key opportunities of DT deployment in the O&G industry?
RQ4: What are the key challenges of DT deployment in the O&G industry?

To answer RQ2, some of the meta data of the selected articles, such as the title, year, authors' affiliation (academic or industry), publisher, type of publication (conference, journal, book chapter) and the country of the authors, were extracted. Additionally, the selected articles were classified into three groups as follows:

- Concept paper: articles that present theoretical and simulation-based work.
- Case-study: articles that present industrial implementations and case-studies.
- Review paper: articles that present literature or technical review, industrial surveys and definitions.

There were some articles that present DT-related concepts followed by case-studies to support their arguments. Such papers were placed in both the concept paper and case-study categories.

**TABLE 2.** Sample definitions for "Digital Twin".

| Reference | Definition |
|---|---|
| [1] | "refers to the digital foot print of the physical systems in the various assets which act like a bridge between physics and digital world" |
| [2] | "digital copy of the physical systems and act as a connection between physics and digital world" |
| [3] | "virtual and simulated model or a true replica of a physical asset" |
| [4] | "an immersive data analytic technology that provides insights on human-infrastructure-machine interactions to enable executives to make contextual decisions" |
| [67] | "a virtual physics and data-based model of a system or an asset that models all the various subsystems, their properties, the interaction among them and the interactions of the system with the environment" |
| [68] | "a virtual model of a physical asset" |

## III. OVERVIEW OF DIGITAL TWIN

This section addresses the first research question (RQ1), i.e., "what is a DT?". The objective of this research question is to provide a comprehensive overview of DT technology for readers from the petroleum industry who may not have first hand experience on DT but want to implement and test DT. Most of the articles among the selected 199 included an introduction to DT. However, there was no single article that provides a comprehensive overview, including definition, frameworks, classifications, how to get started, enabling technologies, and sample DT systems. Therefore, the selected 199 articles, as well as the most cited industrial publications (technical papers) and research papers by these 199 articles, were reviewed to provide a comprehensive introduction to DT.

### A. DEFINITION

DT, which has been more generally adopted in recent years, is often misinterpreted to refer only to 3D visualization of the physical world. Different researchers and institutions, however, have adopted broader definitions of the term "digital twin". Some of the definitions found in the literature are listed in TABLE 2.

Although these definitions differ somewhat from one another, they all refer to a physical asset, a virtual model, data exchange between a physical asset and digital model, data analytics and visualization. According to the Defense Acquisition University's (DAU) glossary, DT is an "integrated multi-physics, multi-scale, probabilistic simulation of an as-built system, enabled by digital thread, that uses the best available models, sensor information, and input data to mirror and predict activities/performance over the life of its corresponding physical twin" [121]. This definition is based on the *digital thread* concept which is defined as an "extensible, configurable and component enterprise-level analytical framework that seamlessly expedites the controlled interplay of authoritative technical data, software, information, and knowledge in the enterprise data-information-knowledge systems, based on the digital system model template, to inform decision makers throughout a system's life cycle by providing the capability to access, integrate and transform disparate data into actionable information" [122]. The definition of digital thread points to another concept called *digital system model* which is defined as a "digital representation of a defense system, generated by all stakeholders that integrates the authoritative technical data and associated artefact which define all aspects of the system for the specific activities throughout the system lifecycle" [123]. Note that this definition is for the digital system model uses the term 'defense system' because this definition focuses on the digital twin studies associated with the DAU. For other sectors, for example O&G, the term 'defense system' can be replaced with any other system, such as 'drilling system', 'gravity-based structure', or 'floating production storage and offloading (FPSO)'.

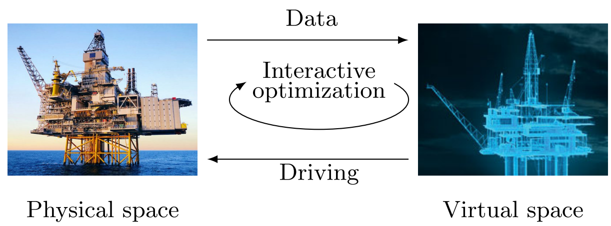


**FIGURE 2.** Digital twin framework with three components (physical space, virtual space, and connection between them).

### B. FRAMEWORKS

There are several frameworks have been developed for DT. The most widely accepted framework includes three major components: physical space, virtual space and connections between these spaces as shown in FIGURE 2 [37]. The physical space contains the physical asset, sensors and actuators, while the virtual space includes multi-physics, multi-scale, probabilistic simulation models which aggregates and analyzes the data and performs simulations to determine the optimal control parameters and conditions for the physical asset. The connections between the physical and virtual spaces ensure seamless data and actuation commands (driving) exchange between these two spaces.

The three-component DT framework was later extended to a five-component framework, which includes physical space, virtual space, DT data fusion module, service systems, and connection/interaction between these four modules (refer to FIGURE 3) [124]. The five-component model, the physical space contains the physical asset, sensors and actuators. The virtual space is the digital mirror for high fidelity simulation of the physical counterpart. The service system contains other enterprise software tools such as visualization services, product quality services, diagnostic services, model calibration services, algorithm services, and various data services. The DT data fusion model acts as a bridge between the physical space, virtual space and service system. This module collects data from the sensors (i.e., from the physical space), the simulation (i.e., from the virtual space), and the service system. The collected data are fused and analyzed by the

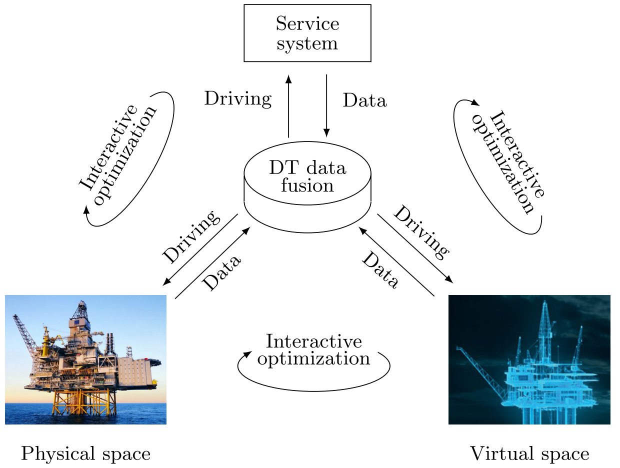


**FIGURE 3.** Digital twin framework with five components (physical space, virtual space, connection between them, data and service).

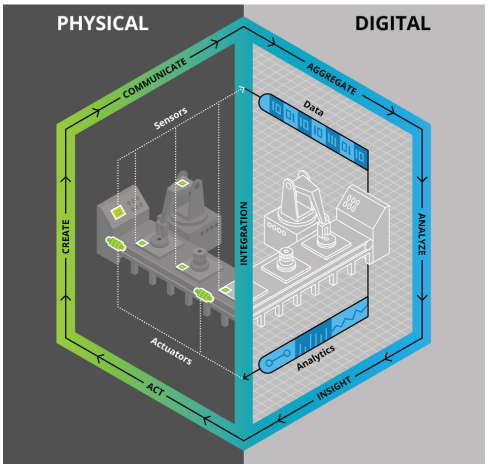


**FIGURE 4.** Manufacturing process digital twin model. Although the model has developed for manufacturing process, it can directly apply for any industry (Source: [125]).

DT data fusion model to generate driving commands for the other three modules.

A recent technical report by Deloitte presents a DT framework which consists of five enabling components and a six step process, as illustrated in FIGURE 4 [125]. The five enabling components include sensors, data, integration, analytics and actuators. Sensors and actuators are located in the physical space while the data analytics takes place in the virtual space. To enable seamless data and command communication between the physical and virtual (digital) worlds, integration technologies must be utilized. The vertical line between physical and digital domains represents the integration technology. Typically, integration technology consists of three components namely: edge processing, communication interfaces, and edge security. Edge processing converts proprietary data protocols into more easily understood data formats. Communication interfaces act as an intermediary between sensor functions and integration functions, while the edge security adds the required security protocols and encryption to protect the DT and sensor data against cyber-attacks. The six iterative steps of digital twin-based operations are create, communicate, aggregate, analyze, insight and act. Sensors are attached to the physical plant to create electrical signals that represent the operational and environmental conditions of the asset. The real-time real-world data is aggregated with other existing data, such as the bill of materials, design specifications, engineering drawings, engineering data sheets, and event logs. Advanced analytics and visualization tools, such as machine learning, big data analytics, virtual reality and augmented reality, are employed to analyze the collected data and to visualize the results. Should it be necessary to perform actions on a physical asset, the DT generates the actions and applies them to the actuators. The application of an action may be subjected to human intervention (review).

### C. CLASSIFICATIONS

DT can be classified into two main categories: plant twin and process twin [35], [54]. The plant twin is a 3D model (digital or physical) which acts as a smart viewer and advanced simulation platform. It provides access to engineering, operations, maintenance and asset performance data allowing the operator to run a series of "what-if" scenarios to plan future construction, commissioning, operation, maintenance, repair and decommissioning activities. Additionally, immersive virtual training can be provided for field personnel using the plant twin to conduct field operations and maintenance activities. Furthermore, emergency evacuation training can also be conducted using the plant twin. In the training cases, the field personnel can navigate within the plant twin using his/her avatar or using a virtual/mixed reality-based application. This allows the field personnel to experience the physical plant as if it were reality. In addition to these training exercises, engineering, procurement and construction (EPC) designs can be verified using the plant twin. This enables the early detection of design errors and required design alternations saving capital expenditure for late-stage design changes.

The process twin is a digital representation of the process and automation system which can be used for studying the behavior and performance of an asset. It acts as a simulation platform to conduct a series of engineering simulations to determine the best operating parameters, optimum operating conditions, and safety processes. In addition, it is used to develop and evaluate operating, maintenance and emergency response procedures before start-up of production. The process plant can also be used for tuning controllers and testing the instrumentation, control and safety systems before the start-up of a plant. Operator training can also be performed using the process twin so that the operator can get firsthand experience of different operating conditions, process scenarios and best practices to respond to these conditions and scenarios.

Siemens, one of the major companies involved in digitalization, further classifies DT into three levels depending on

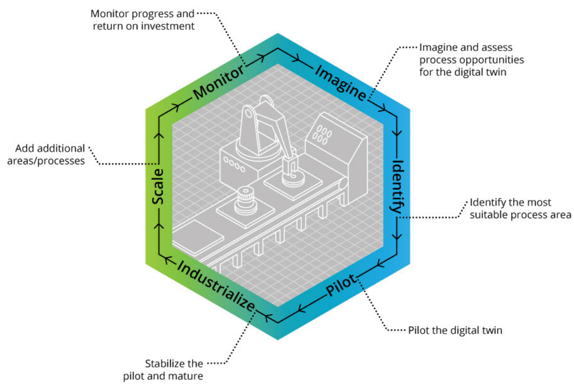


**FIGURE 5.** A sample framework for getting started with the DT (Source: [125]).

the key functionalities [54]. These three levels are equipment-level, system-level and plant-level. The three levels reflect fundamental differences in the degree of detail and accuracy requirements. At the equipment-level, DT includes detailed engineering drawings, engineering designs and engineering and manufacturing data for the equipment being modelling. This data set is updated and maintained throughout the equipment life cycle with the aid of product life cycle management (PLM) software. A system-level twin is constructed by integrating the equipment-level twins into a single functioning unit. These system-level twins are integrated to generate the plant-level twin. The equipment-level twin should possess accurate engineering, manufacturing and design data. The system-level twin includes an accurate representation of the aggregated operation of all of the equipment that the system is built upon. It is typically not accurate with respect to the engineering, manufacturing and design data of all of the equipment. The plant-level twin attempts to replicate the overall plant performance rather than system- or equipment-level performance.

### D. HOW TO GET STARTED

In order to produce a useful DT with appropriate complexity, [125] presents a general framework to implement a DT. The proposed framework is illustrated in FIGURE 5. This framework consists of six steps: (1) imagine the possibilities, (2) identify the process, (3) pilot a program, (4) industrialize the process, (5) scale the twin, and (6) monitor and measure.

For a given product or process, the company (or organization) first needs to imagine and shortlist all the possible benefits that could be achieved using a DT of the product or process. If this analysis suggests that the DT can add economical and technological advantages, the design process of DT advances to the second stage. In this stage, a pilot DT configuration is identified that offers the highest return on investment (ROI) (both economic and technological) and possesses the best chance of being successful. This is followed by implementing a pilot program which acts as a learning platform to determine the opportunities, challenges, risk, and ROI before moving to an industrial scale implementation. The pilot program is an iterative process to fine tune the selection of the sensors and other digital technologies and analytic approaches for the targeted DT. Once the pilot program has demonstrated success, the DT can be industrialized. At that point, the DT development program moves from a siloed implementation to an integrated implementation where it connects with an existing digital backbone for the enterprise. The next step is to determine the possible expansion of the digital twin by combining adjacent processes and any other processes that interact with the pilot. At this stage, the lessons learnt during the initial DT deployment can be exploited to accelerate the expansion process. The final step of deploying DT involves continuously monitoring the value created by the DT and iteratively modifying the existing DT to deliver the maximum benefits.

Note that there are pitfalls that can be associated with implementing DT [125]. The first pitfall is developing an overly simplistic model of the physical asset which may not deliver the value that the DT promises. A second pitfall is developing a super-complex DT which may end up getting lost in the exponentially growing sensor products, hundreds of millions of signals generated by the sensors and an enormous amount of digital technologies.

### E. ENABLING TECHNOLOGIES AND SAMPLE SYSTEMS

Successful implementation of DT requires data to be captured from the physical asset. The captured data need to be analyzed locally at the sensor and/or transmitted to a central processing centre for further analysis. The data must be securely stored and analyzed to uncover the information encapsulated within the data. The results must able to be visualized effectively by an end-user. This implies that acquiring, communicating, warehousing, analyzing and visualizing data are key activities involved in DT. There are numerous digital technologies that enable these five activities. Table 3 summarizes the key enabling technologies identified in the 199 articles.

There are several oil field service companies that offer DT solutions. Examples of DT platforms along with their service provider are listed in TABLE 4.

## IV. PUBLICATION PATTERNS

This section presents the finding related to the second research question (RQ2), i.e., "what does the publication pattern tell us about the current status of DT deployment in the O&G industry?". By analysing the publication patterns, such as the number of publications per years, type of publication (journal, conference, book chapters), country of contribution, level of involvement from the academic sector and industrial sector, key application areas, and key technologies used in implementations, it is possible to get some insight into DT implementation in the O&G industry.

Recall that initially we had 1099 articles which were reduced to 375 articles with the help of an online text analyzing tool. We then manually reviewed these 375 articles and further narrowed them down to 199 articles and finally

**TABLE 3. Key enabling technologies identify from the literature.**

| Technology | References | Focused activity |
|---|---|---|
| Smart sensors | [47], [48], [67], [71] | Data acquisition |
| Industrial internet of things (IIoT)† | [3], [36], [51], [53], [54], [68], [70], [71], [75], [126] | All five activities |
| Big-data and data analytics | [3], [47], [53], [54], [57], [67], [68], [126] | Data analysis |
| Machine-learning, deep-learning and artificial intelligence (AI) | [3], [36], [47], [48], [53], [54], [57], [68], [77] | Data analysis |
| Virtual-, augmented-, and mixed-reality (VR, AR, MR) | [51], [53], [59], [61], [76] | Visualization (data, models, and results) |
| Other virtual (simulated) environments and computer aided design (CAD) models | [1], [2], [45], [49], [50], [56], [60], [71], [73] | Data analysis and visualization |
| Web and cloud enable computing | [36], [47], [48], [54], [60], [126] | Data analysis, storage and visualization |
| High performance computing systems | [67], [76] | Data analysis, storage and visualization |
| Communication networks, and location-based sensors | [55], [57], [65] | Data acquisition and communication |

† In this article, both the industrial internet of things (IIoT) and consumer internet of things (IoT) are together considered as IIoT.

**TABLE 4. Sample DT platforms (Source: [3]).**

| Service provider | Platform |
|---|---|
| ABB (Acquired Obivent Strategies) | Equipment reliability (ER) & asset health centre |
| Detechtion Technologies (Acquired En-base) | Enalsis |
| Bentley (Acquired Ivara and C3global) | AssetWise asset lifecycle information management (ALIM) |
| GE (Acquired Meridium, bit Stew system, service Max and wise) | Predix |
| AspenTech (Acquired Mtell) | Previse |
| DNV-GL | Cascade software |
| Schneider | Avatis |

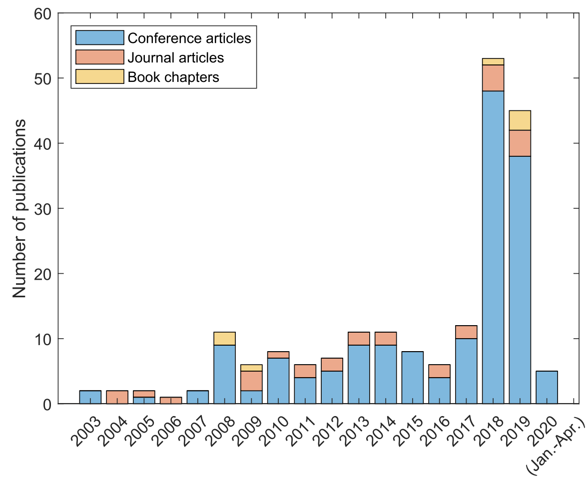


**FIGURE 6. Publication pattern for the selected 199 articles from January 2003 to April 2020.**

selected 82 articles. Consider the analysis of the 1099 articles as "level one sorting", the analysis of 375 articles as "level two sorting", the analysis of 199 articles as "level three sorting", and the analysis of 82 articles as "level four sorting". The 82 articles that resulted from the level four sorting were published in last three years (2017-2019) and the first quarter of 2020.

The level one and two sorting removed the outliers from the selected articles set. The analysis of 199 article provides an insight into the DT-related research activities since 2003, while 82 articles allow us to identify the most recent and highly focussed research activities associated with DT in the O&G industry.

## A. LEVEL THREE SORTING

### 1) PUBLICATION TRAJECTORY AND CLASSIFICATIONS

The annual publication counts for the 199 articles analyzed at level-three sorting are shown in FIGURE 6.

Most of these publications are conference publications.The overall publication rate was less than ten articles (approximately) per year until 2017, and a significant increase occurred in 2018 and 2019. The increase in the publication rate can be attributed to one of the following two factors:

- O&G sector is now embracing digitalization more than in the recent past, or
- O&G sector has been conducting research on DT concepts for about a decade and now these research projects are at a mature stage and are being reported in more publications than in the recent past.

When considering the content of these articles, approximately 75% are "concept" papers, while 19% present "case-studies" and 6% are "review" articles. The higher percentage of case-studies (∼19%) indicates that most of the ongoing research activities are focused on industrial implementation rather than earlier-stage independent research with less defined industrial relevance. The higher percentage, i.e. ∼75%, of "concept" papers is consistent with the growing tendency to give general consideration to how such an emerging technology can play a role in the oil and gas industry.

In our review, if all the authors of a given article are affiliated with academic institutions, the article is considered to be an academic paper. In contrast, if all the authors are affiliated with non-academic entities (operators, service companies, independent research laboratories, government research centers etc.), these papers are classified as industrial articles. There are several articles where some of the authors are from academic institutions while the rest are from the industry partners. For these papers, a ratio-based approach is used to define the portion of the industrial and academic contribution. For example, [67] has four authors where three are from academic institutions while the remaining one is with industrial partners; thus the paper is considered to have 75% academic contribution and 25% industrial contribution. This is an approximation since the authors likely do not make the same level of contribution to the article. However, for the purpose of this paper, the assumption of an equal level of contribution was felt to be reasonable.

For the publications reviewed at the third sorting level, approximately 32% of the contributions came from academic institutions while the 68% contributions came from industrial organizations. This indicates that, within the O&G sector, industrial organizations are embracing DT related technologies and they are the leaders of related research programs compared to the academic institutions. This observation can be attributed to the fact that the industries have the infrastructure and data to conduct a DT research program more readily than academic institutions. Additionally, the O&G industrial sector is undergoing a rigorous transformation to integrate modern digital technologies to enhance safety and improve operation and productivity. As a result, more applied research and development related to digital technologies is being carried out within the industry instead of acquiring it from the academia. The O&G industry has a long history of using 3D modelling, simulation and visualization to enhance the understanding of geological strata, reservoir behavior and production operation. This experience allows industrial-based research and development to more rapidly consider DT technology, implement pilot programs and generate concepts for industry-wide applications compared to research and development based in academia.

### 2) LEADING COUNTRIES

The 199 articles identified during level three sorting are affiliated with research entities in 33 countries. In this review, we recorded publication count for these countries to determine which country is leading the O&G-related DT research activities. If all the authors of a given article are affiliated with research entities located in a single country, the publication count of this country is increased by one. If authors are from multiple countries a ratio-based approach is used to define the contribution by each country. For example, [63] has four authors where three are from the USA while the remaining one is from Switzerland; thus, when considering [63], the paper count for USA is increased by 0.75 and the paper count for Switzerland is increased by 0.25. FIGURE 7 depicts the top ten countries along with their approximated publication count. The top three countries, i.e. the United States (US), Norway, and United Kindom (UK) contribute approximately 97 articles (i.e. 49% of the contributions), while the top ten countries contribute approximately 157 articles (i.e. 79% of the contributions). When considering that major O&G operations are in the North Sea and the Gulf of Mexico, this is an expected publication pattern.

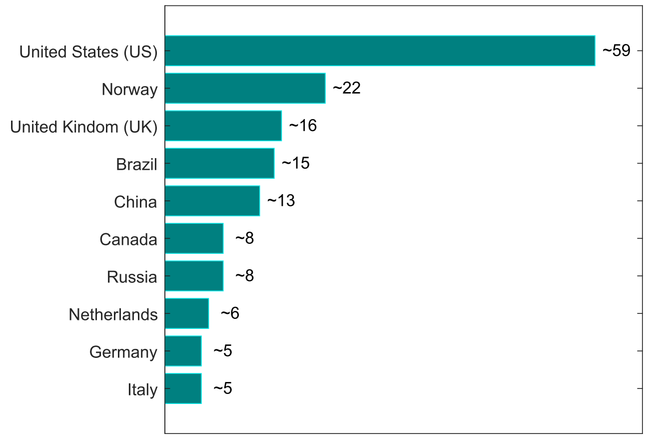


**FIGURE 7. Level three sorting results - top ten countries by publication count.**

### 3) KEY APPLICATIONS

This review found that there is a range of application areas in the O&G industry that are expected to benefit from DT-related technologies. During the review process, we recorded the application areas mentioned in each article. The total number of application areas was then calculated and used as an indicator to rank the key applications. For example, let's assume we only have two articles where the first article focuses on three applications, namely drilling, emergency evacuation and pipelines, while the second article focuses on two applications, namely drilling and asset lifecycle management. The total count for applications is recorded as five where the counts for individual applications are recorded as two for drilling, and one each for pipeline, asset lifecycle management and emergency evacuation. The ratio of the count for a given application to total application count is calculated and is termed as relative popularity of digital twin for that application. For our two paper example, the relative popularity of drilling is 40% and the popularity of the other three applications is 20% each. FIGURE 8 summarizes the top ten application areas along with their relative popularity for 199 articles. From this graph, it can be seen that asset monitoring and maintenance, project planning, and lifecycle management are the most anticipated application areas for DT. In addition, collaboration and knowledge sharing, drilling, virtual learning and training, offshore platform and infrastructure related studies, exploration and geology studies, pipelines, intelligent oilfields, and virtual commissioning are areas of attention from the research community.

### 4) KEY TECHNOLOGIES

There is a range of enabling digital technologies that have been applied when implementing DT for O&G industry

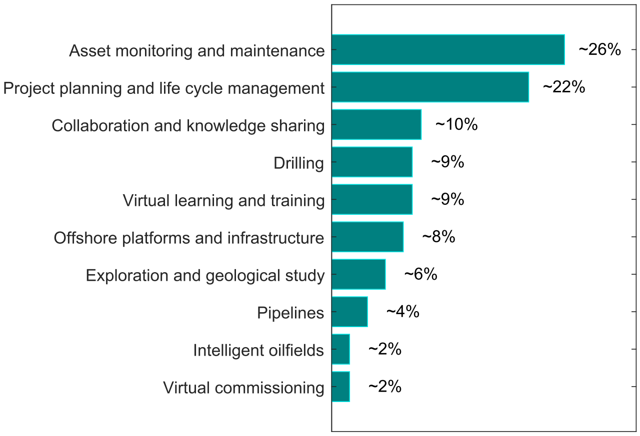


**FIGURE 8.** **Level three sorting results - top ten application areas.**

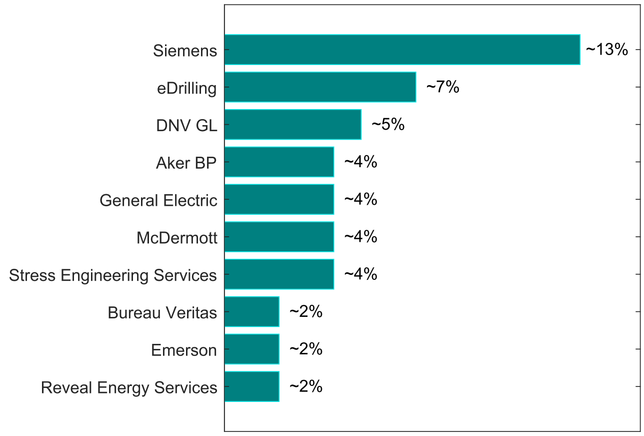


**FIGURE 10.** **Level four sorting results - top ten supply-chain contributors.**

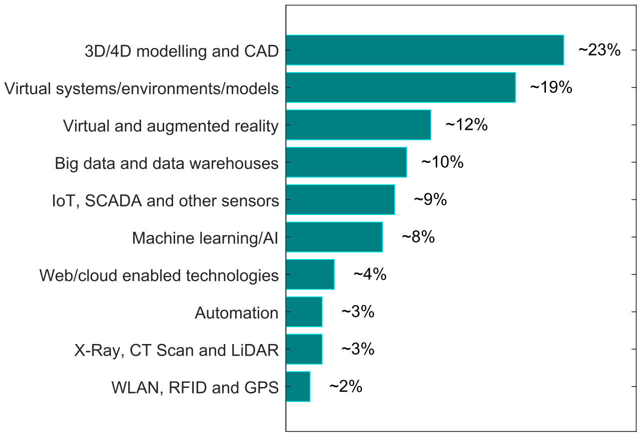


**FIGURE 9.** **Level three sorting results - top ten enabling technologies.**

related applications. During the review process, we counted the number of occurrences of the enabling technologies referenced in each article and this count was used as an indicator to rank the key enabling technologies. FIGURE 9 gives the top ten enabling technologies along with their relative popularity. The first three technologies, (1) 3D/4D modelling and computer-aided design (CAD), (2) virtual systems, environments and models, and (3) virtual and augmented reality, are related to data (or information) modelling and visualization. The rest of the technologies are related to data acquisition, processing, analyzing and decision making.

### *B. LEVEL FOUR SORTING*

#### 1) PUBLICATION TRAJECTORY AND CLASSIFICATIONS

Prior to 2017, O&G industry related publications did not include the keyword "digital twin". All of the early publications used several other related terms, such as "virtual environment", "digital model", and "virtual model". It was reported that C-level executives in the O&G industry found references to "digital twin" by technology companies, such as Seimens or GE, to be ambiguous [54]. More recently, this ambiguity seems to be fading away, and O&G related companies and academic researchers are increasingly using the term "digital twin". In 2017, four conference publications and two journal publications in the O&G industry discussed applications of DT. This publication count increased to 31 conference articles and one journal article in 2018 and to 32 conference articles, 4 journal articles and 3 book chapters in 2019. All the selected articles published in the first quarter of 2020 have used the term "digital twin".

Of these articles, 88% came from the industrial sector while 12% came from academic institutions. This indicates that there exists a gap between industrial research and academic research programs related to DT and its applications to the O&G industry. It is important to reduce this gap as sustainable innovation requires collaboration between the industrial and academic sectors. There appear to be opportunities for academic institutions to extend their O&G-related research programs to include a focus on DT. Additionally, when considering the related industry articles, approximately 95% of the contributions came from the supply chain, while the remaining 5% came from O&G operators. This indicates that the supply chain is engaged in more DT innovation than the other stakeholders. The top ten supply chain companies involved in O&G-related DT research along with their relative contributions for the selected 82 articles is depicted in FIGURE 10. Note that 5% of the contribution made by O&G companies was made in 2019 and 2020, with British Petroleum, Equinor, Saudi Aramco, Shell, and Total are publishing results of works.

#### 2) LEADING COUNTRIES

Eighty-two articles considered at this stage are distributed over 18 countries. Top ten countries by publication count is as shown in FIGURE 11. Among these countries, the US is the major contributor with approximately 30 articles. This is followed by Norway with approximately 15 articles, and the UK, with approximately 11 articles. Together these three countries published 56 articles, while the rest of the countries contribute the remaining 26 articles. When considering

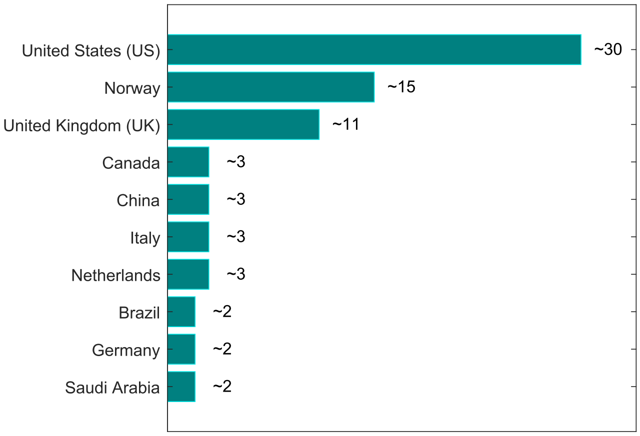


**FIGURE 11.** **Level four sorting results - top ten countries by publication count.**

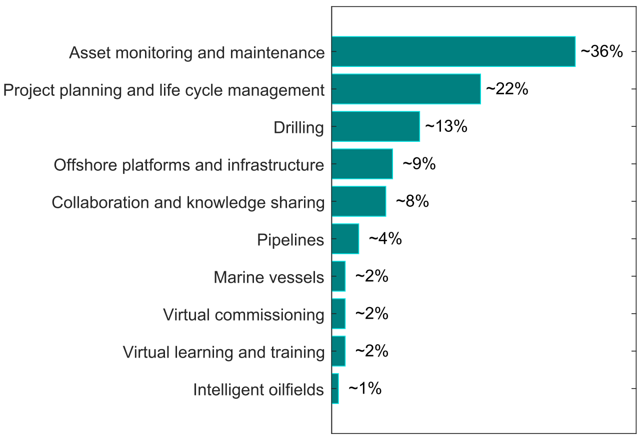


**FIGURE 12.** **Level four sorting results - top ten application areas.**

the major O&G operations at the North Sea and the Gulf of Mexico, this is again a reasonable distribution of articles.

### 3) KEY APPLICATIONS

The top ten application areas found in the 82 articles which included the term ''digital twin'' are very similar to the application areas found in level three sorting. However, the priority ranking is slightly different. The updated top ten application list along with their relative popularities is illustrated in FIGURE 12. It can be seen that asset monitoring and maintenance, project planning, and life cycle management remain the top-ranked applications of DT. However, collaboration and knowledge sharing appear to be of lower priority compared to drilling, and studies on offshore platform and related operations. This may be attributed to the fact that the 88% of the articles considered in the level-four sorting are originated from industrial sector whose primary objective is to improve the safety and productivity of the ongoing operation rather training future workforce.

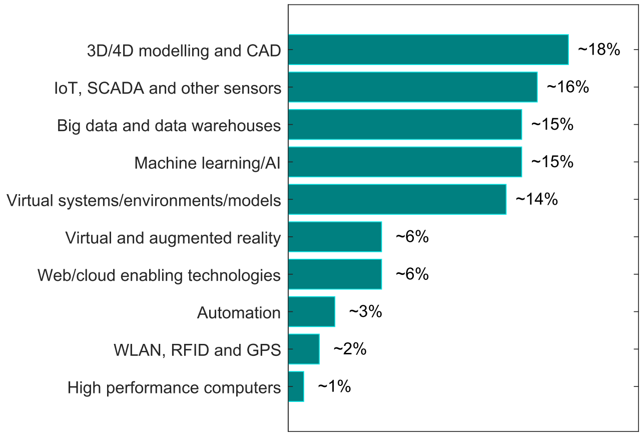


**FIGURE 13.** **Level four sorting results - top ten enabling technologies.**

### 4) KEY TECHNOLOGIES

As shown in FIGURE 13, there are few changes in the order of the top ten enabling technologies identified in level four sorting results compared with the level three sorting results. IoT, SCADA, big data analytics and data warehouses, machine learning, artificial intelligence and other sensor technologies outranked virtual and augmented reality. X-ray, CT scan and LiDAR are no longer within the top ten enabling technologies. Cloud-enabled technologies remains in the seventh position but, its relative popularity has slightly increased. Automation remains in the eighth position. These changes may also be related to the fact that the 88% of the articles considered in the level-four sorting originate from industrial sector whose primary objective is to improve the safety and productivity of the ongoing operation rather to train the future workforce.

## *C. LEADING OR LAGGING?*

Technological adoption in the O&G industry is thought to happen at a slower pace compared to industries such as manufacturing, automotive, aviation and aerospace, healthcare, and retail. Concepts such as data acquisition, data modelling, visualization, simulation, real-time monitoring and predictive control, however, are not new to the O&G industry. Since these are the building blocks of DT, it is important to evaluate trends related to the popularity (or acceptance) of DT within the O&G sector compared to other industries. To achieve this objective, a simple test was performed with the aid of Google search engine. The six search strings, listed in TABLE 5, were entered in the Google web search engine and the number of search returns was recorded. The number of search results returned for these search strings are indicators of the popularity of DT technology across the associated industry sector.

Although the term ''digital twin'' was introduced in 2002, there was little activity related to DT until 2010 (refer to FIGURE 14). In terms of embracing DT technologies, manufacturing and automotive industries are the first to transfer from the incubation stage to the growth stage, which occurred around 2010. Around 2013, aerospace and aviation industry

**TABLE 5.** Google search string by industry.

| Industry | Google search string |
|---|---|
| Manufacturing | "digital twin" AND "manufacturing" |
| Automotive | "digital twin" AND "automotive" |
| Aviation | "digital twin" AND ("aviation" OR "aerospace") |
| Healthcare | "digital twin" AND "healthcare" |
| Retail | "digital twin" AND "retail" |
| Oil and Gas | "digital twin" AND "oil and gas" |

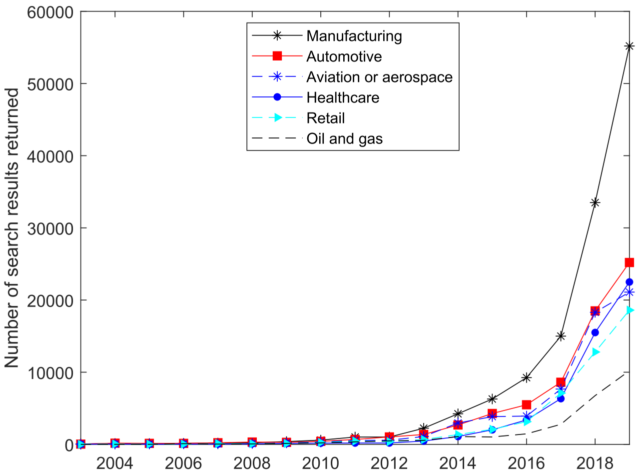


**FIGURE 14.** Comparison of number of DT related search results returned for six industries.


**FIGURE 15.** Crude oil price daily chart for last ten years. The price given in y-axis are in USD per barrel (Source: [127]).

joined these early adopters. The interest in the healthcare and retail industries has not grown as quickly as in manufacturing, but has been faster than in the O&G industry. As suggested repeatedly in the literature, the O&G industry is a lagging industry in terms of adopting DT technology while the manufacturing industry is the global leader.

Until 2014, O&G industry showed a similar interest in DT technologies compared to healthcare and retail industries. However, this trend changed in 2014 and the O&G industry's interest stayed approximately steady for the next two years, while other industries demonstrated an increased interest towards DT. This behavior may be attributed to the rapid decline of crude oil price during this period as shown in FIGURE 15. Once the crude oil price started to move upward, in mid-2016, O&G companies appeared to shift away from cost cutting and resumed investment in innovation. The rapid digitalization associated with Industry 4.0 may have also contributed to the recent interest towards DT technologies by the O&G industry.

## V. OPPORTUNITIES AND CHALLENGES

Before presenting the review finding related to the opportunities and challenges for deploying DTs in the O&G industry, it is useful to define two terminologies to improve the clarity of the presentation. The term "facility" represents the O&G drilling rigs (both the exploration and production phases), production platforms, processing facilities (i.e., refineries), and storage facilities together with the associated infrastructures such as warehouses of spare parts and accommodation buildings for workers. The term "asset" represents the O&G facilities and components installed in these facilities ranging from nuts and bolts to complex separation system.

### A. OPPORTUNITIES

This section presents the findings related to the third research question (RQ3), i.e., "What are the key opportunities of DT deployment in the O&G industry?". While reviewing the selected articles, we recorded the key benefits of deploying DT in the O&G industry. These benefits are summarized below. The clear understanding of the opportunities helps the O&G industry to effectively implement DT so that the value created by the DT is maximized.

#### 1) ASSET PERFORMANCE MANAGEMENT ( [1], [3], [46], [56], [57], [59], [71], [82], [83], [86], [108], [113], [115], [116], [118])

DTs acquire data from the O&G assets and analyze the data in real-time (or near real-time) to provide insights about these assets. These insights include production rates, system bottlenecks, operating conditions, malfunction, control parameters to optimize production, structural integrity level of the assets, potential failure modes and rates, and requirements for near-term repairs and replacements. Additionally, DT provides a single interface for visualization of the risks and key performance indicators of the asset. Operators can utilize these insights and indicators to optimize production, optimize plans for intervention for repairs and replacements, and perform "what-if" simulation scenarios to enhance production, while reducing downtime. Additionally, "what-if" scenarios can be evaluated to determine de-rated operating conditions for assets having potential structural integrity issues. For example, an operator can run a "what-if" simulation on a DT to determine the de-rated operating condition for a pressure vessel with internal wall thinning. With such an application of DT, the operation can continue until the next off-peak cycle or turnaround without increasing the HSE risk. Finding an optimal plan for repair and maintenance and selectively delaying the repair and replacement avoids unplanned interventions and frequent shutdown and restart of assets, thereby extending asset life. In addition to the benefits for managing the performance of an existing asset, the insights generated by the DT can be stored in a knowledge management system and used in the future to optimally develop new projects.

### 2) ASSET RISK ASSESSMENT ( [57], [58], [80], [88], [113], [118], [128])

DT applies machine-learning, deep-learning and artificial intelligence algorithms to detect and correct asset malfunctions. The fitness-for-service of each physical asset connected to the DT is continuously monitored by the DT to identify potential failures and avoid accidents. When an engineering team develops a new operating procedure to enhance production, this new procedure can be evaluated on the DT to examine whether any of the equipment installed in a facility poses a threat to the employees, facility or environment. Once the safe operation is verified on a DT, the new control parameters can be applied to the physical asset. This mitigates HSE risks associated with control parameter updates for facilities. In general, a given production or drilling facility generates a large volume of data which cannot be assessed by a human operator to determine whether the asset complies with the HSE standards and regulations. The big-data analytics capabilities of the DT can address this limitation by monitoring the asset and sending warnings to the responsible parties, including regulatory bodies. DT can also be used to develop a procedure to reinstate asset operation to a level that complies with HSE and other regulatory requirements.

### 3) VIRTUAL TRAINING TO NAVIGATE AND OPERATE ( [49], [76], [128]–[139])

The safe and sustainable operation of O&G facilities generally depend on the level of training and experience of the employees. Globally, O&G companies are facing the challenge of "big-crew change[1]" [140]–[144] where the more than 50% of the experienced workforce will retire in near future creating a skill and talent shortage across the industry as illustrated in FIGURE 16. The knowledge these retiring professionals possess may not be effectively transferred to the next generation (e.g. millennials) due to cultural, demographic and technological challenges. Therefore, effective training programs are needed to orient the new employee to O&G occupations. DT together with the extended reality technologies, including VR, AR and MR, can offer a virtual platform to train the new employees to navigate within O&G facilities, to operate equipment, to monitor and inspect systems, and to interact with on-going operations. This training gives new employees full exposure to O&G facilities and ensures that they are aware of operational procedures. Such virtual training can help reduce the number of interruptions or accidents that may occur when training new employees using operating physical assets.

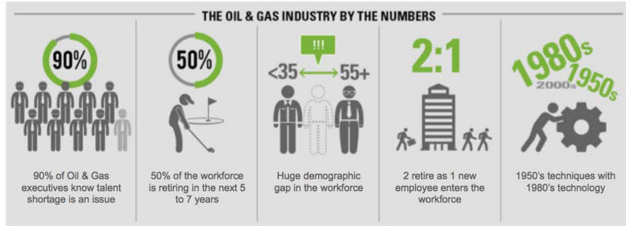


**FIGURE 16.** Demographic challenges of O&G industry (Source: [142]).

### 4) EMERGENCY RESPONSE TRAINING ( [132], [135], [138], [145]–[148])

Regular safety training, such as fire drills and emergency evacuation training, is mandatory within the O&G industry. During such training, equipment may need to be shut down and operation may require to be suspended leading to a drop in productivity from the facility. Additionally, emergency evacuation training on offshore facilities is both costly and may pose unnecessary risks to the personnel on board. Some emergency response plans, such as an ice management plan for offshore Newfoundland [149]–[151], may require floating production operations to be suspended, disconnected, sailed away, sailed back, reconnected, evaluated for fitness-for-service, and restarted. Training offshore crew for such an emergency response increases the facility downtime, and decreases the equipment life due to the shutdown, disconnect, reconnect, and restart activities. These limitations can be reduced or eliminated by using DT for such training.

### 5) SHORTER TIME FOR PLAN TO PRODUCTION ( [54], [71], [99], [115], [152]–[154])

In general, each O&G facility, particularly offshore production facilities, has a unique design depending on the reservoir characteristics and the location of the field. This requires the engineering team to design the platform from scratch, which adds to the time to develop an operating field. With the emerging digital technologies, leading oilfield service companies utilize DT technologies to speed up the design and construction process. These companies have digital models of all their previous projects. These DTs are combined with the site parameters to develop the initial virtual facility for a new project. A series of simulations are then run on this virtual facility to determine the optimum design. Engineering design data are then embedded in the virtual facility. Components delivered by different groups/venders are verified and approved through the collaborative interface of the DT. By following this design approach, the facility design and construction time can be reduced drastically. For example, design cycle time for a jacket, which is the steel frame supporting the deck and the topsides of a fixed offshore platform, has reduced to 3∼4 months from 9 months using a virtual model based approach [54].

[1] "Big-crew change", also known as "great-crew change", is a term referred to the phenomena that the creation of skill shortage due to the retirement of the post-war baby-boomers.

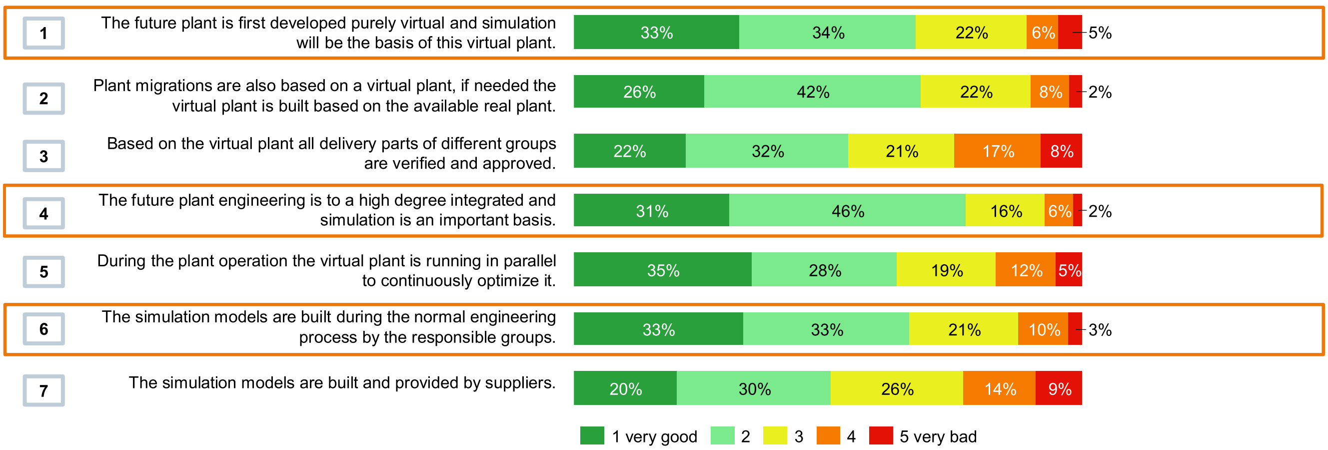


**FIGURE 17.** Industrial and academic opinion on use of simulation within the lifecycle of process plant in 6-8 years (Source: [152]).

Once the design is completed and the facility is constructed, detailed commissioning is completed prior to commencing operations. This is a time-consuming process that is associated with some HSE risk. Using a high-fidelity digital twin, the facility can be pre-tuned, and the control loops can be verified for correct operation. This can reduce the time required for commissioning and decrease the HSE risk. Survey results presented in [152], [153] (refer to FIGURE 17), also suggests that using a virtual facility can be particularly useful in the design, fabrication and operation of facilities.

#### 6) AVOID MISCOMMUNICATION AND INFORMATION WASTAGE ([ [54], [153])

Traditional supply chain tracking and project documentation have two significant limitations, miscommunication and information wastage. For example, at the O&G production platform design stage, if an engineering team updates the size of a valve and communicates this update to the valve manufacturer but has forgotten to inform the piping department, then the piping department keeps manufacturing or purchasing flanges based on the original valve dimensions. As a result, during construction, the construction team will have to delay work while the correct size flange is procured for the new valve. Such miscommunications can be avoided by entering updates digitally into the DT, which will notify the relevant parties of the updates. Notifications can take two forms: (1) emails and messages to all the parties, and/or (2) a visual alert on the DT which remain active until the relevant parties confirm that receipt of the update.

In addition to miscommunication, traditional project management and documentation approaches can result in misplacing data and information when transitioning between phases of field development. This is a consequence of multiple oil-field service companies (or multiple teams within the same company) carrying out the work in the different phases of development. If all development activities are embedded into the DT, data loss can be avoided when transitioning between phases. This application of DT creates opportunities for cost savings by eliminating the repetition of work that has been already done, thereby accelerating the project timeline.

#### 7) COLLABORATIVE DECISION MAKING ( [46], [50], [51], [70], [79], [80])

The O&G industry is a capital-intensive industry in which it is important to maximize the uptime of the facilities. Therefore, making the right decision promptly is crucial to both reducing downtime and HSE risk, while maximizing production and revenue. When an asset encounters a critical situation, multiple experts may review the situation, and discuss and collectively develop a scenario to resolve any issues. Such collaboration among experts is challenging if they are not co-located or near the facility. A traditional teleconferencing-based approach may have limited effectiveness. DTs, however, can enhance collaboration by allowing experts to work from anywhere on the globe and giving them on-demand access to critical data and insights from the DT. Additionally, virtual control rooms can be established so that the experts can collectively discuss, simulate and decide on the best solution to address any critical operating situation. With effective physical and cyber security implementations and reliable communication mechanisms,[2] DT can be used to implement virtual control rooms to address the 4-D obstacles (danger, dirty, distance, and dull) of staffing at offshore and other remote locations.

#### 8) PROCESS AUTOMATION ( [45], [54], [74], [103], [104], [155])

As the DT is connected to physical assets, it has the data generated from the sensors and it is capable of processing

[2]Reliable communication mechanisms should have multiple communication platforms and links to communicate the same data between the offshore or remote facility to the central control room. This multiple redundancy ensures continuous bi-directional communication even though the primary communication mechanism has failed. Additionally, secondary power systems should provide uninterrupted supply power to the data collection, storage, communication and control systems when the main power supply is down.

 

these data to generate insights about operations. Furthermore, it can be used to automate the operations at the O&G drilling, production or processing facilities. Monitoring and analyzing in real-time allows the DT to generate optimal control commands for actuators attached to the equipment. With the help of automation, it is possible to remove human workers from hazardous and remote locations. This indirectly improves the safety of the facility and decreases the accident rate because most accidents occurring at O&G facilities have some element of human error. Additionally, automation can improve the consistency of the operation and enable continuous 24/7 operation.

#### 9) FUTURE SCENARIO DEVELOPMENT ( [14], [22], [35], [156])

Using DT, operators can develop future operating scenarios for existing assets and future development scenarios for new assets. A series of "what-if" simulations can be run to determine the best operating/development scenarios. This can reduce the nonproductive time when updating control parameters or developing a new asset with a consequent improvement in productivity.

#### 10) EFFECTIVE TIME UTILIZATION ( [58])

Existing O&G assets typically have data acquisition capability. The collected data, however, needs to be reviewed, cleaned and assessed to determine current and future operating conditions, as well as to ensure asset reliability, regulatory compliance and to deal with other safety and critical production issues. This is labour-intensive and could be automated using DTs to carry out data collection, analysis and insight generation. The employees could then focus on applying the DT outcomes to improve safety and increase production and revenue rather than spending time on data cleaning and evaluating.

### B. CHALLENGES

This section presents the findings related to the last research question (RQ4), i.e., "what are the key challenges of DT deployment in the O&G industry?". The clear understanding on the challenges helps the O&G industry to implement DTs while effectively mitigating these challenges. While reviewing the selected articles, we recorded the key challenges for implementing DTs in the O&G industry. These findings are summarized below.

#### 1) SCOPE AND FOCUS ( [36], [53], [65], [125])

With the emergence of IIoT, smart sensors, VR, AR, machine learning, deep learning and artificial intelligence, it may possible to conceive of an extremely complex DT that aims to perform everything imaginable. In the process of developing an overly complex DT, the developer may end up getting lost in an exponentially growing number of sensor options and an enormous number of digital technologies that can be exploited to construct the DT. In contrast, more simplistic DTs provide limited insight into the physical asset, requiring multiple DTs for full simulation of the same asset. For example, a pressure valve may have two DTs, one to measure and analyze the pressure profiles of the pressure valve, and a second to analyze the structural integrity of the valve. As a result, DTs can become another collection of siloed data and information sources rather a useful digital assistant. Because of these two extremes, O&G operators, industrial and academic partners and DT designers need to carefully evaluate the requirements of the DT for their organization (or project) and implement it at the optimum depth and breadth.

#### 2) LACK OF STANDARDIZATION ( [36], [54], [65], [71], [157], [158])

While data is the backbone for DT, existing field data typically does not follow a common data standard. Data may be unstructured (e.g. portable document format), semi-structured (e.g. log files from an operator's integrity management program), or structured (e.g. comma separated files, excel spreadsheets). Data integration platforms from different vendors also follow different standards and methods to present their data. Additionally, the existing data is typically not linked to a common database and is often stored in disparate locations. These factors make it challenging to integrate all of the existing and real-time data into a single data analytic module. As a result, an intermediate interpreter is required to convert data from both proprietary and open access data sources to a standard format that the DT can understand.

#### 3) CYBER SECURITY ( [46], [70], [71], [159]–[162])

DT creates a cyber-physical connected environment to perform real-time evaluation of asset performance and to generate control commands and operation strategies for an asset. The connected assets are vulnerable to cyber-attacks. As reported in [162], the energy sector was ranked as the second most prone industry to cyber-attacks in 2016 with approximately 75% of US O&G companies experiencing at least one cybersecurity-related incident. Tampering with sensor or control parameters can lead to catastrophic failures. For example, as reported in [162], "if a cyber attacker were to manipulate the cement slurry data coming out of an offshore development well, blackout monitors' live views of offshore drilling, or delay the well-flow data required for blowout preventers to stop the eruption of fluids, the impact could be devastating". As shown in FIGURE 18, the severity of the cyber-attack and the vulnerability to cyber-attack differ for different stages of the O&G field life cycle. The development drilling and production stages have a high susceptibility for cyber-attacks. When considering the combination of vulnerability and severity with respect to DTs, the cyber threat necessitates greater attention from O&G companies. Advanced cyber-security protocols need to be implemented to protect both the physical and virtual facilities against cyber-attacks.

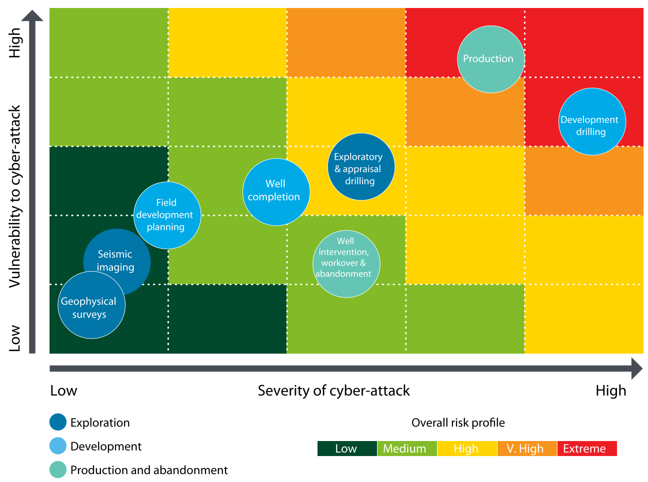


**FIGURE 18. Cyber vulnerability/severity matrix by upstream operations (Source: [162]).**

### 4) DATA OWNERSHIP AND SHARING ( [65], [71])

The data generated within a DT can be used for future developments, including for designing new and improved assets and for development of advanced data science algorithms. Whether or not "data is the new oil" [163]–[168], data will play a key role as industries become more digitalized. The owner of the data will hold the balance of power in a relationship. Technological giants like GE and Siemens are developing DTs for the O&G industry [169]–[173], while the O&G service providers and operators are making use of these products. Clarity with respect to data ownership is critical. It is important to protect intellectual property (IP) rights, to enable secure access, to allocate responsibilities and to define the level of access for stakeholders when sharing the data. Although data sharing can bring enormous advantages to the entire supply chain and ecosystem, current regulations, policies and the mindset of O&G companies, particularly C-level executives, need to be considered with respect to impacts on data sharing. For example, restrictions on data sharing might arise as result of competition between technological, service and operating companies, or as a consequence of cyber-security concerns.

### 5) ACCURACY AND VALIDITY ( [46], [65])

DTs aggregate multiple models, with some parts of the models based on the physical principles with other parts derived empirically from machine learning approaches. It is essential to tune these models to accurately replicate the behavior of the physical assets. Model tuning is an extremely challenging task and there are no set rules or effective tuning procedures. When tuning the models, designers attempt to minimize the discrepancy between the model outputs and the physical asset outputs. This discrepancy, however, may be rooted in a faulty sensor, in uncertainty associated with the data, incorrect parameters, faults in the models, missing critical model components, or a malfunction of the physical asset. Despite the inherent challenges associated with model tuning, the DT is required to be an accurate replica of the physical asset in order to gain the benefits of the DT. Otherwise, the insights derived from the DT are invalid.

### 6) FUNCTIONALITY ( [65], [126])

A DT typically collects a vast amount of raw data from the O&G assets, which is processed to generate insights (information) about the asset. The O&G operators, however, should be able to access the information he/she needs without being distracted by the other information that the DT has generated. Therefore, the DT designer must understand the O&G operators and their requirements prior to designing the DT. The DT should allow O&G operators to customize the data (insights/information) visualization process so that they can select the information of most interest while minimizing distraction from other data.

### 7) UNLOCKING EXPERIENCE ( [36])

Data acquisition and simulation are not new concepts for the O&G industry, and they have been utilizing such technology for decades. Traditionally, these data and simulations have been analyzed by human experts to convert data into insights. The skills built up through such analysis includes the knowledge for interpreting oilfield data, identifying anomalies in the measurements and their root causes. These human experts also have an understanding of solutions which may be implemented to address anomalies. Additionally, they know the physical and empirical concepts underpinning solutions. Such knowledge is usually either locked down in employees' heads or captured in complex enterprise data management system. Decades-old knowledge and expertise are vital for implementing accurate and effective DTs. Unfortunately, unlocking this knowledge and reuse of the concepts and solutions from the previous projects to improve the functionality of DT is exceptionally challenging.

### 8) BUSINESS MODEL, PEOPLE AND POLICIES ( [65], [70], [71])

The integration of a DT transforms traditional work practices and organizational structures of the O&G industry. This transformation may not be appreciated by employees if the DT is unable to deliver tangible and measurable benefits to them. Designing a DT to do everything, however, is impractical. Thus, existing implementations tend to be asset-specific DTs which deliver tangible and measurable benefits for certain groups of employees with little to no benefits for other employees. Those who do not directly benefit from the DT, or who may feel threatened by the DT, may resist DT implementation. Additionally, employees, particularly C-level executives, may have concerns about cyber threats associated with cyber-physical connected systems. As a result, such decision-makers may prefer not to integrate DTs into their operations. Furthermore, some C-level executives are still trying to comprehend the previous wave of the digital transformation, i.e. digital software and smart sensors, and have a lack of vision with respect to adopting DTs into their operations. To address these limitations, it is essential to educate the existing workforce and executives about the benefits of DTs, cyber-security protocols for protecting the connected assets against cyber-attacks, and DT implementation strategies. Additionally, employees must be trained to use the DT, to interpret the insights generated by the DT, and to execute the day-to-day operations collaboratively with the DT. As part of implementing a DT, it is critical to define who has access to the DT and at what level (e.g. read, simulate, command overwrite). Effective new policies must be developed and implemented to avoid data breaches. Regulatory frameworks and operational procedures must protect IP rights. For example, employees may be required to sign non-disclosure agreements so that the data and insights from the DT will not be disclosed to a third party.

#### 9) DATA STORAGE AND ANALYTICS ( [57], [64], [174])

The sensors attached to the O&G assets generate a large volume of data. Such a high volume of data is sometimes referred to as ''big data''. This data is typically corrupted with systematic or unsystematic noise and must be cleaned prior to using it with any machine learning-based simulation. Additionally, this data must be stored for future use necessitating well-maintained data warehouses. These data storage systems need to be protected from cyber-attacks, must be well organized to ensure fast data access, and must utilize user identification protocols to avoid unauthorized data access and modifications. When it comes to data analytics, there are several challenges to implementing machine learning algorithms including deciding (1) whether to employ cloud or on-premise processors and data warehouses for analytics and data storage, (2) which strategy should be executed when deploying machine learning models, and (3) whether to perform batch, semi-batch or real-time data analysis.

#### 10) MAINTENANCE ( [65])

Development of a DT for an O&G facility begins with a preliminary site survey and evolves through the exploration, appraisal, development, operation and abandonment phases. The resulting DT is then available for new projects. This implies that complex software tools, hardware infrastructure, sensors, and asset life cycle data (e.g. measurements, simulations, models, asset status, anomalies, corrective measures, parameters for optimum operations) need to be maintained throughout the asset life cycle and after the asset has been decommissioned. A multidisciplinary project group can be recruited and trained to conduct such maintenance activities. In considering whether to adopt a DT, it is important to consider costs and benefits of maintaining an up-to-date and complete DT.

#### 11) INCREMENTAL VS. DISRUPTIVE ( [71])

Leading O&G operators, service providers and vendors are all investing heavily in new digital technologies. Instead of becoming a disruptive force that leads to higher revenue and reduced HSE risks, many of these digital technologies are adding marginal improvements to the technical and operational capabilities of the current supply chain of the O&G industry. When the improvements are incremental, companies do not fully embrace the benefits promised by digitalization. This issue also holds for adopting DT within the O&G industry. Without proper planning, DT will only add marginal, or in some cases no, benefits to operations.

## VI. SUMMARY

The capital-intensive O&G industry, which has been operating in a lower-for-longer oil price environment and is facing a ''big crew change'', is reforming its traditional business model and beginning to integrate digital technologies to address skill gaps and to maximize production and revenue while reducing HSE risks and capital and operational costs. Recently, industries such as manufacturing, automotive, aviation, and healthcare have demonstrated the benefits that may be achieved using DT technology. O&G operators, oil-field service companies and other stakeholders are also considering the role of DT technology in the O&G industry. DTs are virtual replicas of physical assets based on cyber-physical integration to collect, analyze, and visualize data in order to make more informed decisions and to conduct a series of ''what-if'' scenario analysis to enhance safety, revenue and production. Critical components of DTs are not new to the O&G industry which has been collecting, modelling and simulating data for decades. Most traditional data collection and use by the O&G industry, however, does not cover the entire spectrum of DT.

The top ten enabling technologies for DT, as identified from this literature review, are 3D/4D modelling and CAD; IIoT, SCADA and other smart sensors; big data, data analytics and data warehouses; machine learning, deep learning and artificial intelligence; virtual (simulation) systems, environments and models; virtual and augmented reality; web and cloud-enabled technologies; automation; wireless sensor networks and location trackers (RFID, GPS); and high performance computing. When integrated, these technologies provide a cyber-physical connected simulation environment that can capture data from physical assets, extract insights from the data, and collaboratively improve operations through enhanced safety, revenue, and productivity.

The literature review identified the following top ten O&G-related DT application areas: asset integrity management; project planning and life-cycle management; drilling; offshore platform and infrastructure design and monitoring; collaboration and knowledge sharing; pipeline design and monitoring; virtual learning and training; marine vessel design and maintenance; virtual commissioning, and intelligent oilfields. Except for the collaboration, knowledge sharing, and virtual learning and training, all other applications can be considered under the umbrella of project planning, life cycle management and asset integrity monitoring.

When considering the geographical distribution of the DT-related research in O&G industry, the US is the leading country, followed by Norway, UK, Canada, China, Italy, Netherland, Brazil, Germany, and Saudi Arabia. The publication rate was less than ten articles (approximately) per year until 2017, and a significant increase occurred in 2018 and 2019. Based on an analysis of Google keyword search results, the O&G industry appears to be lagging in the adoption of DTs compared to other industries such as manufacturing, automotive, aviation, healthcare and retail. As reported in much of the literature, the manufacturing industry is the global leader for adopting DT technology within their operations.

The majority of the DT related publications related to O&G applications originated from industry rather than academic institutions. When considering publications explicitly referencing DT (level-four sorting), the review found that only 12% of publications were associated with universities while 88% of publications were associated with O&G operating or service companies. When the enabling DT technologies were considered (level-three sorting) in the literature review, 32% of the publications identified were associated with universities, while 68% of the publications were associated with companies. This suggests that there is growing interest among O&G operating and service companies in DTs and there is an opportunity for universities to enhance their role in collaborations with industry around this technology. With such enhanced collaboration, there is significant opportunity for DTs to improve efficiency, safety, and productivity while complying HSE standards and other regulatory requirements. Additionally, most of the industry affiliated authors, i.e. 95%, come from the supply chain and not from the operators. This suggests that the supply chain is where most innovation occurs around DT technology for the O&G industry.

There are several challenges for implementing DTs in the O&G industry. While there is a risk of becoming overwhelmed by the array of opportunities that DT may offer, it is best to avoid trying to implement a DT that can do everything. Rather the focus needs to be on what the company has to achieve and on selecting a DT approach with the appropriate level of complexity. Adopting a DT will shift the fundamental business model of the O&G industry and modify the roles of its employees and traditional workflows. Such changes may be resisted by existing employees if these changes are not carefully managed. In some cases, employees with new sets of skills may replace current employees.

The success of a DT depends on how well it can integrate existing data to derive insights. Unfortunately, existing data acquisition platforms do not typically follow the same data standards and may generate structured, semi-structured or unstructured data which are difficult to integrate into a common database. This presents a challenge for data fusion within the context of a DT implementation in the O&G industry. There are several ongoing initiatives to address this issue and to establish standard data protocols. Once data is collected, a data warehouse need to be implemented to securely store the data and advanced data analytic tools need to be employed to analyze the data. The selection of data warehouses and data analytic techniques is also a challenge that must be addressed when implementing DTs in the O&G industry. A DT should deliver custom insights rather than distracting the O&G operators with redundant data and insights. To address this challenge, user profiles can be implemented so that each user profile defines the insights that need to be visualized by each O&G operator. For future projects, development of a DT begins at the initial site survey and evolves through exploration, appraisal, development, production, and abandonment. It is critical to maintain the hardware infrastructure and the software connected with the DT for the life cycle of the facility. This can be achieved through a multidisciplinary project group.

Once a cyber-physical link is established between a DT and the physical assets, the physical assets become vulnerable to cyber-attacks. Advanced cyber-security protocols and industry-wide regulation changes are required to improve cyber-security and to define who has access to the DT and their access level (e.g. read, write, overwrite, visualize).

DTs generate a large volume of data on a daily basis, and ownership of this data and protocols for sharing must be well defined prior to commencing DT implementation so as to maximize the benefits that can derived from such data. For example, if an equipment manufacturer can have access to data, they can improve their products to have a longer life and improved performance. In return, an O&G company can use these improved products to reduce the downtime for repairs and replacement. Establishing a mechanism to protect IP rights and share the data with other stakeholders in a secure manner has the potential to add significant value across the O&G business ecosystem.

DTs are based on a set of physics-based or empirical models and run with the noisy sensor data. Tuning a DT to deal with model imperfections, noisy sensor data or fault sensor situations is a significant task and having access to historical data and insights is particularly helpful to successful tuning. Unfortunately, much historical data are usually locked down either in employees' heads or in complex enterprise data management systems. Unlocking this knowledge is among the significant challenges associated with implementing DT in the O&G industry.

Proper implementation of a DT can offer ample opportunities for the O&G industry. It can be used for asset performance management, asset risk assessment, and asset integrity management. In such applications, a DT analyzes all of the available data and derives the insights and optimum control commands to reduce the HSE risk while increasing revenue and production, or decreasing costs. A series of "what if" simulations can be run on the DT to determine future drilling, production or processing scenarios. Continuous data acquisition, real-time monitoring, and "what-if" simulation can generate warnings for near-term equipment failures. DTs can automatically create work orders and schedules for repair and replacement. Such predictive maintenance could reduce costs by avoiding catastrophic failures as well as by extending the asset life by avoiding unnecessary interventions and repairs.

A DT may be configured such that it develops de-rated operating conditions for equipment prone to near-term failure so that the equipment will not fail and can continue to run until the next off-peak operating window or turnaround. With the help of a DT, several processes at a facility can be automated and their operations can be monitored from a central control room located far away from the facility. Note that once a DT performs data collecting, sorting, cleaning and analyzing, the employee can effectively utilize their time to implement the solution based on the insights generated by the DT instead of performing repetitive and routine data processing.

Oil and gas employees work in the complex facilities and must be appropriately trained to navigate within the facility and to operate equipment. DT provides an opportunity for training employees in virtual environments. This helps employees to be more appropriately trained before they step into an O&G facility and helps reduce the probability of accidents that may occur during on-the-job training. In addition to training employees to navigate within the facility and to operate equipment, the virtual environments offered by DT can be used to perform emergency response training. Performing emergency response on a virtual environment offers considerable cost savings for O&G companies, particularly for offshore emergency response training.

In general, field development is a time-consuming process and it takes several years to fully develop an O&G production facility. There is potential to reduce this development time using a DT. For example, the key characteristics of a delineated reservoir can be inserted into an existing DT database to identify the best first virtual facility. Experts can adjust the parameters of the initial virtual facility through a series of simulations in order to develop the optimal virtual facility. The physical facility can then be implemented with the aid of the virtual facility. Overall, the use of a DT has the potential to reduce the design time and hence the time required for development, allowing production operations to begin earlier. Design-related information can be embedded in the DT so that seamless communication can be established between all the stakeholders involved in the design process. Additionally, a DT can help to ensure that information losses do not occur when the design and implementation of the O&G facility moves between phases.

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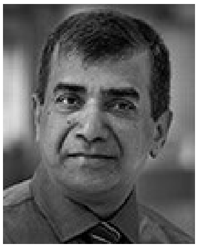

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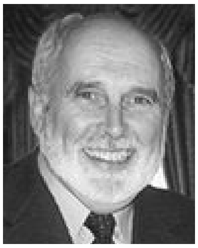

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