IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received September 28, 2021, accepted October 13, 2021, date of publication October 18, 2021, date of current version October 28, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3121302

A Survey on Industry 4.0 for the Oil and Gas Industry: Upstream Sector

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This work was supported in part by the Kementerian Pengajian Tinggi (KPT), and in part by Universiti Teknologi Malaysia under the research Grant, Q.J130000.21A2.05E25, 4B536, 01M98, 4B536 and 01M98.

ABSTRACT The market volatility in the oil and gas (O&G) sector, the dwindling demand for oil due to the impact of COVID-19, and the push for alternative greener energy are driving the need for innovation and digitization in the O&G industry. This has attracted research interest from academia and the industry in the application of industry 4.0 (I4.0) technologies in the O&G sector. The application of some of these I4.0 technologies has been presented in the literature, but the domain still lacks a comprehensive survey of the application of I4.0 in the O&G upstream sector. This paper investigates the state-of-the-art efforts directed toward I4.0 technologies in the O&G upstream sector. To achieve this, first, an overview of the I4.0 is discussed followed by a systematic literature review from an integrative perspective for publications between 2012-2021 with 223 analyzed documents. The benefits and challenges of the adoption of I4.0 have been identified. Moreover, the paper adds value by proposing a framework for the implementation of I4.0 in the O&G upstream sector. Finally, future directions and research opportunities such as framework, edge computing, quantum computing, communication technologies, standardization, and innovative areas related to the implementation of I4.0 in the upstream sector are presented. The findings from this review show that I4.0 technologies are currently being explored and deployed for various aspects of the upstream sector. However, some of the I4.0 technologies like additive manufacturing and virtual reality are least explored.

INDEX TERMS Artificial intelligence (AI), cyber-physical systems (CPS), digital-twin (DT), framework, oil and gas (O&G), industry revolution 4.0 (IR 4.0), industry 4.0 (I4.0), Internet of Things (IoT), simulation, upstream sector.

I. INTRODUCTION

The oil and gas (O&G) industry is the world's primary source of energy with a very complex process for production and distribution. It is noted for the economic transformation of the world, by supporting the demand for heat, electricity, mobility, and other essential petrochemical products of the world's population [1], [2]. The process of production and distribution involves state-of-the-art technology at different levels. These levels are the upstream, the midstream, and the downstream. The upstream segment involves exploration and production activities such as geological surveys, onshore and offshore drilling. The midstream segment involves operations such as transportation, storage, and the trading of crude oil,

The associate editor coordinating the review of this manuscript and approving it for publication was Shih-Wei Lin.

natural gas, and the products that are refined. The downstream segment covers refining and marketing. The upstream sector plays an important role in the O&G industry, hence this paper focuses on the upstream sector.

The O&G industry has recently experienced a downturn due to the COVID-19 pandemic and increasing high market volatility. In addition, the push for carbon taxes, greener and clean energy among several countries and globally is expected to see a long-term decline in the demand and consumption of fossil fuels. Hence, there is the need to identify the challenges of the conventional O&G sectors in order to achieve a cost-effective and more efficient way to keep the O&G industry more competitive.

A. CHALLENGES

The challenges faced by the conventional upstream sector and the need for the adoption of the I4.0 are outlined as follows.

- Dwindling price of oil and volatility - The O&G has witnessed dwindling oil price and high volatility [3] which is expected to affect investor's interest.
- High cost - The cost of operation such as the rise in the cost of new O&G deposits exploration and development, cost of production especially offshore and maintenance cost is still a major issue [4].
- High competition - The breakthrough in technology for the commercialization of unconventional reservoirs such as oil sands, shale gas, and coalbed methane has led to increased competition in the O&G industry. These unconventional reservoirs are complicated and costly to produce O&G on a profitable scale.
- Environmental pollution - Crude oil production is still faced with a high risk of environmental contamination. The call for climate regulation and emission reduction puts more pressure on the O&G industry. In addition, the demand for renewable energy is on the increase and becoming more economical.
- Timely decisions and forecast - The lack of advanced monitoring, data analytics (DA) for asset management and collaboration between production engineers, vendors, partners, consumers currently affect operational efficiency.
- Complexity in drilling and production process - The search for new reserve in hard to reach and extreme places makes drilling and production process complex and introduces health, safety, and environment challenges [5]–[7].

To overcome these challenges, the O&G industry is gradually moving towards the direction of intellectualization, digitization, and automation by leveraging on the industry revolution 4.0 (IR 4.0). The IR 4.0 is aimed at enabling new ways of production, value creation, and real-time optimization by adopting new and emerging technologies. Some of the technologies that have been identified in industry 4.0 (I4.0) are cybersecurity, internet of things (IoT), cloud computing, big data analytics, augmented reality (AR), additive manufacturing (AM), simulations, and system integration [8]. The combination of some of the I4.0 technologies have paved the way for new technologies such as digital twin (DT) and cyber-physical system (CPS). The I4.0 in O&G can be described as the fusion of I4.0 technologies to integrate the physical and the virtual O&G operations and objects in order to maximize productivity, enhance efficiency, improve quality and productivity. There are several vital roles I4.0 plays in the O&G industry and some of which include enhancement of project design and evaluation, deployment of intelligent oilfield, increase the reliability on the ecosystem, and facilitation of cost reduction [1], [9]. A description of the industrial revolution is summarized as follows.

B. INDUSTRY REVOLUTION

The industry has experienced different revolutions, from IR 1.0 to IR 4.0 as shown in Fig 1. The IR 1.0 witnessed the use of steam power to increase human productivity in the 18th century. In the 19th century, the emergence of electricity and assembly line production lead to mass production in IR 2.0. Subsequently, in the 19th century, the use of memory-programmable controls and computers enabled industrial automation for the IR 3.0 era. The advancement of information and communication technology is paving the way for IR 4.0 where machines are able to communicate with each other over the network. These have opened the way for smart concepts such as the smart manufacturing industry, smart maintenance [10], and smart construction [11], [12].

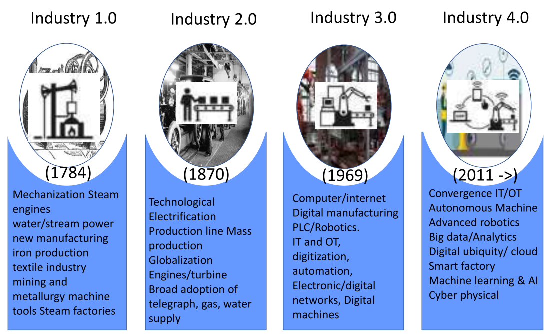

FIGURE 1. **Journey of industrial revolution [13].**

C. O&G UPSTREAM SECTOR

The O&G industry involves complex industrial operations that are focused on three main sectors involving upstream, midstream, and downstream [2], [14]. Fig. 2 illustrates the O&G sector. The upstream sector is the first phase in the life cycle of O&G; which involves the exploration and development, drilling and well completion, production and optimization, reservoir engineering, and control center operations [15]–[17].

There is limited literature that has discussed the I4.0 in the O&G industry [18], [19]. The roles of I4.0 in facilitating the intelligent oilfield in the upstream sector, intelligent pipeline in the midstream sector, and intelligent refinery in the downstream sector were discussed in [19]. In [18], a survey carried

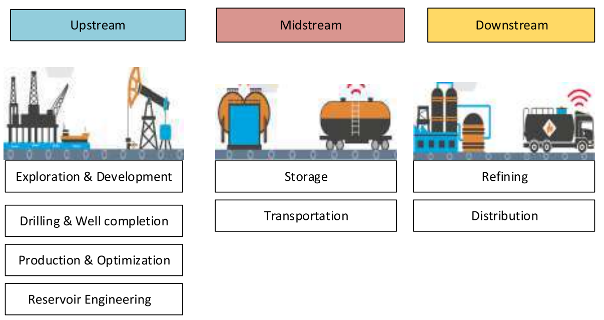

FIGURE 2. O&G industry sectors.

out among 13 suppliers to the O&G industry in Norway identified "little knowledge about the concept I4.0" as one of the inhibitors to digitization in the O&G industry. Although the research publications on the applications of some of the I4.0 component technologies appear to have grown in recent years, there is still a lack of comprehensive review on the state-of-the-art adoption of I4.0 in the O&G upstream sector. To address this gap, the following contributions of this paper are outlined as follows.

D. CONTRIBUTION

- We provide an overview of the I4.0 which includes the IoT, big data (BD) analytics, cloud computing, AM, AR, autonomous robots, cybersecurity, system integration, simulations, and DT and CPS and roles they play in the upstream sector of the O&G industry.
- A systematic literature review (SLR) of the I4.0 technologies for different operations in the upstream sector of the O&G is presented. This includes exploration and development, drilling and well completion, production and optimization, reservoir engineering, control operations, and equipment and operational parts.
- A conceptual framework for I4.0 for the O&G upstream sector is presented.
- We outline future trends and identify some of the research opportunities and processes needed for the integration of I4.0 in the upstream O&G sector.

E. ORGANIZATION

The rest of this paper is structured as follows. Section II provides an overview of I4.0 technologies. The different I4.0 technologies and their roles in the different aspects of the upstream sector are presented. In Section III, the review methodology is presented. Section IV covers the findings and discussion of reviewed papers. This includes the related works and review of the application of I4.0 technologies. The discussion is categorized into the various operations in the upstream sector which include exploration and development, drilling and well completion, production and optimization, reservoir engineering, and control operations. A review of the application of I4.0 in the upstream sector is discussed in detail. In Section V, a conceptual I4.0 framework for the upstream sector is presented and the benefits of the I4.0 are identified in Section VI. Section VII enumerates the open issues and challenges. Section VII provides an insight into the future trends and finally, Section IX concludes the paper.

II. OVERVIEW OF I4.0 TECHNOLOGIES

This section covers an overview of the state-of-the-art of the I4.0 technologies. The technical, architecture, and protocols of the I4.0 technology are not discussed in detail in this paper but references are provided for in-depth details. The term *industrie 4.0* which refers to the industrial revolution 4.0 originated from Germany and was first mentioned at the Hanover Fair in 2011 [20]. There are nine main technologies associated with the I4.0 which are IoT, BD analytics, cloud computing, AM, AR, autonomous robots, cybersecurity, system integration, and simulations [8] as illustrated in Fig. 3. The integration of these technologies paved way for emerging technologies like the DT and CPS. These technologies are described as follows and the review of their applications in the O&G upstream sector is elaborated in Section IV.

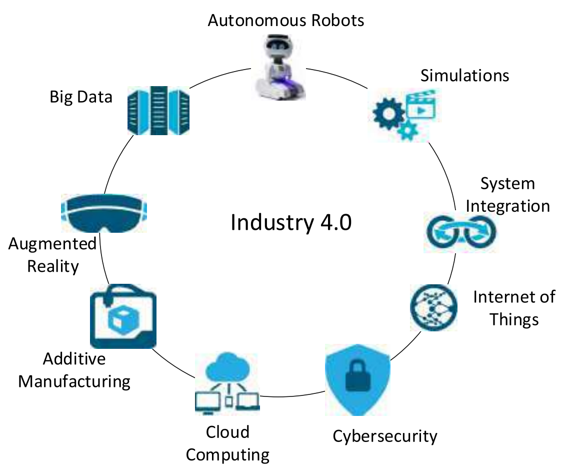

FIGURE 3. Industry 4.0 technologies.

A. INTERNET OF THINGS

The IoT enables machine-to-machine (m2m) communication over a network without requiring human-to-computer interaction [21]. The machines are composed of embedded systems with sensors/actuators, which transmit data using different communication technologies over the internet. The m2m is made possible by the ubiquitous presence of computing resources around us that has enabled devices to interact with each other via defined communication protocols and architectures [21]–[23]. The IoT has evolved over the years with more focus on different industry requirements which has given rise to application-specific IoTs [24]. The IoT has paved the way for several innovations in the industry and opened up the concept of industrial IoT (IIoT) [25]. The IIoT plays a significant role in the industry by providing an efficient and optimized monitoring and control system that reduces cost and enhances productivity.

Fig. 4 shows an IoT architecture that can be deployed for the O&G upstream sector. It consists of the physical layer, communication technology, network layer, and application layer. The physical layer consists of the IoT nodes that are used for data acquisition and control of the O&G equipment and facilities. The nodes transmit data to the gateway or base station via various communication technology. The communication layer comprises wireless communication technologies which can be categorized into short-range and long-range communication. Examples of the short-range communication technology are the Wi-Fi, Bluetooth, and Zigbee while the long-range include the low power wide area (LPWA) technologies such as narrowband IoT, LoRa, and Sigfox. The unlicensed long-range technologies (LoRa and Sigfox) are particularly suitable for remote areas without cellular coverage. The network layer incorporates several technologies such as cloud computing, software-defined network, blockchain, and network servers. The data from the nodes is routed to the application layer in a secured manner via the various network layer technologies. The application layer allows for the processing of the data, analysis, and visualization of the data. The enabling IoT technologies, protocols, and other related terminologies are discussed in detail in [21], [22], [26]. The IoT can be applied in various operations such as control and monitor operations, predictive maintenance, automation and control, health and safety of the O&G industry [15], [23], [27].

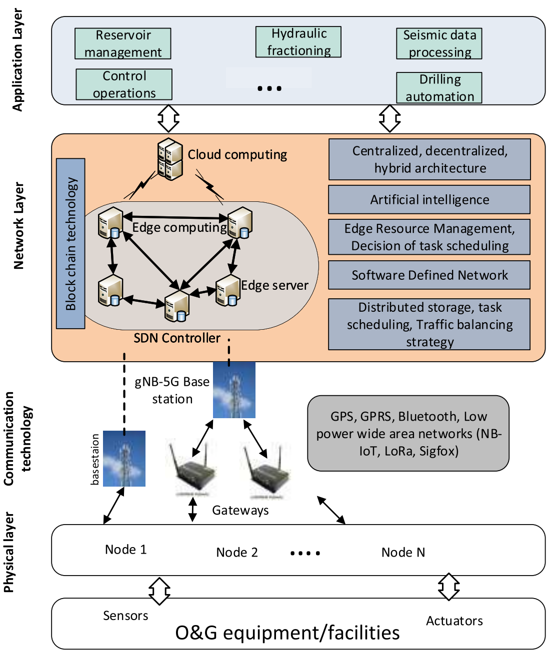

FIGURE 4. IoT architecture for O&G.

B. BIG DATA ANALYTICS

In this section, the concept of BD analytics and the use of AI tools for data analysis is presented. BD deals with the huge amount of data being collected from a variety of sources (volume), the speed at which the data are being collected in real-time (velocity), and the formats in which the data are collected (variety). BD analytics refers to the process of researching massive amounts of data in order to uncover hidden patterns and hidden correlations. The form of data can be structured, semi-structured, and unstructured [28], [29]. BD analytics is fundamental to the I4.0 in the O&G sector. For instance, in seismic acquisition devices, large amount of data are generated for the development of two-dimensional (2D) and three-dimensional (3D) images of the subsurface layers during O&G exploration. Additionally, narrow-azimuth towed streaming (NATS) and wide azimuth (WAZ) tools are used in offshore seismic studies for the collection of data and development of geological images. In addition, drilling tools including logging while drilling (LWD) and measurement while drilling (MWD) convey various data to the surface in real-time. All these tools and innovations are creating a massive amount of data that need further interpretation and analysis [30]. Therefore, the daily generation of huge data sets in the upstream sector is the main driving force of the application of BD in the O&G industry. The utilization of BD can be noticed in exploration, drilling, oil recovery, and production [19], [31], [32].

In order to extract information and insights from the data, data science techniques such as exploratory data analysis and AI are employed. This helps to link related pieces of data together and provide useful insights from existing information. AI involves the use of computer algorithms in an attempt to mimic the operations of human brains or thought, to understand and make decisions [33]. AI also can be defined as the theory and development of computer systems to support decision-making processes that generally require human intelligence [34]. In 2019, AI in the O&G market was valued at USD2 billion and is expected to attain USD 3.81 billion by 2025 [35]. The AI technology can facilitate O&G companies in the digitization of records such as geological data and charts and providing automated analysis. This helps to identify issues such as pipeline corrosion or increased equipment usage in a timely manner [35]. Additionally, the O&G industry can use AI to evaluate the potential impacts of new developments or to assess the environmental risk associated with the new project prior to the development of plans [36]. The branches of AI are shown in Fig. 5. Several AI techniques have been successfully applied in the O&G industry [2], [32], [37]–[40]. Some of the applications include prediction of drilling fluid density [41], drag reduction [42], and identification of potential complications and optimize performance in onshore operations [43].

C. CLOUD COMPUTING

Cloud computing is an essential part of the I4.0 due to the many advantages it provides for businesses and institutions. It involves the uses of on-demand cloud computing services such as servers, storage, networking, software, and intelligence. The use of cloud services can help to save cost, increase production, enhance security, performance and also

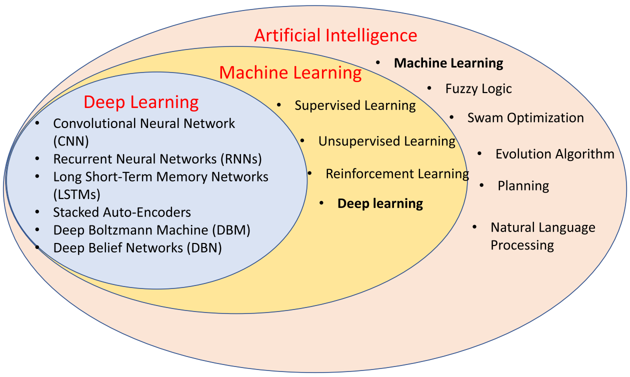

FIGURE 5. Branches of artificial intelligence.

to improve speed and efficiency. The cloud computing services can be deployed either as public or private or hybrid or community cloud architecture. Cloud computing can be rendered either as software-as-a-service (SaaS), infrastructure-as-a-service (IaaS), or platform-as-a-service (PaaS) [44]. The SaaS provides organizations access to the software needed for their operation via the internet without the need to bother about the operating system. The IaaS offers pay-as-you-go for services such as storage, networking, and virtualization. The PaaS provides a platform for creating software that is delivered via the internet. The SaaS, IaaS, and PaaS enable the industry to take advantages such as mobile access to online software, scalability, and reduction of hardware cost. The different cloud computing and architecture are shown in Fig. 6. Although cloud computing offers several advantages, there are certain limitations that have been identified which include degradation of quality-of-service due to delays in time-sensitive applications. Hence, the combination of cloud computing and other forms of computing such as edge/fog computing is explored [45]. More details on the architecture of cloud computing can be seen in [46]–[48].

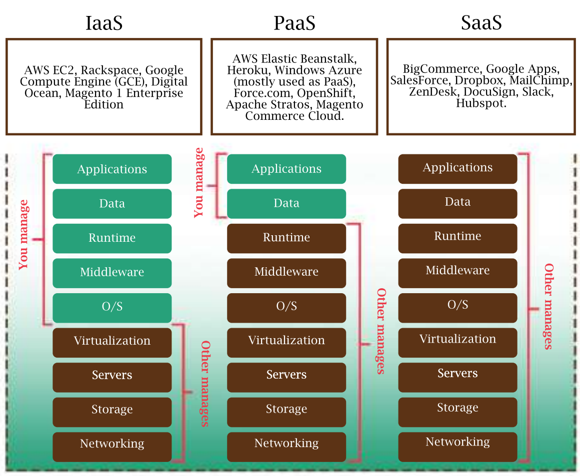

FIGURE 6. Cloud computing services.

D. ADDITIVE MANUFACTURING

The AM is the computerized process of building 3D objects by adding layer-upon-layer of material [49]. It enables the fabrication of end-use products in aircraft, dental restorations, medical implants, automobiles, and several industrial parts. Several 3D manufacturing techniques have been identified which are vat polymerization, material jetting, binder jetting, material extrusion, powder bed fusion, sheet lamination, and direct energy deposition [50], [51]. More details on the description of the different AM manufacturing techniques can be found in [49], [52]. The AM can be used to produce complex geometries with high-strength materials that meet the robust performance and environmental standards needed by the O&G industry [52], [53]. This offers fast and on-demand printing of spear parts which can reduce the high cost of downtime in the O&G industry. The other potential applications of AM within the O&G industry are outlined by Vendra and Achanta [54]. It includes the drill bits and bit models, heat exchangers, turbine blades and sensors, acoustic and fluid filters, drilling tools, as well as downhole logging spare parts. It was reported that the AM-designed applications demonstrate enhanced reliability with about 30 % cost reduction and 70 % lead time reduction [54]. Shell is employing AM (i.e., 3D printing technology) to develop a prototype system connecting a huge vessel to O&G wells in a station in the US Gulf of Mexico (The Stones). The implementation of AM has helped Shell to save the cost of about $40 million by highlighting the design flaws at an early stage. Moreover, the team is able to show US authorities how the 3D printed prototype system remains stable in rough seas and disconnects during strong waves, where the safety of the vessel system and crew members are both equally important [55].

E. AUGMENTED REALITY

The AR uses animations, 3D geometries, and text to turn the environment around us into a digital interface by placing virtual objects in the real world, in real-time [56]. AR can be applied in complex assembly by converting instructional manuals into live videos. This provides AR-based maintenance support for inspection and for checking the status of the machine. In addition, it provides remote supports for field technicians or workmen. The application of AR for facility management in the O&G industry was presented in [57]. It enables personnel to handle complex interactions which include collision detection, navigation, device monitoring, and operations. For instance, the use of AR was used to train personnel for commission instruments which provided calibration training, installation training, instrument configuration, and error simulation [58]. In another work, Fenais *et al.* [59] investigated the risk benefits of employing AR in horizontal directional drilling (HDD) at a pilot project in Phoenix, Arizona. It was found that the implementation of AR enables HDD and other site operators to view the virtual models of subsurface utility pipes at the construction site. AR was able to locate hidden pipelines as well as other significant hindrances that are present in the underground utility. Hence, with such visual information support, the risk of future disasters such as pipeline explosions can be significantly reduced.

F. AUTONOMOUS ROBOTS

The use of automation in the manufacturing industry has made it possible for robots to cooperate, interact with one another and work safely with humans [60]. Automation enables the use of control systems to handle different processes and machinery in the industry. Some of the advantages of industrial automation are cost reduction in wages and salary, maintenance, increase productivity, less error and high quality, high flexibility, reduced turnaround time, increased safety, and accurate information from data collection. This involves the use of robotic process automation (RPA), which aims to reduce repetitive and simple tasks [61], [62]. There are three types of automation which are fixed, programmable, and flexible automation. The application of robotics and automation in the O&G industry was discussed extensively in [5], [6]. The application of robotics in onshore includes pipe inspection, tank inspection, automated gas sampling, and external automated inspection for pipelines using drones/unmanned aerial vehicle (UAV)/unmanned aerial system (UAS) [5], [6].

The use of drones or UAV or UAS in the O&G industry provides safety, efficiency, and is considered cost-effective and has been used extensively for various applications [63]–[67]. The use of drones has been used to complement other forms of surveillance technologies such as satellite, plane or helicopter imagery and ground digital acquisitions and observations. For instance, in [67] the use of UAV was shown to provide key input for reservoir modelling in analogue producing fields which is useful for digital outcrop models of subsurface reservoirs. Some of the applications of the drones are illustrated in Fig. 7.

G. CYBERSECURITY

While I4.0 technologies are aimed at providing smart and advanced manufacturing by marrying physical action with the digital world, it opens up a new level of cyber risk that needs a fully integrated approach for operational technology (OT) and information technology (IT). The attacks could be in the form of physical attacks on critical infrastructural attack or theft of confidential information [68].

Hence, cybersecurity has become an integral part of the I4.0. Several security incidents related to cyberattacks from malware such as the blackenergy [69], stuxnet, wannaCry, ransom [70], Mirai – IoT botnets attack, Triton malware have resulted in large scale disruption across several industries. For instance, Saudi Aramco O&G company a critical provider in the global energy sector witnessed cyberattack which took almost two weeks to recover leading to several damages [71]. Another cyberattack that caused a major disruption in the O&G industry is the Colonial pipeline attack

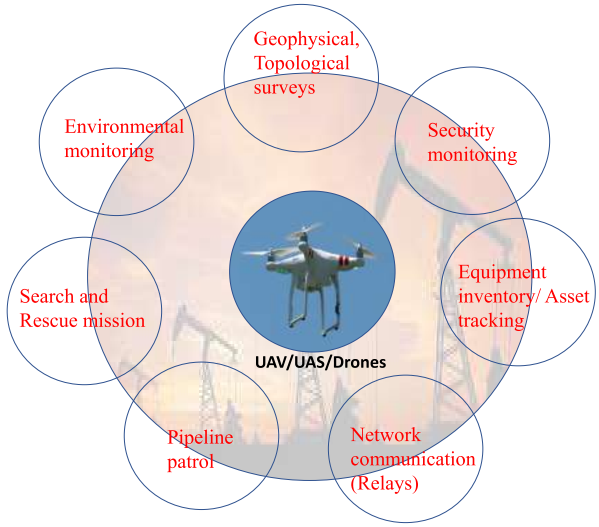

FIGURE 7. Application of drones in O&G sector.

which disrupted supply for several days in certain parts of the United States [72].

There are different layers of data security that have been identified for cybersecurity and they include 1) mission-critical assets, 2) data security, 3) application security, 4) endpoint security, 5) network security, 6) perimeter security, and 7) the human layer. The seven layers are described in Table 1.

TABLE 1. Seven layers data security of cybersecurity.

Layers	Description
Mission critical assets	Mission critical data that requires highest level of protection
Data security	Protects the storage and transfer of data
Application security	Protect and secures application for mission critical assets
Endpoint security	Protects the devices and network
Network security	Prevents authorized access to organization's network
Perimeter security	Provides physical and digital security for entire business
Human layer	Provides policy, controls, reporting that protect your critical assets from human threats

To address the cybersecurity issues in I4.0, many industry standards have been introduced such as the ISO/IEC 27001, the NIST cybersecurity framework, ANSI-ISA-62433 series, IEEE C37.240, ETSI TS 103 645 [73]. These standards provide a structured approach, roles and responsibilities, self-assessment tools, and control objective list to assist businesses in risk management practices. There are other cybersecurity standards recommended by other bodies such as the European Union Agency for Network and Information Security (ENISA), Internet Research Task force (IRTF), and European Cyber Security Organization (ECSO). The standards provide procedures for organizations to assess, identify and provide countermeasures to limit the cybersecurity risk to tolerable levels. Methods such as failure mode and effect analysis (FMEA) provides organizations a method to prioritize IT risk using Risk Priority Number (RPN) [74].

An important technology that is adopted in the I4.0 for cybersecurity is blockchain technology [75]. Blockchain technology which is also known as the distributed ledger technology is based on a peer-to-peer (P2P) topology that enables transparency, traceability, integrity, and tamper-resistance by using the decentralized system with cryptographic hashing [19], [76]. The biggest innovation of blockchain technology is that transactions are distributed to all participants instead of being stored in the central database [77]. It is also known as distributed ledgers where all parties share a common ledger and any ongoing transaction on the blockchain is updated to the ledger of all parties [78]. In recent years, blockchain technology are been implemented and used in the O&G industry; mainly in four aspects including trading, management and decision making, supervision, as well as cybersecurity [19], [77]. Some of the advantages include the ability to track goods, equipment, and services, to ensure data are secured and transactions are transparent [19].

H. SYSTEM INTEGRATION

The system integration component of the I4.0 provides both vertical and horizontal integration within the industry. The vertical integration covers different hierarchies starting from shop floor to top-management level [79]. These combine the digitization of physical objects by gathering data using sensors, actuators, and programmable logic controllers and the data collated using supervisory control and data acquisition (SCADA) [80]. The use of manufacturing execution systems (MES) for collection of the data from the SCADA and the use of enterprise resource planning (ERP) systems for production status are employed at the managerial information layers [81]. This integration facilitates transparency and improved decision-making processes from the managerial level to the shop floor. The system integration can help solve problems associated with top management and specialist for strategic implementation and quality management in the O&G industry [4]. Also, system integration can be used to optimize technical production and operation in the upstream sector. The use of system integration that combines the thermodynamic, economic, and environmental performance indicators is used to save energy in the extraction of O&G fields [82].

I. SIMULATION

Simulation has been used as a decision support tool for solution development, validation, and testing of individual elements or complete systems [83]. The I4.0 extends the use of simulation in all phases of a product life cycle. Simulation analyses are used through all phases of different planning and operating levels of complex systems [84]. Simulation methods are largely employed in the O&G industry and considered to be one of the important steps in planning and optimizing production and getting hydrocarbons from oil wells [85]. For instance, the use of simulation methods is used to overcome the challenges of cost, time faced in obtaining information pertaining to the fluid transport characteristic of shale gas under certain conditions [86], [87], and models for prediction of offshore O&G pipelines [88]. The combination of simulation models and other I4.0 technologies have opened up the technological concepts such as the DT and CPS discussed in the next section.

J. DIGITAL-TWIN AND CYBER-PYHSICAL SYSTEM

The DT is one of the emerging technologies largely applied in the manufacturing [84], [89], [90], automation, construction and building management [91], healthcare [92], petrochemical [91] and utility industry [93]. DT has been defined in the literature in different ways [94]–[96]. Just as the name implies, it simply means a digital or virtual representation of physical assets or products, or services. It collects real-world data to create simulations via integrated models that can be useful in providing decision support in the life cycle of a product or system or service. In creating a DT, the design of the asset, the functionality of the asset, maintenance of the asset in the real world needs to be specified. Then, the technologies that can support the real-time flow of data and operation information between the physical asset and its DT as shown in the conceptual architectural diagram in Fig. 8 [97] need to be acquired. It combines some of the I4.0 technologies. The conceptual architectural diagram consists of six stages which are: create, communicate, aggregate, analyze, insight and act and discussed in detail in [97]. The create stage covers the physical assets and integration of sensors to measure the operational performance of the asset and the environmental parameter that affect the operation of the physical assets. The communicate stage entails the network communication technologies that enable seamless, real-time and bi-directional connectivity between the physical asset and the digital platform. The aggregate stage involves the collection of data and processing between the physical asset and the digital platform. The analyze stage focuses on the visualization and analysis of data while the insight stage involves the use of the analyzed data to provide useful information such as the difference between the DT model and the physical asset analogue performance. The act stage involves the actions or commands are fed back to physical and digital processes based on the insights generated from previous stages.

The CPS is similar to the DT. The CPS is the integration of computing, networking, and physical processes. Physical processes can be controlled in real-time via feedback loops on embedded systems with high computational powers through network monitors. The major difference between the DT and CPS are summarized in Table 2.

There are several applications of DT and CPS in the O&G industry which include drilling, asset monitoring, project planning, and life cycle management offshore platform infrastructure [19], [99]–[101]. The application of I4.0 technologies discussed in this section are further elaborated in Section IV.

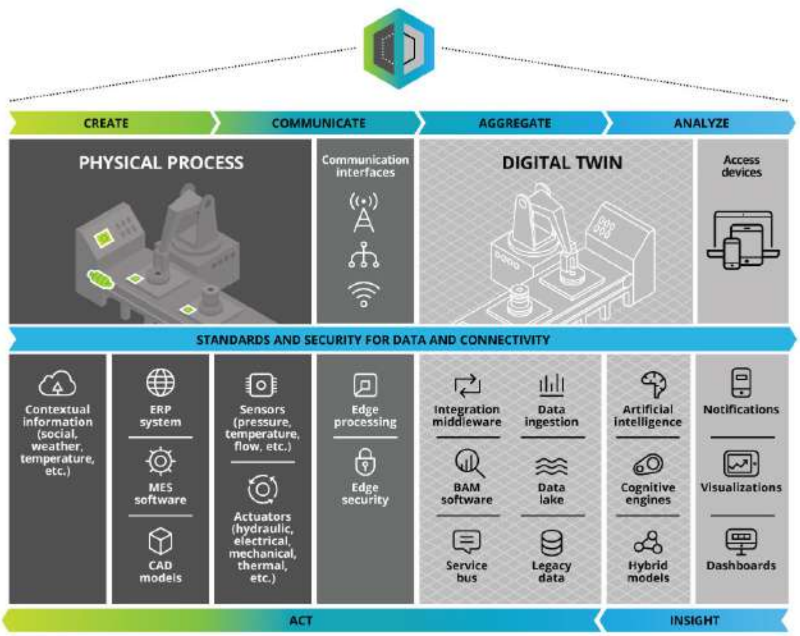

FIGURE 8. A concept of digital-twin architecture [97].

TABLE 2. Difference between DT and CPS [98].

DT	CPS
Creates high-fidelity virtual models of physical objects in virtual space	Couples the cyber world and dynamic physical world using control, communication and computing
Integrates whole elements, the entire business, and the process data to ensure consistency	Data from sensors and actuators are analyzed by cyber world and sent back as commands to control physical process
Modeling and simulation analysis form the core elements	Sensors and actuators form the core elements

TABLE 3. Procedure for the search of articles.

Search Index	Specific content
Database/ source	Scopus, web, google scholar
Keywords	TITLE-ABS-KEY (("4.0" OR "industry 4.0" OR "industry revolution*" OR "cyber*" OR "IoT" OR "Big data" OR "Artificial intelligence" OR "digital twin" OR "autonomous robots" OR "additive manufacturing" OR "system integration") AND ("oil and gas"))
Publications	Reviews, conference papers, journals, tech report

III. REVIEW METHODOLOGY

There are several methods of review that have been identified in the literature [102], [103]. The review types are based on the methods used for searching, evaluating, synthesizing, and analyzing the items that comprise the body of knowledge. Three categories have been identified in [102] which are systematic, semi-systematic, and integrated review. The semi-systematic literature review method was applied in this article due to the diverse discipline and research areas covered. The objective of this research is to find out the state-of-the-art and the application of the I4.0 technologies in the O&G upstream sector.

A comprehensive literature review was conducted to identify the available publication regarding the application of I4.0 technologies in the O&G upstream sector. The literature review covered publications between year 2012 and 2022 published by scholars and practitioners. This includes articles, reviews, conference papers, and technical reports in the English language. The literature was identified in the Scopus database, google scholar, and google. The Scopus database was chosen due to the broad coverage of scientific peer-reviewed publications. Other methods using google scholar and google were chosen in ordered to retrieve technical reports and white papers from practitioners and other published works not found in the Scopus search. An initial search from the Scopus database using the keywords contained in the title, abstract, and index terms was carried out. The keyword used is shown in Table 3. The keyword was carefully selected to focus on publications related to the I4.0 technology components that have been applied in the O&G industry. Based on the keyword search a total number 1544 publications were found in the Scopus database. Based on the identification of publications between the year 2012 and 2021 and removal of duplicates, 1080 publications were identified and screened.

A second search was conducted with the reference lists of all identified reports and articles based on the following research questions.

RQ1: What is the state-of-the-art of industry I4.0 in the O&G upstream sector in the last 10 years?

TABLE 4. Summary of related systematic review journals.

Ref.	Year	Focus	CR1	CR2	CR3	CR4	CR5	CR6	CR7	CR8	CR9
[19]	2019	I4.0 technologies such as in DT, AR, blockchain, BD, IoT in O&G	×	√	×	Google Scholar, Web of Science, ScienceDirect	√	×	√	×	×
[27]	2020	IoT in O&G	√	√	×	Scopus, OnePetro, IEEE explore, Springer, Web of Science	×	√	×	×	√
[34]	2019	AI and other decision support systems in O&G	√	√	×	Scopus, Web of Science, Onepetrol, Knovel, IEEE Xplore, American Society of Mechanical Engineers (ASME) digital collection and Google scholar	√	√	√	√	×
[99]	2020	DT in O&G	√	√	×	Scopus, OnePetro, IEEE Xplore, Springer, Elsevier	√	√	√	×	√
[105]	2020	BD in O&G	√	√	×	OnePetro, IEEE Xplore, Springer, Elsevier	√	×	×	×	×

CR1-time-limit consideration, CR2-sample size, CR3-PRISMA flow diagram, CR4-database, CR5-exploration and development, CR6- drilling and well completion, CR7-production and optimization, CR8- reservoir engineering CR9-control operations.

RQ2: What are the applications of the I4.0 in the O&G upstream sector?

RQ3: What is the framework for the implementation of I4.0 in the upstream sector?

RQ4: What are the benefits and challenges faced in the adoption of I4.0 technologies in the O&G upstream sector?

RQ5: What are the future trends in the application of I4.0 in the upstream sector?

The 1080 items were further screened by skimming through the titles of the publication and abstract for content-based inclusion using the five research questions. 228 items were found not related to the objective of the research and 46 items were not accessible. A total of 809 publications from the Scopus database were accessed for eligibility and classified into review, journal, and conference papers. A total of 67 review papers, 637 conference papers and 105 journals. A final selection process was carried out by giving priority to peer-reviewed journals, SLR review papers, and conference papers whose topics have not been well covered in the journal papers. The same process was applied to the documents from google scholar and google websites. A total of 223 documents were considered for full reading and included in the review process. The preferred reporting items for systematic reviews and meta-analyses (PRISMA) flow diagram is shown in Fig. 9.

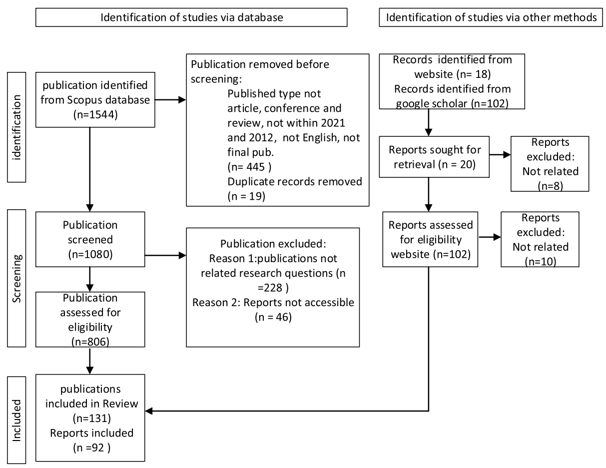

FIGURE 9. PRISMA flow diagram.

IV. FINDINGS AND DISCUSSION

The findings from the 223 documents and discussion are presented in this section.

A. RELATED PAPERS

To answer RQ1 and RQ2, related papers on the I4.0 technologies were analyzed. Although several review papers on the application of different I4.0 technologies were identified. Only 5 which focused on systematic literature review (SLR) were analyzed [27], [34], [99], [104], [105] and summarized in Table 4. A review of IoT within the context of the O&G industry was presented in [27] and a review of DT within the context of the O&G industry was presented in [99]. In [99], the key application areas such as asset integrity monitoring, project planning, and life cycle management were identified and the following challenges: cybersecurity, lack of standardization, and uncertainty were discussed. Nguyen *et al.* [105] focused on the role of big data (BD) in the O&G industry. This covers the application of BD in the exploration, drilling, reservoir, production, refining and transportation in O&G industry. While this works focused on specific components of I4.0 technologies for the O&G sector, Lu *et al.* [19] presented a systematic review on oil and gas 4.0. The roles of I4.0 technologies in facilitating the intelligent oilfield in the upstream sector, intelligent pipeline in the midstream sector, and intelligent refinery in the downstream sector were discussed in [19]. Shafiee *et al.* [34], presented a review on decision-making support in the O&G upstream sector. Different decision-making support methods were identified which include AI. From the review of the existing literature, there is still a lack of comprehensive survey on the I4.0 technologies in the upstream sector. Hence, this paper provides a comprehensive survey on the various I4.0 technologies that can be applied to the various operation and processes in the upstream sector. The findings are discussed in the next section.

The review of the application of I4.0 technologies in the O&G upstream sector is discussed under the following exploration and development, drilling and well completion, production and optimization, reservoir engineering, control center operations, and equipment and operational parts. The discussion presented here provides answers to RQ2.

B. EXPLORATION AND DEVELOPMENT

The primary step in the upstream sector is related to O&G exploration, and this step is regarded as one of the most expensive activities with high accident risks [9], [106]–[108]. The O&G exploration involves searching and identifying hydrocarbon located underneath the earth's surface [109] and it can be performed onshore (on land) or offshore (in shallow waters or deep waters). The first phase of exploration is known as seismic study (or geological data study), where the location of the O&G reserves is determined via seismic exploration by using a detailed map with high-resolution acoustic data [5]. The purpose of the seismic study is to assist interpreters (geologists and geophysics) in identifying geologic features. Table 5 shows the seismology of onshore and offshore in O&G industry [5] and Fig. 10 illustrates the seismic interpretation workflow in O&G exploration of the upstream sector using I4.0 [9].

TABLE 5. Seismology of onshore and offshore in O&G industry.

Onshore	Offshore
Involves the use of Vibroseis for the generation and sending of seismic waves deep into the earth.	Pressure waves generated from the short bursts of huge energy are released to travel through the water column to the sea bed and beyond that to the earth's core.
Reflected waves are recorded by geophones located on the surface of the earth.	The array of acoustic sensors know as hydrophones are used to capture reflected waves.
The cross-section of the earth with potential O&G are evaluated by reservoir engineers, geophysicists and geologists from seismic data recorded using the geophones.	Once seismic data is captured by hydrophones, the use of multiple remotely operated vehicles (ROVs) equipped with suitable sensors are deployed for more data collection in order to establish the potential presence of O&G.

Technology and supercomputers with advanced algorithms play an important role to reduce the cost and time involved in O&G exploration [110]. For example, the development of ground penetrating radar (GPR) technology is employed together with BD for subsurface investigation and exploration, which enables the experts to make fast and important decisions. On the other hand, Exxon Mobil used full wavefield inversion (FWI) combined with supercomputer technology to produce high-definition images into

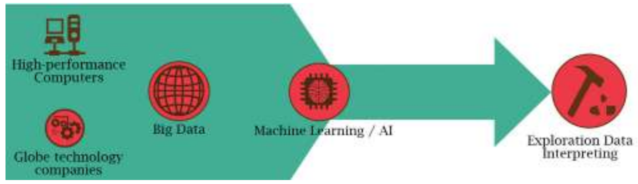

FIGURE 10. Seismic interpretation workflow in O&G exploration of the upstream sector using I4.0 [9].

subsurface geologic structures and the physical characteristics of rocks [111]. These capabilities help to identify the hydrocarbon resources more accurately in the exploration phase, as well as in development and production phases [111].

Nowadays, due to digitization in the exploration phase, O&G companies have increased their capabilities to monitor, record, and analyze data far more efficiently using advanced technologies [31]. The interpretation of seismic reflection data involves high-performance computers, advanced visualization techniques, and the generation of various seismic data types and attributes. The use of seismic data involves two processes which are data acquisition and data processing and they are discussed as follows.

1) DATA ACQUISITION

The acquisition of seismic data involves the use of a large number of seismic sensors known as geophones. The geophones are ground motion sensors that convert ground vibrations into voltages by capturing reflected waves (10 - 100 Hz) sent by vibration source. These sensors are usually deployed over large areas via seismic cables which limits flexibility and increases the cost of deployment [112]. To address these challenges, wireless geophone sensor networks [112] and the use of subsurface cameras [113] are proposed. The use of geophone sensors networks proposed in [112] makes use of a reconfigurable antenna, wireless node, and gateway for the collection of seismic data in order to overcome the challenges faced with wired seismic cables. A similar geophysical sensor network proposed in [113] computes wireless 3D subsurface images in real-time using wireless geophysical sensors. While these methods seem promising there are still several open issues associated with the use of geophysical sensor network methods some of which includes interference issues, power consumption and short-range communication, adaptability of different geophysical sensors/methods to different subsurface geophysical properties.

2) DATA PROCESSING

Due to the BD generated from the seismic attributes, and the difficulty in translating these data to geological information, the use of AI and machine learning (ML) is being employed in the interpretation to improve evaluations [114], [115]. Analyzing and interpreting these data with conventional methods such as seismic amplitude displays alone can be very challenging and less accurate [114]. Hence, the studies from [114], [116] have shown the use of BD analytic and AI in seismic data analysis. For instance, the use of unsupervised ML and BD analytic methods for seismic data analysis can provide better understanding of geologic patterns [114].

Roden [114] employed unsupervised ML such as principal component analysis (PCA) for selection of seismic attributes and self-organizing maps (SOM) for classification and interpretation of the seismic data in a five-stage approach. The stages included 1) identification of geological issues, 2) application of PCA for selection of seismic attribute, 3) SOM ML tool is applied to identify natural clusters in the data, 4) 2D color map is applied to the clusters to identify natural patterns, and 5) use of the patterns for geological interpretations. The use of the PCA and SOM multi-attribute approach gives better risk assessment and interpretation needed by geoscientist. Studies conducted by Olneva *et al.* [116] demonstrated the advantage of BD analytic and ML techniques for discovery of new and unique exploration criteria in the West Siberian Petroleum Basin. An approach called "from particulars to general" by Olneva *et al.* [116] made use of ML algorithms to identify separate objects in a seismic and geological pattern with a regional database of 40,000 sq.km of 3D data. The advantage of this approach is that it enables the creation of library for typical seismic images which can be used for pattern recognition. The identification of geological leads of hydrocarbon using ML learning technique for semantic segmentation and post-processing resulting in fairly accurate predictions [117].

C. DRILLING AND WELL COMPLETION

Once the O&G reserves are identified, the production from beneath the earth will take place [14], [106]. These production processes include drilling, extraction, and oil recovery. Access to reservoir rocks requires drilling which is one of the most important processes and remains crucial to O&G production [107]. The drilling operations are carried out to either confirm the presence of a reservoir or to commence the production and commercialization of the O&G. The onshore drilling is considered easier compared to offshore drilling because, in the offshore fields, artificial platforms (movable or permanent) are required for support base. Additionally, in the offshore fields, ROVs equipped with visual cameras and sensors are used to collect real-time data which are sent to control centers. The real-time data from the ROVs are used for decision-making during the complete process of drilling [5]. This helps to enhance efficiency and personal safety during drilling inspections and damage control. The various application of I4.0 in drilling and well completions from published works are discussed as follows.

1) DRILLING OPERATIONS

The I4.0 technologies are facilitating the digitization of drilling operations in the upstream sector of the O&G. These include data acquisition from bottom hole location with MWD, acquisition of surrounding geological formations with real-time LWD, and enhancement of drilling efficiency [118]. The acquisition of data from sensors and IoT, BD analytics, AI, DT, modeling is allowing for better decision making in drilling events and performance prediction and optimization.

The use of AI techniques such as artificial neural networks (ANN), radial basis function (RBF), fuzzy logic (FL), support vector machine (SVM), and functional networks (FN) have been explored in the prediction of pore pressure while drilling [119], drilling optimization [120], forecasting of gas-to-oil ratio (GOR) from a generic hydraulically fractured reservoir [121], selection of drill bits [122], hole cleaning in horizontal wells [123] and condition-based maintenance systems for downhole tools [124]. Other areas of application such as the use of AI in the detection and mitigation of lost circulation incidents during drilling [125]–[127] and prediction of drilling problems [128], [129] have shown promising results. This helps to increase the productive time of drilling in O&G wells. The use of AI has been adopted to improve the accuracy of prediction of rock characteristics which are determined by elastic parameters like Poisson's ratio and Young's modulus [130]–[133]. Such accuracy minimizes the risk associated with well drilling operations. In addition, the use of AI has been used to estimate the rate of penetration (ROP) which is associated with the speed at which drilling is performed [134]–[137]. The use of AI offers a real-time prediction of the ROP based on surface operational parameters such as weight on bit, rotations per minute, mud flow, and differential pressures.

Furthermore, the use of AI has been proposed to improve health and safety by using DL to monitor and detect safety violations by personnel on drilling platforms [138]. Health and safety of drilling workers can also be monitored using IoT devices such as heart rate monitor, toxic gas monitor, gesture detectors, slip and fall detectors, smart helmets, motion active sensors, as well as a self-contained breathing apparatus [23].

Robots can be used to execute operational decisions based on AI in the oil wells. For instance, Liu *et al.* [65] developed a UAV-based air monitoring system for methane (CH4) monitoring over the oil fields. The system consisted of low-cost gas sensors, a microcontroller, a LoRa wireless transceiver, and a SD card reader. It was tested at two different oil fields in North Dakota, and the results indicated that the system was capable of measuring CH4 concentrations over the oil fields. Similarly, the use of semi-autonomous industrial robots was used for methane leak inspection in [139]. The application of AI for accurate sand production prediction in wells [140] and for shale well production [141] have also shown promising results. The use of discrete event simulation DT in studying the operational risk in oil sand mining and processing of bitumen in response to geological uncertainty was shown to be a good coordination tool [142], enhancement of drilling operations using IoT and AI models [143] and detection of fault in submersible screw pumps in oil wells [144]. The use of AI in the detection of casing damage due to non-uniform in-situ stress has been explored in [145]–[147]. The AI aids the prediction of the casing damage by using historical and real-time data. This helps to optimize the maintenance intervals of the casing.

2) PREDICTION

I4.0 technologies have been applied to improve the accuracy in several drilling processes. For instance, AI/ML technology is used to predict pore pressure [119], prediction of pore structure type [148], to predict oil recovery and the gas-to-oil ratio [121], [149]–[151], as well as for drilling and well completion [152]. DT integrated AI platforms have been explored to predict the remaining useful life of a subsea tribosystem [153]. The use of AI in the prediction of the multi-phase flow physical parameters such as velocity, pressure, and phase fraction results in less computational time when compared to computational fluid dynamic [154]. In [155], Hatampour *et al.* demonstrated the use of AI in the prediction of nuclear magnetic resonance (NMR) total porosity and free fluid porosity estimation from seismic data.

The application of AI has been explored in the prediction of corrosion rate of metal casing string in downhole casing leaks in O&G producing wells. AI can help to improve the wellbore integrity management [156] and prediction of the hydrate formation condition that occurs during O&G drilling [157]. The understanding of geomechanical properties in well formation using AI enables the prediction of future wells [158]. A reliable model was developed using ANFIS for predicting the amount of dissolved gas in oil at reservoir conditions [159]. The prediction of troubles in the drilling process and automation of log curves digitization was addressed using radial basis function neural network AI technique [160]. The estimation of turbulence coefficient (D) based on skin factor, reservoir rock, and fluid properties using AI techniques was presented in [161]. The use of AI in the prediction of bottom-hole pressures in multiphase flow wells was presented in [162]. Similarly, the use of AI in the prediction of volume fractions in gas-oil-water multiphase flow system was presented in [163]. Other applications of AI in the exploration and development include prediction of oil formation volume factor [164], prediction of bottom-hole pressures in multiphase flow [162], and prediction of volume fractions in gas-oil-water multiphase flow system [163].

3) RISK ANALYSIS

The demand for intelligent fields, smart wells, and real-time analysis has increased the utilization of I4.0 technology in the O&G industry. For example, BD was used to smarten the drilling platforms and pipeline infrastructure in [165], to evaluate drilling rig efficiency and performance [166], [167], as well as to reduce the risk of drilling operations [168]. Johnston *et al.* [168] applied BD analytics in the attempt to minimize the operational risks in drilling and wells domains. Expertise and BD analytics are used to analyze the huge amount of data from approximately 350 O&G wells in the UK North Sea. The data sets include the drilling parameters, well logs data, and geological formation data. The results showed a clear correlation of borehole quality with the drilling parameters, however, that was dependent on the geology and region. Moreover, it was also found that BD analytics is capable to be applied as a quality control tool in future operations in O&G. In addition, drones or UAVs can be deployed to oversee operations of any risky task. Shukla and Karki [6] outlined several robotic technologies that are used to facilitate drilling operations in the modern time. For example, the ROVs, UAVs, under-water welding robots, and under-water manipulators are utilized in offshore O&G facilities.

4) DATA INTEGRITY

To achieve efficient drilling operations, data from different surfaces, downhole sensors, drilling operational data such as logged activities, operator data, and incident reports are collected. Additional data such as weight on bit, revolution per minute, depth, and torque obtained from the drilling rig sensors are collected to predict penetration rates as well as the equipment failure [30], [31]. From the prediction of the rate of penetration, predictive data models which take into account all the above data and necessary parameters are developed to optimize the oil extraction process [31]. This predictive analytics help in the reduction of drilling time which results in a smooth oil extraction process [31]. There are high risks involved in crude oil production either onshore or offshore [2]. Hence, there is an urgent need for the O&G industry in exploring new technologies to collect, process, and manage information to ensure efficient, safe, and reliable production processes at low operating costs [2].

Blockchain technology can be used to set standards that can be followed for collaboration among stakeholders and service providers that are involved in executing and automating drilling. Additionally, it will enhance data security by allowing secure sharing of sensitive data within the system [9]. Blockchain technology has been employed to design and construct well and facilities [78], to track drilling equipment history and maintenance [169], automating drilling [78], as well as to optimize drilling operations [78]. Lakhanpal *et al.* [78] reported that proper data sharing can be achieved with the implementation of blockchain technology and IoT for the drilling as well as the production operations in O&G industry. For instance, if the types and efficiency of artificial lift utilized in a legacy well are recorded in a blockchain database, the support engineers are able to make an appropriate strategy for the well based on the provided information. Moreover, the availability of stimulation history of a formation on a blockchain allows engineers to make a proper selection to optimize the well productivity.

D. PRODUCTION AND OPTIMIZATION

Analysis of BD in a short period for decision making is challenging to production engineers. Advances in ML have created a novel workflow that can reduce the workload on engineers. For instance, ML techniques have been applied in production pattern data recognition. ANN model can be used to forecast end pressure with knowledge from patterns in data [170]. Various ML applications are used for numerous pumps to implement predictive maintenance, select optimal operations regimes to save cost, and optimize production [171]. Apart from application for equipment maintenance, well treatment operation such as hydraulic fracturing and chemical treatment is another area with high-cost saving potential. Therefore, I4.0 technologies have found usefulness in artificial lift optimization, hydraulic fracturing, and fluid separation.

1) ARTIFICIAL LIFT OPTIMIZATION

Well performance in the unconventional formation such as shale generates several challenges during hydrocarbon production. Subsequently, resulting in drastic production decline in a very short period. Hence, artificial lift systems (ALS) are installed in oil wells to improve drawdown and flow rates, minimize pressure loss in the production tubing and to cut cost. Moreover, to achieve optimum recovery within a short period, appropriate ALS must be selected. Selecting appropriate ALS for a well depends on the production condition, completion depth, well trajectory surface facilities, safety condition, cost, reservoir rock and fluid properties. These selection criteria sometimes need an upgrade or replacement to keep up with the subsurface and surface condition resulting in loss of man-hour. Hence, modern technology such as IoT, AI, and ML can be used to improve operations abilities to make systematic decisions and forecast future occurrences based on past events and production trend [172]. Kandziora *et al.* [173] used a unique AI-based application that allows the operator to prevent electrical submersible pump failure 12 days before the actual failure occurred and at the same time optimizing production.

2) HYDRAULIC FRACTURING

Well treatment operations are carried out to stimulate the flow of hydrocarbon in old oil wells or increase the initial flow rate of new oil wells. Data obtained from produced well treatment jobs can be used to predict the efficacy of future hydraulic fracturing jobs through ML investigation. An accurate prediction in terms of additional oil production enables reliable estimation of investment. Ben *et al.* [174] used ML to predict well head pressure in real-time during hydraulic fracturing jobs. They tested several ML methods on the historic data of 100 hydraulic fracturing stages from several wells in the Delaware Basin. The ML algorithm predicted the well head pressure with acceptable accuracy. Therefore, the algorithm produced can assist engineers to monitor and optimize the pumping schedule. Likewise, Makhotin *et al.* [175] used ML to predict oil rate after hydraulic fracturing at one of Siberia oil field and [176] used AI to forecast well performance using hydraulic fracture parameters. Their study has brought about modern-day data driven technique to unconventional reservoirs.

3) FLUID SEPARATION

Surface processing plant needs optimization to minimize intermediate components and the flash from the crude oil during primary and secondary separation process to obtain quality oil. This can be achieved by the choice of operating pressure in surface separators, which have a notable effect on the quality and quantity of oil produced at the stock tank. AI can be used to select optimum middle-stage separation pressure and temperature for different crude oil. Mahmoud *et al.* [177] used an optimized algorithm to forecast the optimal operational condition that will increase crude oil recovery.

4) PIPELINE AND FIELD OPERATION

Some of the characteristics of intelligent oilfields are deployment of self-diagnostics, control and monitoring systems, autonomous operations, use of advance mathematical models for control of equipment, and real-time exchange of data for controlled objects [178]. Oil pipeline monitoring plays important role in the O&G industry because several important parameters obtained from the pipeline are representative data used in production. The monitoring of pipelines is not only for production measurement but for many other purposes such as security, preventive and prediction of pipeline maintenance, pipe leakage, and equipment control as well as for automation systems. Location detection and pipeline route information are essential for pipeline surveillance. This helps to identify the position of pipeline incidents and to easily trace reported incidents by using global positioning systems and geographical information systems [179]. There are several causes of O&G pipeline failure that have been identified in [180]. They include corrosion, external factors, human negligence, installation and erection, and manufacturing. The use of wireless sensor networks (WSN) is a common practice now in pipeline monitoring [180]–[182]. The combination of WSN, IoT, BD and AI enable remote access to data obtained from the pipeline and enhance smart monitoring [183]–[188]. The data collected via IoT needs to be analyzed using the appropriate framework for decision making to minimize the risk associated with corrosion, erosion, wear and tear [189]. AI has been applied to predict the rate of erosion in pipe fittings [190], modeling of two-phase-flow in pipes [191], and prediction of defects in pipelines [192]. An example of the application of wireless monitoring of pipeline using the WSN is shown in Fig. 11.

This paves the way for the concept of intelligent oil field (IoF) or smart field or digital oil field. The use of the I4.0 technologies enable the O&G industry to carry out multi-site remote collaboration, monitor complex reservoir environments, enhance production and maximizing the net present value (NPV) of cumulative field production. The use of CPS for crude-oil scheduling network for smart field operations was presented in [193] and [194].

The uses of AI has been employed to model the scour pattern around submerged pipes located in sedimentary

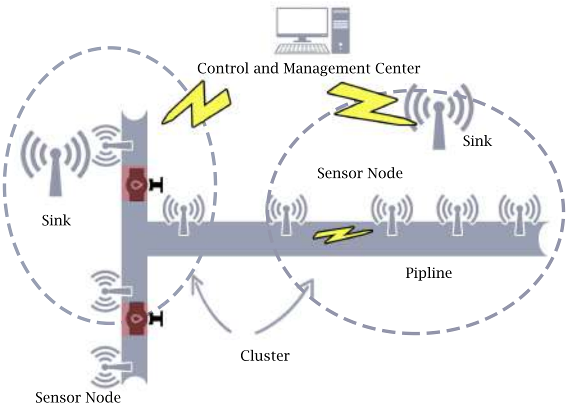

FIGURE 11. Illustration of pipe monitoring using wireless sensor network [182].

beds [195], use of BD analytics for safety factors in the pipelines [196], use of ML to automate and reduce variability in manual output in the development of corrosion loop for pipes [197]. AI has also been applied in the prediction of optimum wellhead choke size which determines the flow rate in pipelines [198] and choke flow coefficient for both nozzle and orifice type chokes with adequate precision [199]. BD analytics has enabled real-time query and management of O&G well production data in China national petroleum corporation [200]. The security of the pipeline infrastructure from third-party attacks is crucial as more attacks are witnessed in the O&G industry. To this end, projects such as PipeSecure2020 are being initiated to define new layers of protection for the security of gas pipelines [201].

E. RESERVOIR ENGINEERING

In the area of reservoir engineering, the interpretation, modelling, and prediction of the parameter involved in reservoir simulations are based mainly on the stratigraphic rock analysis [31], [114]. The prediction of rock characteristics is carried out using comprehensive geological information in different regions across the world [114]. However, a significant obstacle for reservoir engineers is how to integrate the 3D seismic data, wellbore data, relative permeability, downhole pressure, and sand production [202], [203]. Employing BD analytics to a variety of enormous information can be used to generate information that assists engineers to understand better the reservoir changes over time [204]. The high volume of data is collected through small-scale and cost-effective sensor devices and transmitted by the IoT technique. Subsequently, the data is integrated into the BD system and is normalized into a time sequence. This allows reservoir engineers to continuously monitor the reservoirs using the stored results in chronological order. Moreover, integration of BD technique and cloud computing enables the reservoir engineers to adjust the development parameters in real-time, such as optimization of gas lift, optimization of formation water injection, spacing, and pattern of water displacement [202]. The application of I4.0 technologies are discussed under the following headings: reservoir management, enhanced oil recovery (EOR), reservoir characterization, reservoir simulations, and carbon capture.

1) RESERVOIR MANAGEMENT

Reservoir management involves the use of technology, information and resources to control operations in order to obtain the maximum possible economic recovery from a reservoir. This involves optimization of oil production, operating cost and capital investments in order to achieve maximum NPV. The concept of reservoir management and its operations have been categorized in [205] under four main categories which are reservoir operations, completions operations, well operations, and top side facility operations. The reservoir operations management involves the ability to manage several operations such as multi-layer reservoir properties estimation, steam flood monitoring, monitoring of water or gas injection, monitoring of chemical flood and event detection. The completions operation management involves inflow profiling, detection of water or gas breakthrough, forecasting of production performance and assessment of well completions integrity. The well operations management include the detection of downhole sensor malfunctions, closed loop monitoring, and control of chemical injection rate, real-time virtual metering at gauged and ungauged locations knowledge discovery, and diagnostics, prognostics and prescriptive in well monitoring. The top side facility operations management involves pipeline integrity management, compressor and pump performance monitoring, and flow forecasting for optimizing pipeline operations. For effective management operations, in-well measurements and subsurface monitoring of wells and reservoirs in real-time are needed. Downhole BD from multiple downhole distributed sensors (such as temperatures, acoustic, strain, frequency, pressure, flow rate) and data from time-lapse seismic and electrical potential and production logging tools are obtained and used for data driven decision supports. This process involves the use of different I4.0 technologies such as IoT, BD and AI, and cloud computing. For instance, [202] applied IoT, BD and simulations to optimize the application of EOR projects in Daqing oilfield China. Real-time data collected from various sensors via IoT were integrated to BD system for computation of different production parameters. These parameters were fed as inputs to numerical reservoir simulation models. The application of these systems helped to reduce prediction error by more than 46 % when compared to traditional reservoir simulation which operated base on geo-parameters. Bello *et al.* [205] presented the application of BD, AI, cloud computing in different case studies related to reservoir management. This include the use of ML for estimation of O&G flow rates and forecasting in multiphase production wells, characterization of matrix acidizing operations using permanent downhole gauges (PDG), distributed temperature sensors (DTS) and distributed acoustic sensors (DAS), analysis of PDG and DTS data for flow profiling in vertical gas well and analysis of flow profiling using PDG and production logging tool (PTL) for automated production performance of well system. The use of AI, BD and cloud computing have helped to reduce the error between predicted values and actual values in the reservoir management [205], [206]. Physics-based models have also been combined with AI models for automatic detection of clusters by employing spatial and temporal field data [207]. Furthermore, the evaluation and disclosure of reservoir which includes confirmed reserves, probable reserves and possible reserves to the security and exchange commission (SEC) has to be well managed by the O&G industry. The use of AI has been used to enhance the evaluation and management of the SEC O&G reserves between China and SEC [208].

2) ENHANCED OIL RECOVERY

The global demand for oil continues to increase and the oil production rate declines due to the lack of new oil fields and a decline in production from existing oil wells. This have resulted in considerable research on EOR approaches (gas, chemical and thermal) to improve the productivity of reservoirs [209], [210]. However, lack of a specific recommendation for reservoirs has limited EOR applications [211]. Hence, the selection of the appropriate EOR method can save cost and increase oil recovery. The most common methods used in the O&G are conventional EOR screening (CEORS) and the advanced EOR screening (AEORS). CEORS utilizes pre-defined screening criteria such as acceptable ranges of reservoir rock and fluids properties to determine the best EOR method to implement [212]. AEORS includes the use of ML algorithm to discover the valuable screening rules (relationship between the reservoir properties and successful implementation of EOR methods) from past successful EOR projects [212]. Consequently, Nasr *et al.* [213] investigated the application of three ML algorithms namely rapid basis function-artificial neural network (RBF-ANN), adaptive-network-based fuzzy inference system (ANFIS) and multilayer perception-artificial neural network (MLP-ANN) forecast the efficacy of silica nanofluid displacement experiment using sandstone and carbonate core samples. They concluded that ANFIS model had the shortest implementation time with the least fitting problem. Hence, it can be used for selecting the effectiveness of silica-EOR projects. In similitude, Giro *et al.* [211] used AI to correlate physical and chemical representations of injected fluids, including EOR materials with reservoir-specific information on lithology, porosity, permeability, oil, water, and salinity condition to recommend EOR injection fluids. This allows users to consider the EOR methods based on availability and cost. SVM method was used to determine the optimum surfactant structures as a predictive tool EOR [214].

3) RESERVOIR CHARACTERIZATION

Reservoir characterization is the estimation of petrophysical properties such as permeability, water saturation, porosity, grain composition and sand fraction of the reservoir subsurface responsible for the presence of hydrocarbon [211]. Nevertheless, estimation of these reservoir properties is a cumbersome process due to heterogeneous nature of the subsurface (pore space and reservoir geometry) [215]. Consequently, conventional formation evaluation based on well logs to establish a statistically significant correlation between the reservoir storage and fluid flow characteristics cannot provide enough information for deriving reservoir characteristics [216]. For instance, lateral variation in sand continuity in carbonate reservoir provides inaccurate prediction of permeability far away from the well location. Also, when the number of wells is less, estimation using well logs do not provide satisfactory results [216]. AI has been used to circumvent these problems by integrating ML with an expert system to predict depositional facies, which can be validated with facies interpretation from conventional cores in test wells [217]. Elkatatny *et al.* [218] employed ANN to predict the permeability of heterogeneous carbonate reservoir while the prediction of porosity and permeability were carried out using FN and SVM [219]. Optimal selection of support vector regression hyper-parameters for prediction of permeability in well characterization was explored in [220] and ant colony optimization was used to predict permeability of gas reservoir [221].

Wang *et al.* [222] utilized the random forest ensemble ML method to implement an inverse modelling approach to predict time-lapse saturation profile. Real field production and injection data were used to mitigate against the labor-intensive, time-consuming, and expensive traditional method of using seismic, well logs, and core data. Seismic data on the other hand are prone to the strong background sound and the relationship between seismic data and projected reservoir properties vary from one location to another [211]. A deep neural network (DNN) can be used to solve problems usually associated with longitudinal waves in reservoir characterization. Yang *et al.* [223] used cluster analysis and DNN to optimize seismic features prone to O&G response. The seismic gas reservoir distribution forecasted using this method had higher accuracy and was consistent with actual drilling information. BD analytics and simulation models enable the early detection of reservoir souring [224]. The use of BD analysis has been used to develop a simulation platform to predict reservoir parameters and evaluate oil well productivity in the south china sea [225]. AI has been applied in the development of models to determine the reservoir fluid properties such as bubble point pressure (Pb) and gas solubility (Rs). These properties play important role in reservoir management. The use of FN and type-2 fuzzy logic systems have been explored in the prediction of porosity and permeability of the O&G reservoirs [226], [227].

4) RESERVOIR SIMULATION

Reservoir simulation has been recognized as an economical means to solve complex reservoir problems in a reasonable time frame [228]. Large data from existing reservoirs are used to develop reservoir simulation models. In the absence of data for new fields and reservoirs, heterogeneous data from statistical characteristics from existing fields or reservoirs within geologic environments are often used. Numerical and simulation models are needed to make economic decisions and are particularly useful in the study of unconventional reservoirs. Crude oil recovery from unconventional reservoirs includes shale, coal, tight sand, and oil sand. These reservoirs contain massive amounts of oil and natural gas, but they present a technological challenge to both geoscientists and engineers in terms of producing economically on a commercial scale. For instance, the application of DT which combines physical and virtual model was used to study the capillarity, sorption, and injection salinity mechanism in unconventional reservoirs [100]. The effect of the mechanism on transport phenomena was characterized mathematically and illustrated via simulations by using multiscale algorithms. The application of analytical and physics-related computational algorithms on BD generated from unconventional reservoirs that are needed for decision making was presented in [229]. These computational algorithms were applied to model and simulate the complexity of unconventional reservoirs. ANN was explored in choosing the best location for injection in gas-assisted gravity drainage for reaching the optimized pressure and production rate in a fractured carbonate reservoir [230]. The result showed high efficiency and ANN as a powerful tool for optimizing the location of the injection. The use of AI was used to improve history match in the simulation of reservoir model [231].

5) CARBON CAPTURE AND STORAGE

The O&G industry is expected to play a significant role in carbon capture and storage (CSS). The CCS involves capturing carbon dioxide emission from energy-related sources before it mixes with the atmosphere, is compressed, and transported to be kept in a storage site. This storage site could be porous geological formations that are thousands of meters underneath the surface of the earth. Examples of storage sites are former O&G fields either onshore or offshore. The application of I4.0 technologies can be deployed to determine and manage the best storage sites. For instance, a numerical simulation (compositional field scale) model was used to examine fluid flow dynamic forces of a current CO2-EOR project in Texas, USA. A hybrid scheme that utilizes particle swarm optimization (PSO) and ANN was used to envisage time-series project responses (hydrocarbon production, CO2 storage, and reservoir pressure data) to optimize CO2-EOR process. The CO2 storage capacity increased by 21.69 % and oil production by 8.74 %. This shows the success of the combined optimization for CO2-sequestration and oil recovery can be used in making decisions for other CO2-EOR cases [232].

F. CONTROL CENTER OPERATIONS

In the O&G industry, the control center is an important part of operations and it is a command center for control of all the processes and monitoring of all the parameters. The control rooms deploy SCADA systems that are interfaced with displays and monitors [233]. The operations in the control centers include emergency shut down, and monitoring of equipment such as pumps and compressors. In many cases, the control centers still require human intervention to handle these operations and therefore have to be manned 24/7. With the deployment of I4.0, intelligent data centers can monitor and control several operations using data collected from smart objects with fewer human interventions anywhere and everywhere [15], [234]. The use of IIoT allows for remote control and multi-site coordination of control center operations. The control centers are equipped with remote monitoring software and analytics that helps to process and convert the numerous stream of data into actionable instructions. Fig. 12 shows a control center in O&G industrial operation for process control and monitoring. Other functions of the control center include data storage and visualization.

The performance and condition of devices such as control valve positioners, mission-critical valves can be monitored remotely from the control center and proactive maintenance can be scheduled automatically [235]. Control centers are now being operated using DT and CPS technologies [236]–[238]. Thanks to advanced communication technologies such as highway addressable remote transducer (HART), WirelessHART® (IEC 62591) and FOUNDATION Fieldbus capabilities [235]. The use of blockchain and IoT technology helps to reduce downtime and improves the reliability of the O&G facilities. Blockchain and IoT technology were applied to reduce failure rates in pumps, increase reliability while ensuring transparency and traceability [239]. However, control centers require adequate skills and this is carried out by using simulators that are developed for the O&G industry to train personnel [240].

FIGURE 12. Example of control center operation for O&G industry [241].

Currently, AR is considered a useful support tool for the exchange of information between the workers on-site and designers of the O&G products [242]. This aids in modification and on-site improvements of the O&G products. However, one of the major challenges of the control room is cyberattacks. Hence, attempts have been made to develop network security risk evaluation method for

SCADA systems [243] and cybersecurity measures for industrial control systems [244], [245].

G. EQUIPMENT AND OPERATIONAL PARTS

The study in [246] has shown the progress in the application of AM in the O&G industry. The benefit of AM application in O&G is the ability to provide on-demand production of consumables or failure-prone components directly on-site or near-site and production of components and sub-assemblies with complex features and shapes. Two categories of metal AM technologies are powder bed fusion (PBF) and directed energy deposition (DED) [247]. Some of the applications include the use of laser aided AM (LAAM) [248], wire and arc AM (WAAM) for fabrication of superduplex stainless steel [249], [250], and metal AM for manufacturing turbomachinery components [251].

While AM provides several benefits, there are several issues that could slow the adoption of AM in the O&G upstream sector. The characteristic and performance of AM materials in harsh, corrosive environments which require minimum downtime need to be subjected to a rigorous test. Another issues is the repeatability of the AM process with effects on the microstructure of the build component. An example is the susceptibility to hydrogen embrittlement based on different build orientations of AM 718 alloy [252] and testing relative to a particular AM material and heat treatment of UNS(4) S17400 [253]. Hence, standards are being formulated to facilitate improvements in design equipment and faster prototyping [254], [255].

H. SUMMARY

The reviewed literature shows that the I4.0 technologies have been widely explored in the O&G upstream sector. Some of the technologies like BD analytics, AI, IoT, simulations, cloud computing, AM, AR, system integration are actively been applied in the O&G upstream sector. From the review the application of AI has been widely explored and results have shown remarkable performance compared to the traditional method of estimation and prediction. The use of AI helps to overcome some of the limitations associated with numerical simulation techniques such as computation complexity and time consumption while offering better accuracy. However, some of the AI techniques are faced with limitations of data size, dimensionality making them inappropriate for certain tasks. To overcome these limitations, the use of hybrid-AI techniques was demonstrated in [131], [207], [220], [226]. The application of AM and AR are still emerging areas with limited published works compared to other I4.0 technologies. This may indicate slow adoption in the O&G sector. This is due to the need for a high level of standardization required for the application of AM materials in harsh environments and also the need to determine use cases where AR is best applied. Cybersecurity remains a vital area and requires continuous research and efforts to safeguard critical infrastructure and confidential information.

The majority of the published works reviewed are still at conceptual and laboratory stage. However, some of the I4.0 technologies have been adopted for industrial scale application. For instance, the deployment of AM by Siemens in the production of turbine [256], DT in aweelah Gas Compression Plant in the United Arab Emirates (UAE) [257], ML in optimization of Wapiti horizontal gas well [258], unmanned smart field in United Arab Emirates [259]. In addition, several industry players are already providing digitized services to the O&G by using some of the I4.0 technologies. A more recent collaboration between Exxon Mobil and the Massachusetts Institute of Technology (MIT) energy initiative utilized AI robots to navigate and explore oceans, as well as to detect oil seeps [152]. Similarly, an autonomous robot for O&G site (ARGOS) robots is used to carry out inspections at the locations where exploration is taking place, during the day or night as well as to optimize subsurface data analysis by the collaboration of Total Societe Anonyme (S.A.) and Google cloud companies [152]. The partnership between British Petroleum (BP) and Belmont Technology Inc/Houston developed a cloud-based geoscience platform called "Sandy" to perform simulations, interpret geology, geophysics, historic, reservoir project information, and link the information together to create a robust image of BP's subsurface assets [35]. The partnership between Shell and Microsoft developed Azure C3 IoT software platform and intelligent drilling solution (Geodesic^{TM}) aimed at improving the accuracy and consistency in the directional control of a horizontal well in order to reach the most productive layers of rock containing hydrocarbon [260]. The solutions were designed to make real-time decisions and better predict their outcomes through the streaming of drilling data and process algorithms. The solution enables geologists and drillers to visualize payzone in a unique environment by using the features such as an easy user interface (drilling simulator), and a suite of tested algorithms [260]. Other industries like Baker Hughes (GE), Equinor, and Chevron are also leading the digital innovation and engineering.

V. I4.0 FRAMEWORK FOR UPSTREAM O&G SECTOR

To answer RQ3, a discussion on the framework for I4.0 is presented in this section. The review of literature has shown the wide adoption of I4.0 technologies in the O&G upstream sector. However, there is a lack of a framework that allows for seamless integration and application of the different technologies. Efforts have been made to propose and develop architecture for the adoption of some of the I4.0 technologies. An example is the proposed service oriented architecture (SOA) to address the issues of BD in the O&G industry [261]. An IoF architecture for the vertical integration in the O&G industry that incorporates the industry standard IEC 61499 and OPC UA was proposed in [262]. This architecture focused on the CPS with three different abstraction models.

The frameworks that aids the deployment of I4.0 in the O&G industry will play an important role in early adoption. The deployment of industry 4.0 cuts across different

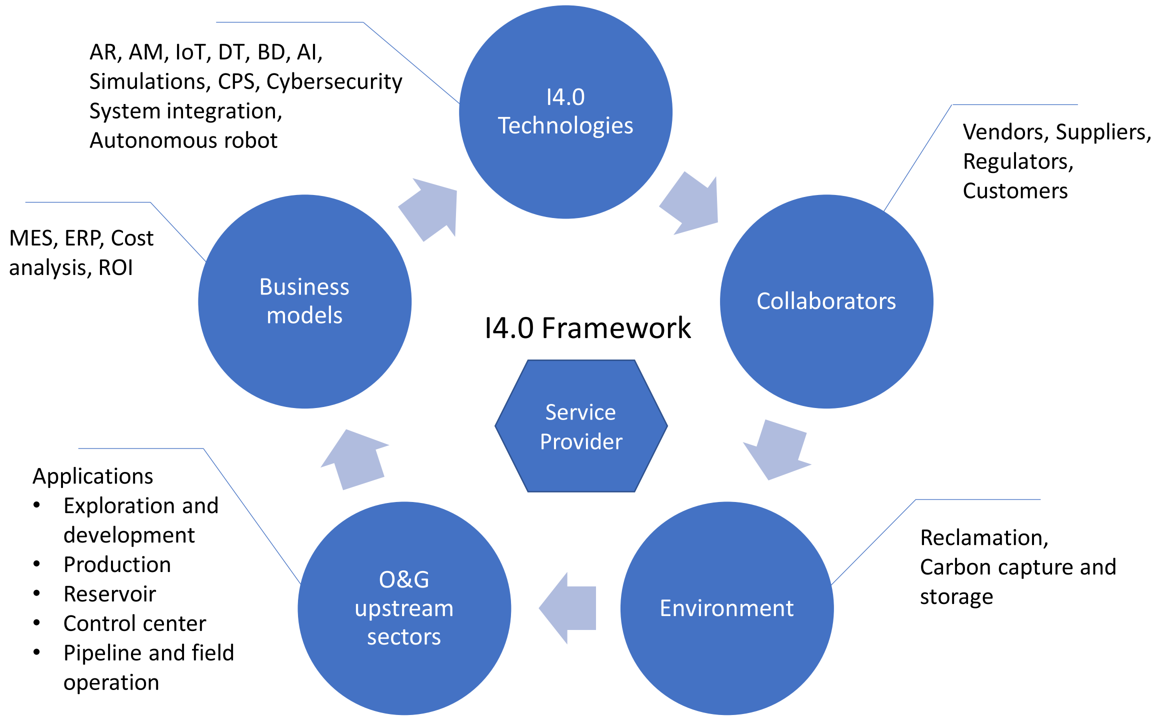

FIGURE 13. **I4.0 framework for O&G upstream sector.**

disciplines and requires cross-disciplinary collaboration [263]. Hence, frameworks that support the integration of third-party systems to communicate effectively without undermining the security and privacy of data are needed. There is a need for standard protocols for communication between the different I4.0 devices and systems in order to facilitate the exchange of information. Notably, there are existing architectures that have been proposed for I4.0 and examples include Reference Architecture Model for Industry 4.0 (RAMI 4.0), Production harmonizEd Reconfiguration of Flexible Robots and Machinery (PERFoRM), project Production harmonizEd Reconfiguration of Flexible Robots and Machinery (IMPROVE), and project Basic System Industrie 4.0 (BaSys 4.0) [264], [265]. However, these architectures address a specific field of application. In view of this, a framework that incorporates five major elements which are I4.0 technologies, collaborators, environment, business models, and applications in the O&G upstream sector is needed and shown in Fig. 13.

The I4.0 framework can be used by service providers to deliver I4.0 services either as PaaS, SaaS, or IaaS. This framework needs to provide support for the different I4.0 technologies. This can be achieved by deploying architecture that allows the different technologies to interplay while addressing the different O&G upstream applications. Business models need to be incorporated into the framework to allow for investors to simulate the return on investment (ROI) and other business analyses such as the cost-benefit ratio (CBR). Existing tools such as the MES and ERP have been integrated for better decision making, however, intelligent business models that can be used to manage the volatility in O&G demands and prices and also target future sustainable goals are needed. Economic analysis based on original oil in place, capital investment, reserve and recovery rate, reservoir performance, and market forecast can help make wise business decisions using the framework. The framework also needs to provide support for collaboration from different entities such as vendors, suppliers, producers, regulators, and customers. Another important element of the framework is the environment. This involves the use of I4.0 in the process of reclamation at the end of a project's life cycle and for CCS, environmental protection against pollution [266], and detection and predictive maintenance of oil spills [267].

VI. BENEFITS OF I4.0

Following the application of the I4.0 technologies in the O&G upstream sector discussed in Section III, we highlight the benefits of I4.0 technologies in this section to address RQ4.

A. COST REDUCTION

There are several ways costs can be reduced in the upstream sector. For instance, the use of UAV/droves can be used instead of manned aircraft for geographical and topographical surveys and reconnaissance activities in the early stage of hydrocarbon exploration [63]. Predictive analytic can be employed in asset operations and maintenance in order to reduce downtime and responding to early warnings of asset failures [10], [178]. The application of AI can help in the early identification of non-productive time (NPT) in drilling operations which helps to improve return on investment.

B. RESOURCE MANAGEMENT

Special expertise and continuous supervision are required in O&G operations to ensure its processes operate smoothly. The workforce productivity, asset management, and operations schedule can be improved with the I4.0 technologies. For instance, [15] proposed a trustworthy monitoring system using IoT technology that can lead to a reduction in production downtime as well as disruptions. As a result, a safer working environment and better asset maintenance can be achieved in the O&G industry. In addition, the I4.0 technology can provide better management in terms of scheduling, resource optimization, and project management using intelligent coordination tools. The identification of hot zones in shale reservoirs with few parameters has been made possible with the use of the BD tool [268]. This makes it possible to identify reservoirs with the potential to yield highly productive wells at an early stage. BD has enabled the visualization of hydrocarbon deposits in Russia and worldwide which includes static and dynamic parameters enabling comparative analytical studies [269].

C. COMPETITIVE EDGE

The application of AI in geology, geophysics, historic and reservoir project information helps to create knowledge-graphs that make complex data used for O&G exploration and production more accessible. The ability to link several sources of data such as inventory, equipment, asset management, cost analysis, production, predictive maintenance using AI will help generate new insights for companies to stay ahead of the competition.

D. POLLUTION MANAGEMENT

One of the major drawbacks of the O&G sector is pollution. The consequences of pollution could be devastating for the environment and local communities. It disrupts wildlife, water sources, human health, livelihood, and creative activities. The use of I4.0 technologies such as the DT, IoT, AI enables smart oil fields which can help minimize environmental disasters from the hydrocarbon extraction process [270].

E. HEALTH AND SAFETY

Accidents have a considerable impact during the O&G production which frequently leads to an increase in the time and cost of drilling, construction, and operation work. For example, in the upstream production phase, the support engineers employed mud logging to detect accidents while drilling. This can be less efficient due to the fact that the engineers have to monitor several wells online and drilling accident patterns are only considered after an accident has occurred. Therefore, the adoption of the I4.0 technology system for detection of early signals of failures can significantly minimize the accident rate to ensure safe, reliable, and efficient operation at a low operational cost [271]. The prediction of formation in the drilling process using AI can improve safety [272]. Furthermore, the use of UAV/drones for surveillance can reduce the risk in remote, contaminated areas or areas that posses a threat to personnel. The use of IoT aids the control and management of hazardous situations in the O&G industry [273].

VII. OPEN ISSUES AND CHALLENGES

The open issues and possible challenges relating to the deployment of I4.0 in the exploration and production of O&G are discussed in this section. While I4.0 in the O&G industry offers real-time data collection, analysis, and transparency across every aspect of the manufacturing operation, there are several hurdles that need to be overcome which are discussed as follows. The challenges are categorized into technical, environmental, and business.

A. TECHNICAL CHALLENGES

Some of the technical issues faced in the adoption of I4.0 in the upstream sectors are discussed as follows.

1) SECURITY

The amount of cyberattacks by hackers, criminals, and governments continues to increase [274]. The sharing of information via the internet requires the security of data and information from the transmitting node, communication link, network, and receiving node with global identification and end-to-end data encryption [275]. The expansion of the O&G cyber environment to leverage the I4.0 technologies may expose companies and their assets to a high risk of cyberattack. The attacks could be on the connected computing devices, equipment infrastructure or through personnel or applications deployed, or the telecommunication systems or transmitted or stored information [274]. The attacks on confidential material of the O&G companies by hackers can lead to massive profit loss or legal disputes [276]. Several incidents and attack patterns on the O&G sector occur at different layers such as the hardware, firmware and software, network, operation and security process, and IoT layers as discussed in [245]. In the event of cyberattacks, accidents and environmental pollution can occur. This could lead to major loss and damage to the company's reputation and possible public outcry. Therefore, continual efforts to protect every node of the network and implement cybersecurity standards against external attacks and data misuse will continue to be a major priority for every O&G company.

2) INTEROPERABILITY

The integration of several I4.0 technologies for deployment in the O&G is expected to face interoperability challenges. Many devices and processes need to be tightly interweaved between hardware and software between different organizations and entities. This includes integration between physical and software systems, integration among different economic sectors (finance, commerce, logistics), and integration among different industries [81]. The exchange of quality and timely information for collaborations is needed. This is likely to pose challenges in managing a complex information technology environment for the integration of IT and OT. Some of the major issues are the lack of a common data standard that allows for information processing [277] and the handling of the exchange of real-time and non-real-time data. To address some of these issues a multi-level models for data interoperability in the O&G industry was presented in [278].

3) SCALABILITY

The deployment of I4.0 technologies needs to account for scalability in terms of the number of sensors and actuators to be managed, the amount of data to be processed and stored, and the analytics needed. A scalable architecture that can evolve rapidly with the market demand and technological changes, scale with increasing numbers of participants, and integration of additional tools [279] while minimizing cost needs to be addressed.

4) DEPLOYMENT ISSUES

Decisions on the choice of technology to adopt from the I4.0 technologies while maintaining the business growth and revenue can be a challenge to decision-makers. This is due to the readiness of other players such as vendors, customers, partners, employees, regulators, and logistics. The trade-off between investment in the I4.0 technologies and managing risk while lowering cost can be a difficult decision process.

5) BIG DATA AND ITS ANALYTICS

The major challenge in data collection is to determine which data to be collected, identify the process of data collection and how to formulate and analyze the data. This will require considering what information provides the quality and efficiency of related factors to the physical assets or models that need to be monitored. For instance, as the malfunction of drilling equipment will reduce the drilling efficiency in the production of the upstream sector, the equipment state and its operation history should be monitored and analyzed to predict problems so that people can respond in advance [276]. In addition, the application of AI/ML algorithms may require data to be labeled in order to be able to apply the correct algorithms. To achieve this, it will require different analysis to be carried out that amounts to several man-hours.

B. ENVIRONMENTAL CHALLENGES

There are several environmental pressures that can arise in the deployment and adoption of I4.0 technologies. First O&G companies may need to dispose of obsolete equipment [280] which may lead to the demand for resources such as land and other ecological services. The obsolescence of machinery and equipment may lead to an increase in the amount of waste in the environment. The development of hardware for the digitization of the O&G equipment can also lead to an increase in demand for raw materials such as lithium and other heavy rare earth elements that are difficult to extract, purify and recycle [281], [282].

C. BUSINESS CHALLENGES

The I4.0 is expected to introduce disruption to the O&G industry. There are many business-related issues that need to be addressed in the implementation of I4.0 and some of these issues are highlighted as follows.

1) SKILL SET

The O&G companies are facing a shortage of skilled field experts and workers due to the emergence of new technologies and in some cases the retirement of skilled workforce in the industry [23]. Studies found in [283] showed O&G organizations lack staff with the technical know-how of BD analytics and had to rely on consultants. Some of the important technical skills needed are cybersecurity, developers and software engineering, data science, networking, programming, and IoT. In addition, inadequate innovative technologies to bring together, promote, reuse and manage knowledge due to the scattered nature of information presents a challenge to the O&G industry [284].

2) TRANSPARENCY

The lack of transparency and accountability regarding financial data and other information considered confidential among the O&G industry partners poses a challenge to the adoption of I4.0 in the O&G industry [10]. This also can be associated with the risk in the adoption of new technologies.

3) BUSINESS MODELS

New business models that bring people, systems and partners across the extended value chains are required for the successful implementation of the I4.0. New business models that adapts fast to changes in technology and propels growth and investment decision-making while minimizing cost and risk are needed. Also, quantitative life cycle profit analysis that accounts for return on investment of the I4.0 technologies is crucial to overcome the barriers of early adoption.

4) FUTURE INVESTMENT

The high market volatility faced by the O&G industry and the change of government policies by major countries towards greener energy could be a major hurdle for attracting investment for the I4.0 technologies. The lack of funds for research and development in the O&G industry is a major challenge in the development of innovative technology [285].

VIII. FUTURE TRENDS

In this section, we identify the key areas that are expected to attract research interest from academia and the industry. The implementation of I4.0 technology is not limited to improving the operations of O&G companies, but it is also able to transform the business model of the companies. Therefore, it is crucial to examine how I4.0 aligns with the future aims, culture, strengths, and strategy of an organization.

A. I4.0 FRAMEWORKS AND PROTOCOLS

Although there are existing architectures and protocols that govern some of the I4.0 technologies [265]. Some of these architectures are targeted for general-purpose applications. A framework that allows for the integration of the I4.0 technologies and is tailored to the O&G upstream sector is expected to attract research interest. The implementation of the I4.0 framework will require collaboration from various standardization bodies.

B. SOFTWARE DEVELOPMENT

The development of software for implementation of the I4.0 is expected to attract more research interest. Timely development, implementation, and commercialization using commercial tools are expected to drive the implementation of software [286].

C. EDGE COMPUTING

Edge computing offers a distributed approach for processing of data, control functions, and storage of high bandwidth content closer to devices rather than a remote network [287]–[289]. This helps to mitigate network delays and low latency associated with centralized cloud computing. The edge computing devices can either be a local device, localized data center, or regional data center. As a result of the low fault-tolerant process involved in the oil extractions, the need to process data collected from smart oil fields in real-time makes edge computing a suitable candidate [270]. However, some of the challenges that need to be overcome in the deployment of edge computing are the resource-constrained nature of edge nodes, the difficulty of configuration and maintenance in remote areas, and security [270]. This opens up research opportunities such as robust resource allocation [270], [288], [290]–[292].

D. SECURITY AND PRIVACY

Due to the importance of security and privacy, more research is needed in ensuring seamless communication in the deployment of I4.0 in the O&G industry. Implementing increased security and privacy will open up several research opportunities such as predictive and analytical software tools for detecting cyberattacks. In addition, more software tools to simulate cyberattacks on the O&G infrastructure are vital and expected to attract future research interest. The simulation tools that can identify vulnerabilities, plan recovery time, and indicate risk analysis among the I4.0 technologies will continue to be researched and developed. Global policies that ensure collaborative efforts towards minimizing cyberattacks among governments, industry, and academia remain crucial.

E. COMMUNICATION TECHNOLOGIES

A reliable communication that supports different requirements with respect to bandwidth, latency, and availability is crucial for the reliable exchange of information in the implementation of I4.0 in the O&G industry. Several of the upstream operations are located in remote locations or offshore where there is limited cellular coverage. Satellite communication has been employed for data transfers in remote areas, however, there are certain limitations associated with it. The satellite communication suffers from high latency which makes it unsuitable for time-sensitive operations/tasks, prone to weather and sunspots effects which affect operations. Hence, there is need for deployment of complementary communication technologies that offers long-range and high data rate to support the I4.0 technology deployment. The deployment of LPWA communication technology [293] can extend the cellular coverage and application of fifth-generation (5G) network solutions such as the massive multiple-input multiple-output (MIMO) base stations would provide better latency, higher reliability, and high data rate communication. The deployment of IoT in the upstream sector requires communication technology that supports long-range and remote communication. The LPWA communication technologies have been developed to support the IoT or IIoT. Examples of the LPWA are LoRa, Sigfox, Narrow Band-LTE [21], [294]. This LPWA enables long-range communication, low power consumption, higher penetration powers, and design for low transmission packet sizes [295]. This is vital in I4.0 to aid automation and access to machines remotely. The use of LPWA technology for O&G has been demonstrated in [296]. Other communication technologies such as the internet of underwater things, optical wireless communications are expected to play a major role in the O&G production [297].

F. QUANTUM COMPUTING

The low cost of data storage, increase in processing and computing speed, enhanced algorithms for data processing, and various open cloud platforms will continue to drive BD in the O&G industry [298]. The conventional computation may not be efficient in handling such BD and hence the application of quantum computing is attracting research interest. Quantum computing is expected to offer a more efficient solution to problem-solving compared to classical computational methods and systems [299]. The use of quantum computers, quantum algorithms, and quantum devices [299], [300] is expected to accelerate the deployment of I4.0 technologies such as DT and CPS.

G. DIGITAL-TWIN

The implementation of DT spans from early design to decommissioning, hence there is a need for collaboration from contractors, vendors, standard organizations/bodies, and professionals in order to ensure a trusted system. This opens up research areas in different modeling techniques such as mathematical models, analytical models for structures and hydrodynamics, time-domain models for components and systems, and algorithms for software-driven systems [93]. More research work is expected in the application of DT in simulations of hydraulic fracturing and rock properties of unconventional reservoirs by linking many aspects of the physical mechanism, theoretical models, and algorithms.

H. ADDITIVE MANUFACTURING

More research efforts are expected in the adoption of AM in the O&G industry like the adoption of new AM techniques such as bender jetting, metal powder bed metal AM processing, and qualification and materials characteristic testing requirements [246].

I. STANDARDIZATION

The intellectualization, digitization, and automation using I4.0 technologies are there to help minimize loss, increase efficiency and drive towards sustainable goals. However, there is a need for standardization in measurement methods in order to quantify and analyze improvements made by deploying the I4.0 technologies. For example, methods for measurement of the carbon footprint reduced by automating and digitizing some of the O&G operations need to be standardized. This will help operators perform historical comparisons and identify areas to focus on, thereby reducing waste and maximizing resources.

J. I4.0 INNOVATIVE AREAS

The application of the I4.0 technologies is expected to play important role in new innovations and open up new research in the O&G industry. This includes the application of AI in improving the accuracy, providing a non-destructive and more economic method in the prospecting and predicting the distribution of oil reservoirs [301]. The use of I4.0 technologies can be used to enhance the control performance of multi-functional oil-injection equipment that was developed to absorb oil, remove impurities and fill oil in deep-sea hydraulic systems [302]. The application of I4.0 is expected to drive down the current cost of deployment of carbon capture and storage. Hence, more research is needed in the deployment of I4.0 technologies for monitoring and control of depleted O&G fields used for the storage of CO2. The I4.0 is expected to drive the advancement in reservoir engineering by addressing the challenges faced in reservoirs with deeper burial depths [303] and exploration of 3D digital core technology based on micro/nano CT in the exploration and development of tight reservoirs [304].

IX. CONCLUSION

In this paper, an overview of the I4.0 technologies in the upstream O&G sector has been presented. The various operations of the upstream sector were discussed and the various applicable I4.0 technologies were identified. The study focused on the following research questions RQ1: What is the state-of-the-art of I4.0 in the O&G upstream sector in the last 10 years? RQ2: What are the applications of the I4.0 in the O&G upstream sector? RQ3: What is the framework for the implementation of I4.0 in the upstream sector? RQ4: What are the benefits and challenges faced in the adoption of I4.0 technologies in the O&G upstream sector? RQ5: What are the future trends in the application of I4.0 in the upstream sector? To answer this RQ1-RQ5, a systematic literature review of adopted I4.0 technologies in the O&G upstream sector from published work was presented under the following categories: exploration and development, drilling and well completion, production and optimization, reservoir engineering, control operations, and equipment and operational parts. A systematic approach comprised of several phases was used to select relevant papers reviewed in this article. A total of 223 documents were reviewed from the year 2012 - 2021. While efforts have been made to select relevant papers in this study, there are some publications that might have been omitted due to the few databases used, search terms, and methods of inclusion. The findings from this study show that I4.0 technologies have been explored in various operations in the upstream sector. The use of AI has been largely deployed while the application of AM and AR are still emerging areas of research and deployment.

Several benefits and challenges in the adoption of I4.0 technologies in the O&G industry upstream sector were identified. Benefits include cost reduction, health and safety, a competitive edge that drives profit-making, pollution management, and environmental protection. However, technical, environmental and business challenges need to be overcome. Some of the future trends and research opportunities in the area of security, communications technology, quantum computing, frameworks and protocols, DT, standardization, and innovative areas envisaged were discussed.

A framework that incorporates five major elements which are I4.0 technologies, collaborators, environment, business models, and applications in the O&G upstream sector is proposed. Digital efforts towards the O&G industry are growing and will continue to actualize cutting-edge I4.0 technologies to cultivate growth and success. Some of the I4.0 have been adopted in different sectors of the upstream O&G industry. However, more efforts are needed for seamless integration of the components of the I4.0 technologies in order to provide an ecosystem that shares insights, heterogeneous datasets more fluidly and achieves sustainable goals. The O&G industry personnel and research community from multidisciplinary backgrounds will find this survey helpful in understanding the application of the I4.0 technologies in the upstream sector.

ACRONYMS AND TERMS

1D	- One dimensional.
2D	- Two dimensional.
3D	- Three dimensional.
5G	- Fifth generation.
AI	- Artificial intelligence.
ALS	- Artificial lift system.
AM	- Additive manufacturing.
AEORS	- Advanced EOR screening.
ANFIS	- Adaptive-network-based fuzzy inference system.
ANN	- Artificial neural networks.
AR	- Augmented reality.
ARGOS	- Autonomous robot for gas & oil site.
BD	- Big data.

BP	- British Petroleum.
CBR	- Cost-benefit ratio.
CEORS	- Conventional EOR screening.
CPS	- Cyber-physical system.
CCS	- Carbon capture and storage.
CO2	- Carbon dioxide.
DA	- Data analytics.
DAS	- Distributed acoustic sensors.
DED	- Directed energy deposition.
DNN	- Deep neural network.
DT	- Digital-twin.
DTS	- Distributed temperature sensors.
EOR	- Enhanced oil recovery.
ERP	- Enterprise resource planning.
FWI	- Full wavefield inversion.
GPR	- Ground penetrating radar.
HDD	- Horizontal directional drilling.
IaaS	- Infrastructure-as-a-service.
IoT	- Internet of things.
IIoT	- Industrial internet of things.
I4.0	- Industry 4.0.
IoF	- Intelligent oil field.
IR 1.0	- Industry revolution 1.0.
IR 2.0	- Industry revolution 2.0.
IR 3.0	- Industry revolution 3.0.
IR 4.0	- Industry revolution 4.0.
IT	- Information technology.
LoRa	- Long range.
LAAM	- Laser aided AM.
LPWA	- Low power wide area.
LWD	- Logging while drilling.
M2M	- Machine-to-machine.
MES	- Manufacturing execution systems.
ML	- Machine learning.
MWD	- Measurement while drilling.
NPT	- Non-productive time.
O&G	- Oil and gas.
OT	- Operational technology.
P2P	- Peer-to-peer.
PaaS	- Platform-as-a-service.
PCA	- Principal component analysis.
PDG	- Permanent downhole gauges.
RBF	- Radial basis function.
ROVs	- Remotely operated vehicles.
S.A.	- Societe Anonyme.
SaaS	- Software-as-a-service.
SCADA	- Supervisory control and data acquisition.
SOA	- Service oriented architecture.
SOM	- Self-organizing maps.
SVM	- Support vector machine.
UAS	- Unmanned aerial system.
UAV	- Unmanned aerial vehicle.
VR	- Virtual reality.
WAZ	- Wide azimuth.
WSN	- Wireless sensor network.

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