



# Digital transformation: a review on artificial intelligence techniques in drilling and production applications

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## Abstract

The use of digital and artificial intelligence technologies has expanded and influenced business models and the opening of opportunities for the generation of value in several organizations, in a movement known as industry 4.0. The oil industry has been following the path of several other industrial sectors and has implemented digitalization to solve different challenges and problems. The present work, supported by extensive research carried out in the specialized literature, shows relevant applications of digital transformation to solve problems in drilling and production operations during the life cycle of an oil well. The main issues addressed in the research were stuck pipes and hydrate formation. The achievements show that control systems and the various sensors used during drilling and the useful life of an oil well generate data that creates opportunities for the use of computational and artificial intelligence techniques. New technologies associated with digital transformation include smart surveillance systems, real-time monitoring, and intelligent equipment. In a well oil environment, these novelties are associated with fault detection and prediction systems to avoid or reduce problems or accidents that may cause costs or, in extreme cases, lead to the loss of the well. The study also points out that the oil industries, research centers, and universities are increasingly working together to understand the challenges and overcome the problems associated with the implementation and greater use of digital transformation technologies.

**Keywords** Artificial intelligence · Production · Drilling · Oil well · Oil and gas industry

## 1 Introduction

The oil industry is capital intensive and faces immense technological, economic, logistical, and operational challenges, and for this reason, large companies invest heavily in R&DI (research, development, and innovation). In this century, you can count on digital transformation, which allows the use of

a large mass of data acquired continuously in installations (drilling rigs, production platforms, oil and gas pipelines, refineries, processing units) to support more accurate decision-making process.

In the upstream segment (Exploration & Production), the most active in Brazil, a leading thread for research is the well, the pipeline built to connect the surface to a possible

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reservoir that contains hydrocarbons (oil and natural gas) on the subsurface. Its construction takes place in the drilling stage, which is shorter, and will be followed (in case of success) by the production stage, which will extend for years or even several decades, making it possible to recover the investments made and obtain large profits amounts. This complex operation faces a myriad of challenges, which forces the sector to tackle it with great resilience and efficiency.

This article seeks to do a broad research on the applications of digital transformation — especially those related with artificial intelligence (AI) — in oil wells, with the objective of avoiding or reducing the occurrence of problems or accidents that can cause quite high costs in drilling and production operations, or, in extreme cases, lead to the loss of the well.

## 2 Research objectives

The study sought to examine the application of digital transformation, concerning specifically to artificial intelligence (AI) techniques in oil wells. The following research objectives were formulated to fulfill the main purpose of the study:

- (i) To do a broad literature research on the applications of AI in oil wells.
- (ii) To examine which the techniques are most used.
- (iii) To assess the impact of AI techniques on companies.

## 3 Methodology

Our main object was to present a comprehensive view on how artificial intelligence methods have been used in the real-world data/problems, in the oil and gas field. The methodology (Fig. 1) relies upon AI application performed by companies and its description in journals and conferences proceedings.

First step was a brief exploration, regarding scientific articles, through the databases of Scopus, ScienceDirect, Engineering Village, and Web of Science, using the Brazilian public Portal provided by CAPES (<https://www.periodicos.capes.gov.br>). This step was only a data collection to select keywords to be used in the second step. From this first attempt, many papers were download and a co-occurrence map was built using the software VOS viewer, taking into consideration AI methods (Fig. 2). From that, eight papers (Fig. 3) were selected to improve

the understanding of the research areas, helping to choose the keywords to be used in the next phase.

The second step only examined papers published in the OnePetro database (<https://www.onepetro.org/>); thus, this is used as a reference for research carried out by the oil industry business. Searching for articles in the OnePetro Portal developed both the context of the technique and the context of the problem, and it included the terms workover/intervention activities in wells, and words found related to the artificial intelligence techniques/computational. Accounting only the results of the OnePetro database, approximately 500 articles were initially selected for which selection criteria related to the (1) if the paper was a case study, (2) if AI techniques were implemented, and (3) if data was provided. The result was a quantitative of 142 papers.

Third step included reading, reviewing, and debating all 142 papers. All papers were categorized in terms of application, methods and tools, and variables. Thus, from this compendium, in the fourth step, we reached a final total of 39 papers, considered relevant to be used as the base of this literature review. Of these 39 articles, 17 refer to applications in drilling oil wells and 22 to applications in oil production.

The research activities were carried out at the Dimensional and Computational Metrology Laboratory (LMDC) of the Engineering School of UFF - Universidade Federal Fluminense, as part of a research, development, and innovation project supported by Petrobras-Petróleo Brasileiro SA.

The first step of the bibliographical search returned 11,296 papers. VOS Viewer [1] was used for exploring these findings and creating the co-occurrence map (Fig. 2). There are four clusters related to “assessment/modeling/simulation/case study,” “forecasting/neural network/times series,” “study/pattern/recognition,” and “prediction” aspects of digital transformation and artificial/computational intelligence applications in oil wells.

Eight papers related to digital transformation applications associated with the occurrence of problems in the oil well environment were selected (Fig. 3). The reading of them allowed identification and selection of keywords associated with drilling and production. Keywords used to research papers on drilling were “drilling,” “artificial intelligence,” “machine learning,” “fuzzy,” “data,” “neural network,” “oil industry,” “real time,” “application,” “analysis,” “time series,” and “non-productive time.” For finding papers on digital application to oil production, the following keywords were used: “production system,” “hydrate formation,” “artificial intelligence,” “plug blockage,” “field monitoring,” “flow assurance,” “machine learning,” “analytics,” “fuzzy,” “neural network,” “oil industry,” “data,” “warning,” “application,” “analysis,” and “time series.”

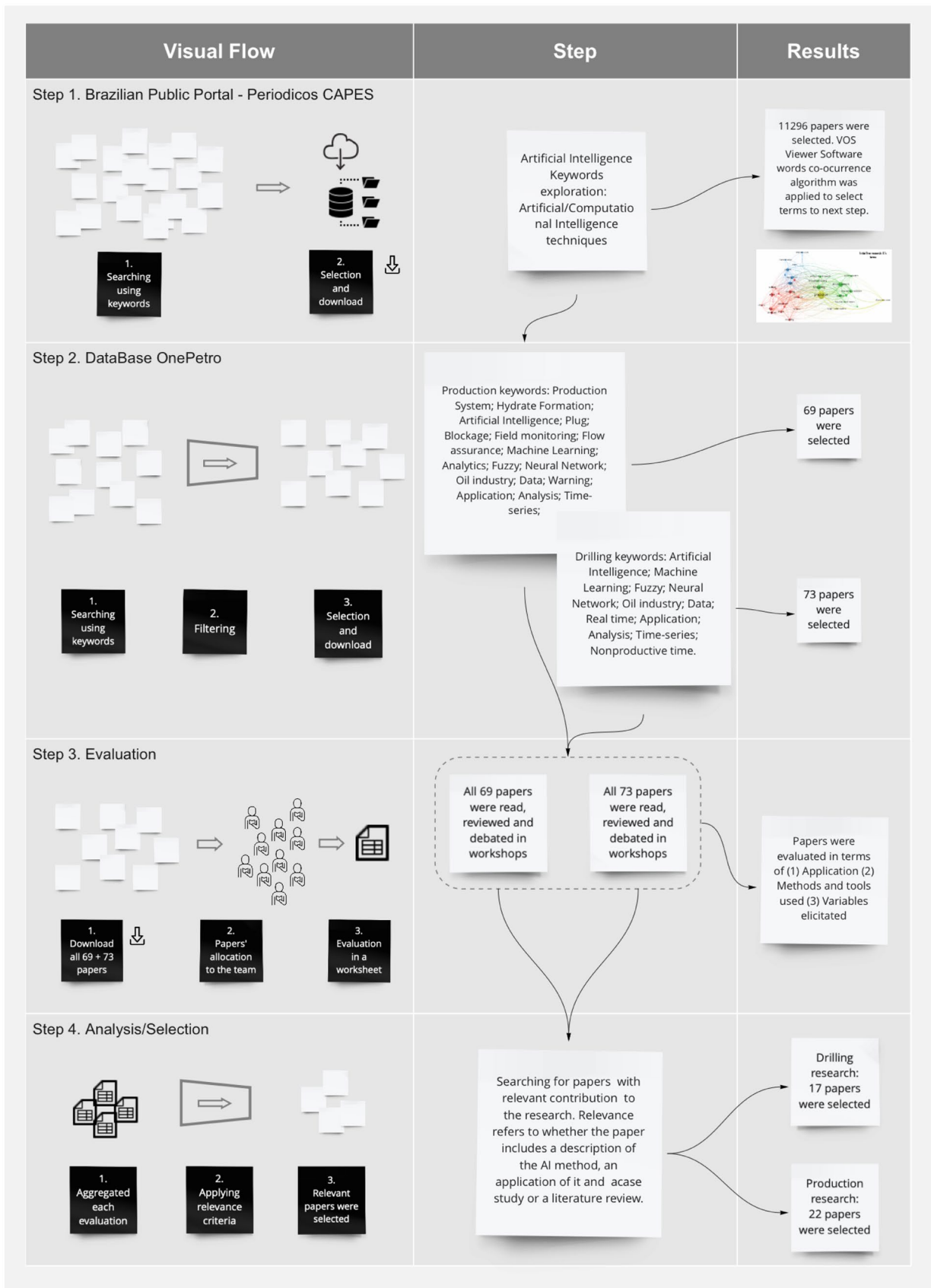


Fig. 1 Methodology

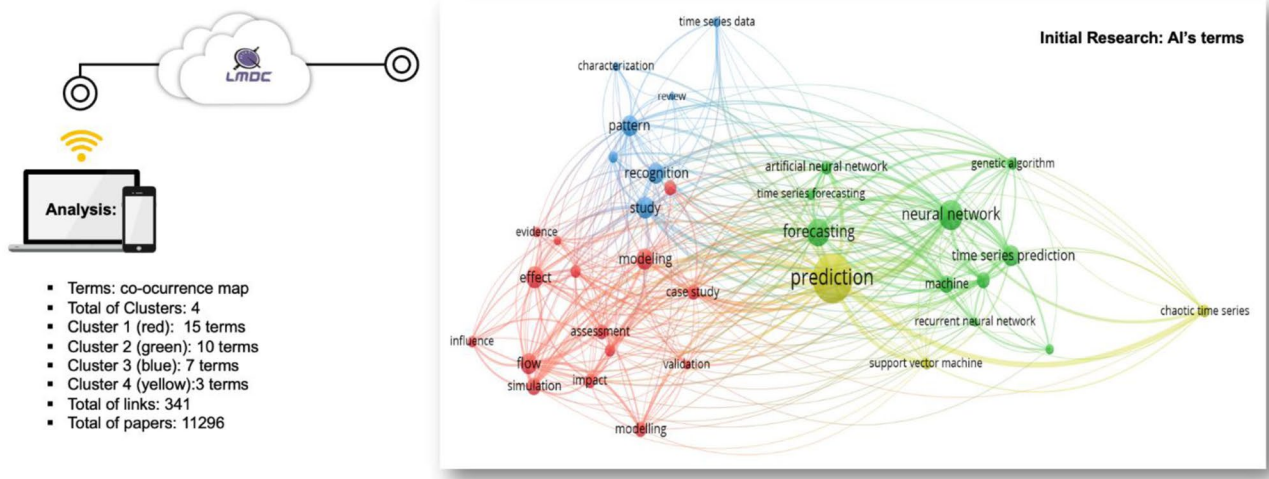


Fig. 2 Initial research: artificial intelligence keywords

## 4 Literature review

### 4.1 Wells: drilling and production

Oil is the main source of the Brazilian energy matrix with a 34% share and production of more than 2.94 million barrels per day (bpd) in 2020, making the country a growing exporter. Gas is responsible for 12.4% of the energy consumed in the country and production reached 127.4 million m<sup>3</sup>/day in the same period, of which less than half reached the market due to the reinjection in the reservoirs, consumption in the facilities themselves and eventual burning [2].

The focus in this work is the upstream (Exploration & Production — E&P), and it involves the drilling activity of wells that passes through the entire E&P segment and has a high financial importance [3].

The well is a connection between a point on the surface where the rig is placed and a point on the subsurface that must be reached. Once a commercial reservoir is found, the work moves to the production stage, lifting oil and natural gas from the reservoir to the surface and then, to primary processing [4].

In Brazil, almost 97% of the oil and 82% of the natural gas produced come from offshore fields, mainly those located in deep waters and ultra-deep waters Thus, drilling



Fig. 3 Initial findings



and production activities in a well have different characteristics. In the drilling, we can highlight [3] the following:

- Shorter initial activity, the well is completed in days, weeks or, at most, months.
- Activity is nomadic with the rig moving to a new location (which may be near or far, even on another continent), for the next well to be drilled. A well is drilled by a single rig, but a rig drills numerous wells in succession. Thus, the well-rig relationship is temporary.
- The well diameter in the drilling phase is much larger.
- Equipment is more expensive, has much larger dimensions, and suffers impacts and mechanical shocks of much larger intensity.
- The number of parameters measured in real time is much higher (around 50).
- State changes (normal, transient, failure) occur at shorter intervals, which requires more immediate alarm systems.

Naturally, the production stage has inverse characteristics, such as [4] the following:

- Long duration, for years and even decades. Several fields in the Campos basin (located in Rio de Janeiro — Brazil) that started production in the 1980s are still in operation. Marlim, an offshore oilfield in Campos's basin, which has been producing since 1991, had its concession period extended until 2052.
- The production units remain stationary on the field for many years, if it proves to be economical and, therefore, are dimensioned for the characteristics of the reservoir. It is a specific project, and it will need modifications to work in another field.
- As production follows drilling stage, the diameter of the well is smaller; that is, the last phase of drilling will be revested, which will make the space for production operations still very small in relation to the initial drilling diameters.
- Production process is continuous, generally without major mechanical impacts, with smaller and cheaper equipment dimensions.
- The number of parameters measured is much smaller, basically pressure and temperature, but at different points in the well.
- It is common to face more permanent processes, which present smoother changes that happen through longer periods of time. This context provides a longer time interval to alarm and manager possible problems.

## 4.2 Research, development, and innovation

The oil industry has the financial capacity for heavy investments in R&DI (Research, Development, Innovation) and,

at the same time, faces major technological challenges; in the same way as other capital-intensive activities, such as aeronautics, pharmaceuticals, automobiles, and information technology. Naturally, those with a small profit margin and very fragmented market, such as textiles, are not able to do so.

Offshore drilling/production is an excellent example of technological challenges to face, since a multidisciplinary range of expertise — in addition to the traditional knowledge of mechanical engineering applied to onshore activity — such as logistics, naval engineering, automation, materials, and chemistry, among others, must be incorporated into it. The logistics ones, for example, are needed due to the limited space for storage in the offshore installations and the restrictions regarding the capacity to support heavy loads. To this end, the installation of equipment on the seabed and the use of nanomaterials are being studied.

The marine area must guarantee the buoyancy and stability of the platforms, subjected to the action of winds, waves, and maritime currents that take several directions at different depth intervals. This demands the action of materials engineering to provide lighter and more resistant materials, which guarantee longevity and integrity to the installations.

Chemical engineering seeks solutions for the thermal shock that occurs with fluids with a high concentration of water and gas, coming from deep reservoirs at high temperature in contrast to the low temperatures on the seabed. This can cause the formation of hydrates, with the solidification of the fluids produced preventing their movement through the pipes.

Naturally, other technological advances in seismic processing, reservoir simulation, well completion, nanotechnology, and biotechnology could be cited, besides the activities in the downstream segment. It is the oil companies that guide the technological routes in the sector, driving the future offers from suppliers. The innovations tend to be expensive; since there are no initial economies of scale, the development time can be long, in addition to the high risk inherent in the activity.

## 4.3 Digital transformation

The oil industry is highly instrumented; it works with many variables for long-term projects, and it exposes its professionals to a variety of risks in hostile environments. There has been a growing adoption of digital transformation resources using information technology for the sensing, acquisition, and treatment of data from wells, platforms, pipelines, and processing units, in real-time. Complementary, digital transformations and its availability in onshore offices facilitate disabling the operational locations and enabling remote work and even the home office, as occurred after the COVID-19 pandemic

in 2020: there is a clear trend of permanent reduction of personnel on board.

In the past century, the storage of computational data was restricted and expensive, and feeding was laborious; today, the stored volume is extremely high (several sensors spread across the well and rig, registering dozens of variables at intervals of a few seconds). All those data cannot be manipulated and analyzed with human capacity alone. Data provided by the “internet of things” (automation and sensing) and artificial intelligence techniques are available, such as expert systems, machine learning (big data applications such as neural networks), and digital twin (virtual replica of a physical object, able to provide perspectives, and data on its use). To guarantee credibility, one should invest in proper synchronism in collecting data from various variables, in satisfactory connection for data transfer between the sources and the offices, and in acceptable data treatment/purge (outliers, missing) [5].

In oil and gas sector, digital transformation is an emerging driver which can play a pivotal role in the industry, redefining its boundaries [6]. Among the applications made possible by digital transformation, we can mention [7–9] the following:

- In exploration, the processing of seismic images, accelerating their interpretation, and the use of digital methods to calculate the physical properties of rocks.
- In drilling, the prevention of accidents, such as mechanical column arrest or severe losses of circulation, in addition to projects to change the geometry of the bits so that they attack the rock at a more favorable cutting angle.
- In production, the use of intelligent completion to avoid future interventions in wells (workover, which requires the expensive use of rigs) with problems such as fouling, string bore, and hydrates formation.
- The use of digital twins in refineries (representing the detailed operation of the entire installation and 360° view) and in the decommissioning of platforms (allowing asset integrity management).
- The use of remote sensing in oil and gas pipelines (operational control), which extend over long distances, which makes physical supervision difficult.

Knowledge of automation and robotics is also required to operate ROVs (remotely operated underwater vehicles) and drones. ROVs work at depths that cannot be reached by divers. Drones are used in places and heights that are difficult to access, and for transportation of small loads and inspection of equipment integrity [10].

## 4.4 Well problems

### 4.4.1 Drilling problems

Drilling services encompass productive, non-productive, and wasted time activities. In the first group are those that allow advancement in the depth of the well, such as drilling or coring. Non-productive operations are those that do not generate progress, but are necessary for the execution of the well, such as casing, cementing, circulating, drill stem testing, and logging. The goal is to carry out the shortest possible time, if they are within the conditions of safety and best market practices.

Finally, we have some wastes in the operations, commonly called invisible lost time (ILT), which obviously must be avoided, such as waiting (sea conditions, services, materials, personnel), repairs (in equipment, installations), and accidents (and their treatments). This last group includes reaming, side track/reperforation, loss of circulation, kick/blow out, and fishing [11].

- Reaming corresponds to the time spent to rework intervals already drilled from the well, but which have restrictions or reductions in diameter, making it difficult or impossible to proceed with operations safely. As an example, the previous bit showed wear with a reduced well diameter, having a slightly conical and non-cylindrical shape.
- Sidetrack/reperforating takes place when an accident involves the loss of an interval length of the well and a plug is put, and a sidetrack is made at a point higher than that of the accident; then, the corresponding interval is reperforated until the previous depth is reached.
- Loss of circulation occurs when the pressure exerted in the well is higher than that of the penetrated formations — especially when they are very permeable, unconsolidated, or fractured —, generating an invasion (total or partial) of the drilling fluid in them. This can damage possible reservoirs, jeopardize the well by reducing the hydrostatic column, and cause the column to become stuck. The severity of the accident depends on the width of the fracture, the pumping pressure, and the flow volume. It can be classified into small loss (1 to 10 bbl/h), partial loss (10 to 500 bbl/h), or total loss (above 500 bbl/h). In its handling, filling materials and high viscosity drilling fluids are used.
- Kick is the invasion of the well by fluids from the formation that is being drilled, or from some other previously crossed, but not adequately isolated. If the flow is not controlled, it can become a blowout, a very dangerous accident that can put the well, the rig, and

the working teams at risk. Fortunately, they occur with low frequency, but their consequences can be very serious, especially when the fluid expelled from the well is natural gas.

- Fishing is an activity that consists of releasing a string (or part of it) stuck or removing any material or object that has fallen or left in the well, preventing the normal continuation of operations. They include the time spent in threat of imprisonment; destroying fish; trying to touch, retrieve, or release fish; and fishing. The time consumed in this operation is very variable, ranging from a few minutes to several months; and, sometimes, without the fishing being successful, resulting in the loss of the fish and the section (or all) of the well. Often, the fishing diagnosis is obvious, as in the case of breaking, falling or unscrewing part of the string, and falling of bit cones. However, when a pipe sticking occurs, this diagnosis is not so simple. It can get stuck due to mechanical causes or differential pressure. In the latter case, there is a positive pressure difference between the well and the penetrated formations, causing the string pipes to adhere to the well wall [12].

Among the mechanical causes, we can highlight sticking by unconsolidated or fractured zones, under gauge hole, key seating, and swelling sticking [13]

- Sticking by unconsolidated or fractured zones: when the previously drilled formations fall or break, that is, pieces of the well walls in the form of chips, stones, or blocks. Most common in unstable, unconsolidated, or unstable formations.
- Under gauge hole: the most common type is bit wedging, when the wear of the previously used drill causes a funneled well (effective diameter less than the nominal one). It can also occur due to block wedging (upper stretches of the well that come loose and fall), iron (objects that fall into the well due to staff malpractice), or stabilizers (poor sizing of the equipment).
- Key seating: a small diameter channel is formed in the hole wall by the continuous work of the body of a decentralized tube. It occurs, in general, in wells with alternating layers of hard and soft formations, or when there are changes in the direction or inclination of the well (tortuosity) due to the disposition of the formations. The mechanical action occurs in the rotation movement of the column and during the trippings, which is the operation to remove the entire drilling column from the well (aiming to replace the drill bit or change the composition of the column elements) and then lower it to the bottom.

- Swelling sticking: when geometric constraints occur due to the expansion of drilled formations, such as swelling of hydratable clays.

#### 4.4.2 Production problems

The oil production involves processes that can cause problems, resulting in a loss in production or failure of equipment installed at the oil well [14]. To remedy these losses, intervention or workover operations are necessary, requiring the interruption of the well production. Intervention in wells is the most complex and expensive operation necessary to maintain the production of oil wells; their planning and execution make it possible to minimize risks and ensure profitability in the development of oil fields [15, 16]. Authors such as Frota [16], Miura [17], and Suaznabar [14] classify the main causes of loss of production in an underwater oil well in three types: flow assurance, mechanical or integrity failure, and reservoir problems.

Production losses associated with flow assurance are related to the existence of restrictions on the flowline. Depending on the composition of the fluid, variations in pressure and temperature can cause solids to form or deposit in the production line, generating production losses [18–20]. The main solids that can form are hydrates, paraffin, asphaltenes, naphthenes, and incrustations (scales). Hydrates are crystalline solids like ice, constituted by a mixture of water and gas (light hydrocarbons). They are formed in conditions of low temperature and high pressure [21], under normal production conditions or, preferably, when there is an interruption in the well production or when production resumes [16].

Paraffins, asphaltenes, and naphthenes are organic compounds with a high molecular weight. Their formation and deposition depend on the original composition of the hydrocarbon produced and, on the pressure, and temperature conditions along the production line [22]. When production is interrupted or stopped, the temperature conditions in the flow line decrease. In this situation, these compounds can form and aggregate, producing a gel structure or even a solid and causing severe problems during production [23].

Scales are deposits formed by the precipitation of salts present in the formation water due to changes in physical–chemical conditions and variations in pressure and temperature along the flow line. In the secondary recovery processes, seawater injected into the wells can create conditions for scale formation. The main components of scale are carbonates and sulfates of calcium, barium, and strontium. In the secondary recovery processes, seawater injected into the wells can create conditions for scale formation [24].

Other losses in production are associated with changes in flow regime conditions. Instabilities in flow conditions can evolve into the formation of anomalies such as slugging. Slugs are accumulations of water or oil formed in specific positions along the subsea production line, due to the separation of gaseous and liquid phases in a multiphase flow. The region close to the verticalization of the flowline and irregularities in the topography of the seabed are places that favor the positioning of the slugs. Slugging can cause damage to equipment in the well and the industrial plant [25].

Production losses also can be associated with mechanical failures or well integrity. The components of the well create a solidary barrier that prevents leaks. If there is a problem with one of them, the barrier ceases to exist. Failures in integrity cause environmental, safety, and devaluation problems for companies' assets, in addition to affecting oil production [26]. The main components of a well that can fail are the production line, Christmas tree, wellhead, DHSV-downhole safety valve, gas lift valve, production tubing, and production casing. The DHSV is a safety device installed in the production string in the subsurface that prevents oil or gas leakage into the environment when there is severe damage to the wellhead. Factors that affect the integrity of a production string, causing holes in its pipes [27], are faults in the connections between tubes of the production string, corrosion by CO<sub>2</sub> (carbon dioxide) and H<sub>2</sub>S (hydrogen sulfide) present in the produced fluids, and erosion due to the production of solid particles, like sand. Well integrity problems also can occur when cementation fails. The cement used to insulate formations can undergo corrosion and degradation over time. Gas may migrate through the cement, with fluid flow in the contact between the casing and the cement and between it and the formation, leading to a leak or blowout [28].

Finally, some production losses are associated with the reservoir. Gas or water provides the reservoir energy source at the beginning of the productive life of an oil well. Differential pressure gradients occur in the vicinity of the well in situations of high oil production rates. In this case, the gas-oil or oil-water interfaces can assume a conical configuration, causing excess gas and water production and, subsequently, economic losses. Excessive water production demands treatment and adequate final disposal to avoid environmental impacts, generating a decrease in the well's profitability [29]. Production of fines and sand can occur if the reservoir rocks are not consolidated. These particles increase the BSW (basic water and sediment) values of the well [30]. In this case, particles affect flow conditions and can cause failures in the well, erosion of pipes and equipment.

Besides these specific production problems described in this section, which occur in the environment associated

with the production lines, from the reservoir, through the oil well to the surface, oil companies apply AI technologies for several other objectives related to the oil field production. In this work, we show recent applications of digital technologies for the implementation of digital oil fields, oil production optimization and prediction, and oil field monitoring. Digital transformation also builds new perspectives for oil and gas production in hydrate formation zones. The literature review points out that new efforts are being made to implement AI tools in predictive maintenance of equipment and early detection of failure risks in artificial lifting systems.

## 5 Results: applications of artificial intelligence techniques

### 5.1 Bibliometric analysis

From the literature research, as explained in Sect. 3, 142 papers were found, distributing between drilling and production activities. From them, we performed a bibliometric analysis as will be shown in Figs. 4, 5, 6, 7, and 8.

The AI area is more recent (late twentieth century) and enters O&G studies later. But it has an intense growth as can be seen in the difference in publications between the last two decades. The year 2020 has low participation because the pandemic (COVID 19) generated an intense reduction in activities in general and, specifically, due to an economic restriction, we were forced to suspend our research, concluding it earlier than expected, limiting our results to the beginning of 2020 (instead of 2021, as expected).

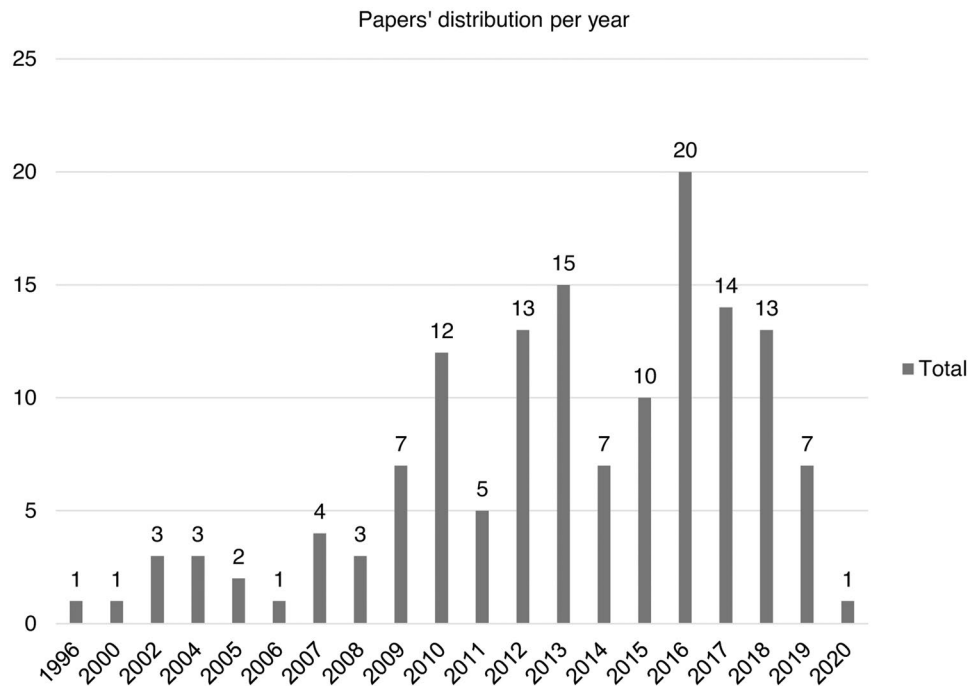
In terms of publications (Fig. 5), there is a strong concentration on SPE events (3 out of the top 5). This makes sense as several articles are from professionals in the oil industry (large companies) who have a strong relationship with this worldwide institution.

It is observed that there is no network formation among the authors who make up the base formed by the 142 articles (Fig. 6). This is especially true because most of the articles retrieved were produced by researchers allocated to companies, and professionals who, although not academic researchers, are allocated to core activities. In this case, it is understood that this scenario is specifically since the data used in artificial intelligence projects is proprietary data, which does not encourage networking.

In addition, publications from the chosen database, that is, OnePetro, have a differentiated nature, being concerned with works that address specific issues of the industry, which meets the objectives of this research, but weakens the results in terms of bibliometric analysis of networks of cooperation in the area.



**Fig. 4** Journal and Conference Proceedings distribution



The four clusters together (Table 1) demonstrate an articulation among the keywords applied in the research, and papers collected in all steps of our methodology. Based on the total of 142 papers selected, we used the VOS Viewer

software to create a term co-occurrence map based on text data that included titles and abstracts.

The counting method applied was full counting through which all occurrence of a term in a document are counted

**Fig. 5** Journals and/or Conference Proceedings contribution

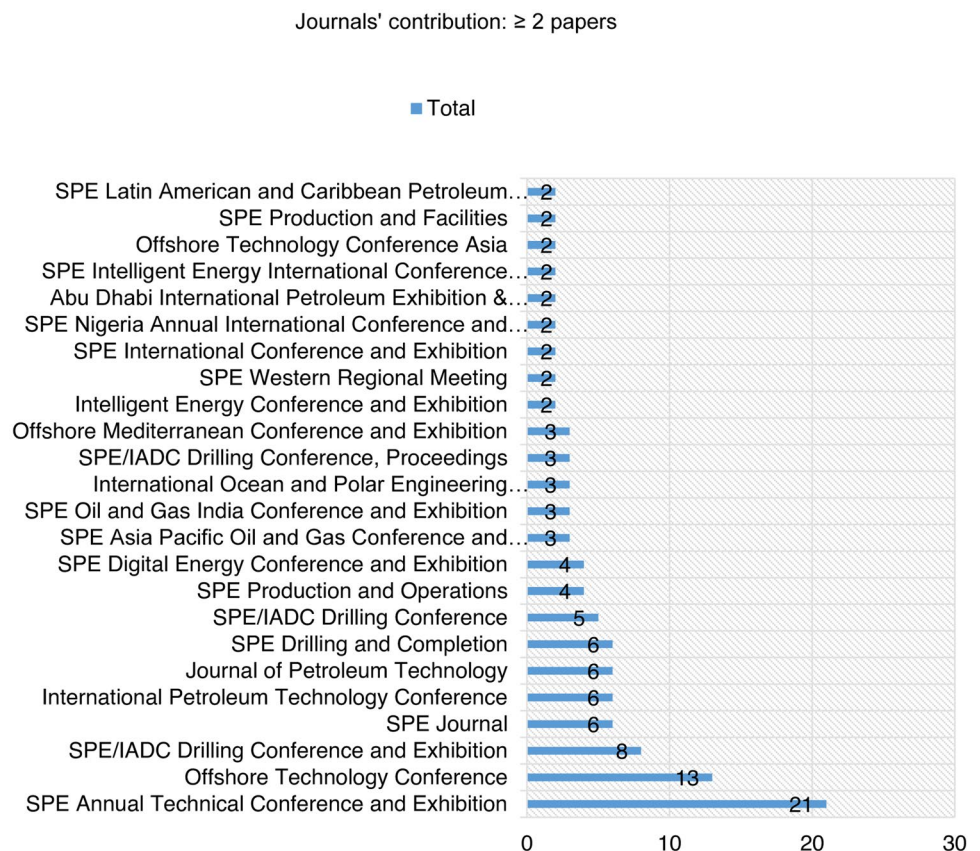












Table 1 Clusters

Cluster 1 - Red	Cluster 2 - Green	Cluster 3 - Blue	Cluster 4 - Yellow
<b>Cluster 1 (26 items)</b>	<b>Cluster 2 (24 items)</b>	<b>Cluster 3 (23 items)</b>	<b>Cluster 4 (6 items)</b>
amount	ability	artificial neural network	application
change	algorithm	cost	aspect
condition	artificial intelligence	driller	environment
correlation	automation	drilling	function
effect	benefit	drilling problem	hgs
flow	data	event	reliability
flow assurance	database	impact	
fluid	development	intervention	
formation	drilling operation	non productive time	
gas	efficiency	npt	
gas hydrate	failure	occurrence	
gas industry	field data	pipe	
hydrate	implementation	pipe incident	
hydrate blockage	interpretation	project	
hydrate formation	knowledge	real time data	
inhibitor	methodology	recommendation	
pipeline	monitoring	rtoc	
production	number	stuck pipe	
rate	process	torque	
state	quality	trend	
study	rig	wellbore	
temperature	safety	wellbore stability	
test	sensor	workflow	
variable	variety		
water			
work			

Al-Baiyat and Heinze [36] made the prediction of stuck pipes occurrences, both for mechanical reasons and for pressure differential ones. They employed a neural network with 3 layers and 19 neurons. The results achieved for pressure differential sticking were better, but the number of training examples was limited (48) and 18 more were used for testing.

Jahanbakhshi et al. [37] also addressed the problem of stuck pipes by pressure differential in Iranian offshore fields with AI techniques. They used neural networks (18 neurons) and SVM (with Gaussian kernel, filter with two parameters).

Mason et al. [38] evaluated the use of a support system to monitor the descent of liner or liner tubing (shorter liners that are seated on the previous liner and not on the surface). The main objectives of the study were to increase control over tripping in, reducing non-productive time and detecting points at risk of stickings. Variables such as well diameter, measured and vertical well depth, shoe depth, lithology, degree of inclination, drag and weight, internal pressure, and external pressure of the casing were considered.

Veeningen et al. [39] presented a system for acquiring data from sensors in the drilling string and transmitting it in real time through a broadband network. The main use

would be in high inclination wells, which present problems of instability and cleanliness, in addition to vibration in the elements of the drilling string. The focus of the work was on the installation of acquisition equipment and on the transmission of data captured by the sensors. The following parameters were considered: depth of sensors and well, pressure at different points in the column, pressure in the annular, and logging (gamma ray, resistivity, and density).

Bardasz et al. [40] studied a well monitoring system in real time that compares such data with a database of min–max values of several studied parameters. The panel emits visual and audible alarms for real data that exceed the accepted limits so that technicians can make decisions in an appropriate and timely manner, but the algorithms employed were not detailed. It uses conventional parameters of drilling (weight on the drill, rotation, flow volume, torque, penetration rate), fluid (density, plastic viscosity, filtrate, gel strength, salinity), lithology, and characteristics of the perforated rocks and ongoing operations.

Ambrus et al. [41] also studied a well data monitoring system that checked the quality of the data received from the sensors using Bayesian networks.

Chamkalani et al. [42] used AI techniques to predict problems during drilling. SVM and simulated annealing were used, the latter is a stochastic optimization algorithm, a meta-heuristic for global optimization that performs local searches deciding between the current state of the variable and a change in the system, in a probabilistic way.

Dursun et al. [43] developed a new approach for selecting attributes, with the aim of identifying those of greatest importance and that are critical to certain problems. Attribute selection is often useful as a stage prior to the machine learning process and applies a classification algorithm using only the selected attributes. In the case of pipe sticking, 85 attributes were considered, and the algorithm used was Naïve Bayes, which is a probabilistic classifier and uses concepts from Bayesian Statistics and assumes strong independence among the predictors.

Gandelman et al. [44] present a system for collecting and analyzing drilling data in real time that uses interpretation rules to compare the predicted values with real historical values, based on possible divergences between the curves of the measured data. The study base includes the monitoring of more than 70 wells, drilled since 2008 in the Santos basin and the Gulf of Mexico. Previously, the analysis was carried out only by specialists, who often presented subjective and divergent opinions.

Johnson et al. [45] evaluated the performance of a specific system for determining formation pressures in risky areas and their ability to reliably transmit the obtained data to the surface, through signals. The article uses MPD (managed pressure drilling), a technique for drilling depleted or highly fractured areas (such as limestone), which have a narrow margin between its pore pressure and its fracture pressure, in this case, there is a high risk of loss of circulation or kick. The objective is to quickly adjust the well bottom pressure, regulating the pressure through the annular space between the drilling string and the well walls. Variables considered such as: pore pressure, fracture pressure, wellbottom pressure, drilling mud flow, and rheological properties of the drilling fluid.

Salminen et al. [46] also study the prediction pipe sticking in real time. They use numerical and statistical analysis and basically compute the changes, deviations, and rates of change between the data previously observed and the data being received. The maximum allowed value, according to observed data, is stored, and used in real time, in a comparative way. The alert for the problem is generated on average 38 min before the event happens, and no false alert has occurred. The data used to give the alert must comply with certain restrictions (availability and consistency). The drilling mud properties are not measured at a frequency sufficient to be useful (it should be continuous measurement).

Marques [47] developed a dynamic classification for the prediction, detection, and classification of mechanical stickings events in drilling wells. The work involves the acquisition of data from dozens of variables in Brazilian wells of high depth, its treatment to eliminate unreliable values and the filling of the missing data by the most appropriate technique for the case, and free text data obtained from daily operation reports. A heat map algorithm is proposed based on the behavior of the main variables related to sticking pipe, where it is possible to identify favorable or critical conditions for the drilling continuity. The 8 most sensitive variables are weight on the hook, weight on bit, string rotation, torque, drag, vibration (stickslip), equivalent circulation density, and pressure on the surface lines. Each variable receives a weight between 1 and 4 depending on its possible contribution to the accident, and the resulting risk of sticking receives a dynamic rating ranging from 7 (minimum risk) to 21 (maximum risk).

### 5.3 Production applications

Applications of digital technologies in production problems were related in 22 papers. Table 3, in the Appendix, summarizes the main results and findings, showing the problems, the data and information available, and the digital technology used. In this section, we present the scope of each paper with the issue and the AI technology-based methodology and solution proposed by the correspondent authors.

Alimonti and Falcone [48, 49] point out that the monitoring of oil producing wells in real time is the best way to obtain information to optimize the performance of an oil field. The authors show that the integration, by AI techniques, of the parameter data measured in the wells with the fluid dynamic models can provide real-time information on the flow conditions. They propose an approach that associates oil flow data with the extraction of knowledge and identification of patterns by neural networks in databases (KDD) and fuzzy logic for the analysis of producer wells. The authors point out that the integration of artificial intelligence tools with traditional models allows monitoring the oil flow guarantee conditions and the optimization of production in the wells in real time.

Danquigny et al. [50] use digital technologies to develop a well performance monitoring tool, implemented by Total in the offshore field of Sendji, Congo, to improve oil production and reduce operating costs in wells with gas lift. The well performance monitoring system is equipped with data visualization tools and different alarms, designed to alert engineers and technicians about well integrity problems and loss of production. The optimization of the oil field

production is achieved after the integration of operations of the entire production chain, from the reservoir, well environment, production system, equipment and process facilities, and conditions for the delivery of produced oil.

Liu et al. [51] propose a data mining approach for learning normal patterns and failures in records of historical series of data obtained from pumps operating in oil wells. The authors apply a sliding window technique for the analysis of time series and compare different data mining algorithms—decision trees (ADTree), support vector machines, and Bayesian networks — for the classification of oil well failures.

Creek et al. [52] analyzed the application and integration of existing technologies to manage the formation of hydrates and avoid potential blockage in the well. As it is a study of oil company employees, it has a more pragmatic objective. It does not seek to determine the occurrence of the problem and raise an alarm, but it is in the next phase, when hydrates are already constituted, and techniques are applied so that this level does not increase and aiming operations such as workover are not necessary. It uses the “do nothing approach” techniques to avoid blocking the well by hydrates, not the initial hydrate formation. The main objective is not to incur in expensive intervention operations and maintain production if hydrate formation is limited, up to 22%.

Siregar et al. [53] developed an academy — industry integration survey work in Asia, focusing on 2 major projects that link studies of research centers with the demands of the region’s oil and natural gas companies. It considers several “deliverables,” such as technical reports, publications in specialized journals, computer program developments, and course graduation projects. One of the projects is the Dual Gas lift Model, a genetic algorithm to determine the optimal allocation of gas to inject into the production string.

Rebeschini et al. [54] present a system built with support in artificial neural networks to forecast oil, BSW, and water production, in real time and for a period of up to 30 days, for 20 wells in an oil field in Kuwait. To overcome the problems caused by inaccuracy, data absence or corruption of data obtained in real time, and to improve the performance of neural networks, the authors use nodal analysis and time series. The main scope of the work is the presentation of the methodology used for this purpose.

Patri et al. [55] present an approach using time series analysis for the detection and prediction of failures, in real time, from data acquired from sensors associated with submersible electric pumps, used for artificial elevation in oil fields. The method developed by the authors aims to identify shapelets — short instances of data

— representative of normal behavior or failure behavior in the data sequence produced by the sensors of a given electric pump. To perform fault detection and prediction, a decision tree-based classifier continuously compares the data strings produced in real time with the shapelets previously identified in the historical series.

Li et al. [56] also try to anticipate problems with falling production and increased water cuts in the oil volumes produced. The focus is not on variables measured in real time in the well, but on studies and analysis of historical production data that indicate the occurrence of the unwanted events mentioned.

Cheung et al. [57] study a quick and efficient way to integrate different data sources for solving problems in the production of wells in a joint study between university and company. It uses data mining techniques incorporated from different sources, such as databases, time series, social networks, and unstructured free texts, as in operational reports. It is also concerned with the time interval between the occurrence of problems and their detection (“the real failure occurs before the human operator can perceive it”). As a practical example, it cites the prediction of failures in valves in gas compressors and the prediction of failures in general equipment, with the use of service orders and maintenance records.

Glénat et al. [58] applied artificial neural networks in the development of two monitoring techniques that allow the continuity of safe production conditions within the hydrate formation zones. The techniques provide timely information about changes in the composition of fluids — water, gas, and oil — that arrive at the production plant and measure the concentration of additives and substances (e.g., methanol and salinity) that mitigate or inhibit the formation of hydrate plugs. Neural networks are used to correlate the dosage of inhibitors in the produced water, its salinity, and the electrical conductivity and acoustic speed. The authors were successful in applying the techniques in three oil fields, in Great Britain, Qatar, and France.

Abdul-Aziz et al. [59] present an intelligent alarm and notification system in real time, implanted in oil wells with mechanical pumping, for surveillance and monitoring of the conditions of the assets and optimization of production.

Uribe et al. [60] carry out a technical feasibility study for a project to manage wells with a high risk of hydrate formation. It looks for a specific operational solution for an offshore oil field in the Gulf of Mexico with restrictions for traditional hydrate control treatments, due to pre-existing physical conditions or that would imply high cost.

Carpenter [61] describes a machine learning approach that uses SVM — support vector machine as a binary classifier to detect abnormal conditions in compressor systems,

and their possible causes, responsible for delays in oil production. The SVM algorithm models the normal compressor behavior in real time, thus, the responsible technicians receive alarms through digital means, informing about the need for intervention for a predictive maintenance, which reduces the equipment downtime.

Jain et al. [62] describe an intelligent management system developed to retrieve and evaluate 700 well flow and integrity assurance data by Cairn Oil & Gas in India. In the article, the authors point out that the approach adopted allows an automatic execution of performance monitoring and analysis of operations in oil wells, aiming to increase production and reduce operational costs. The system incorporates data from various sources of the production system and allows monitoring, planning, and evaluating intervention activities with chemicals, monitoring corrosion levels, and evaluating the need for the use of encrustation inhibitors.

Pennel et al. [63] applied machine learning models for the diagnosis and prediction of failures and low performance conditions in artificial gas lift and mechanical lifting systems, which use rod pumps. The steps for preparing the models, which reach an accuracy greater than 99%, were data evaluation, pattern extraction, event diagnosis, and event classification. The authors work with a database of sensor time series and control data for 800 oil wells, over 100 GB. The failure events and low-performance conditions identified by the specialists, from the data recorded for the wells, were labeled, and aligned with the corresponding standards in the sensors. The events were used to train different models developed with Random Forest algorithms, gradient boosted tree, and neural networks.

Bassamzadeh and Ghanem [64] use Bayesian networks to develop a model for probabilistic prediction of oil production in wells located in areas with little data, using data available from other wells located in different places in the same oil field. They used Bayesian networks to create a model with less dimensionality and that can quickly predict the characteristics of the oil reservoir. They applied the model to a set of real data from the Gulf of Mexico, reaching an accuracy of 86% in the prediction of oil production.

Balaji et al. [65] present a bibliographic review, with examples of applications, on database methods used in the oil industry to optimize production. The authors show the potential and difficulties of database methods in relation to traditional approaches based on physical laws and point out that, gradually, the industry changes the culture to accept their adoption.

Bomba et al. [66], through a literature review, show the main relevant aspects about the evolution of the flow

assurance discipline. The authors point out that the artificial intelligence tools and machine learning will be fundamental for future research in the area, which must advance in the understanding of multiphase flows, and which will also involve classifications and predictions, as well as prevention strategies and remediation methods, such as hydrate identification and management.

Bratland [67] presents an approach that integrates dimensional analysis, phenomenal models, and neural networks to simulate multiphase flows — water, oil, and gas — with the purpose of improving the flow guarantee conditions. He trains neural networks with data from the literature or provided by simulations that can improve the performance of the model, through the identification of parameter values necessary to simulate the flow. The author applies the model to the 121-km-long Ormen Lange pipeline in Norway.

Qin et al. [68] point out that companies are adopting risk management methodologies for operations in areas favorable to hydrate formation, due to the prohibitive costs to avoid their formation in deep waters. The authors present a tool that estimates the rate of growth of hydrates and the possibility of forming plugs, supported by machine learning techniques, using neural networks, SVM, and decision trees.

Cadei et al. [69] describe the development of a tool based on machine learning, applied to production in a gas field of the Italian oil company ENI, which contains hydrogen sulfide and carbon dioxide. The tool uses time series with data from 420 sensors to monitor the status of the equipment and detect failures that lead to an increase in the acidity of the gas produced. The authors developed the tool using Random Forest and gradient boosting trees algorithms and use a gradient boosting classifier with 78% accuracy (AUC) in the prediction of excess hydrogen sulfide, with an advance of two to ten hours.

Vielliard et al. [70] participated in a project of real-time hydrate management in the world's longest subsea tieback at Zohr offshore natural gas field, located in the Mediterranean Sea, 180 km off the coast of Egypt. The authors mention that it is the first time in the industry that a real-time hydrate management system has been achieved subsea for a gas field. Information obtained from subsea sensors is used to determine the ideal dosage of hydrate inhibitors. Subsea measurements are validated with flow assurance modeling and data analytics to identify trends and anticipate onshore fluid arrival conditions weeks in advance. The focus is not on alarming the occurrence of a problem but on how to optimize the consumption of hydrate inhibitors for each well in the field.



## 6 Relevant research results for digital transformation on drilling and production applications

The main objective of this research, concerning the application of digital transformation in drilling and production problems in oil companies, was fulfilled through a systematic literature review.

The research allows the identification of the most used AI techniques for the solution of problems and challenges faced by enterprises. At the same time, identifying and grouping issues, in which digital transformation has been used in this sector, allow us to know and assess the impact of AI techniques on oil companies.

Tables 2 and 3, in Appendix, show the information presented by the 39 articles studied in the fourth step of the methodology. In these tables, we highlight the issues (problems and challenges) faced by oil companies, the input variables and parameters associated with data and information, the artificial intelligence technique/digital technologies used, and the results and applications supported by AI technologies.

In this section, we summarize the relevant results and findings of the research. The problems and challenges showed in Tables 2 and 3 were grouped in function of their similarities and relationship with specific contexts of the application of AI technologies in the oil industry, for drilling and for production issues.

From the 17 papers related to drilling applications (Table 2), we classify the problems and challenges in the following groups:

- Mechanical and differential pressure stuck pipe;
- Loss of circulation;
- Well instability (with faults and loss of circulation or drill string vibration);
- Widening of extended reach wells;
- Kick occurrences;
- Specific drilling operations monitoring;
- Drilling data quality validation

These drilling issues, except for the last two, are related to classical situations that cause waste in the operations (invisible lost time), as described in Sect. 4.4.1, increasing the costs of drilling [11]. Oil companies have been using digital technologies to reduce the losses in drilling. In this sense, these companies strive to become data-driven companies and construct innovation by incorporating new technologies into traditional operations. The last challenge, drilling data quality validation, is an example of this trend.

Table 3 summarizes the relevant aspects presented by 22 papers associated with production issues and associated applications. The issues were detailed and classified in the following groups:

- Production in hydrate formation zones and flow assurance;
- Digital oil field smart operations;
- Oil production optimization and performance monitoring;
- Failure detection and prediction in artificial lift systems;
- Predictive maintenance of equipment;
- Development of an academic and oil industry research system.

Here, it is relevant an explanation. Some authors [66] include issues of hydrates in production lines in the broader scope of the flow assurance discipline, in this work, we emphasize the hydrate questions due to the focus on the use of digital technologies. Some of the papers deal with a specific question, for example, oil production in hydrate zones. Other papers highlight more than one problem, such as detection of equipment failures, problems of instability in the production of wells, and the development of smart worksheets. The decision to choose what group allocates these papers was based mainly on the evaluation of the central problem associated with the article title and the novelty present in it, having as reference the objectives of our article. In any case, a few works could be grouped a little differently depending on the purpose of the authors.

### 6.1 Relevant results on drilling applications

In drilling, the problems related to stuck pipe, also called pipe sticking in the literature, include mechanical and differential pressure stuck pipe prediction [35, 36, 42, 43, 46], differential pressure stuck pipe [33, 37], and mechanical stuck pipe [47].

Loss of circulation is related by Moazzeni et al. [35] and by Johnson et al. [45]. Well instability associated with partial or total loss of circulation in the well is pointed out by Beacom et al. [31], and including cleaning problems and drill string vibration is related by Veeningen et al. [39]. Mason et al. [32] study widening of extended reach wells, and Nybø et al. [34] describe kick occurrences. Mason et al. [38] and Bardasz et al. [40] use digital technologies to the monitoring of specific drilling operations in real-time. Ambrus et al. [41] and Gandelman et al. [44] show cases of data quality validation in drilling operations.

**Table 4** Drilling issues and main used AI techniques/digital technologies

Problem-Challenge	Used AI techniques/digital technologies
Mechanical and differential pressure stuck pipe	Neural networks, support vector machine, naïve Bayes, rule-based classifier, real-time data analysis
Loss of circulation	Neural networks
Well instability (with faults and loss of circulation or drill string vibration)	Real-time data analysis
Widening of extended reach wells	Real-time and historical data analysis
Kick occurrences	Real-time and historical data analysis
Specific drilling operations monitoring	Historical data analysis
Drilling data quality validation	Real-time and historical data analysis, Bayesian networks

Table 4 summarizes the artificial intelligence technique used for constructing the application for each problem described and the for two challenges, described in the last two lines of the table. Artificial neural networks, support vector machines, Bayesian networks, and Naïve Bayes are relevant

tools used to solve drilling problems in this literature review, in association with statistical data analysis (Tables 4 and 2).

The main inputs — data and parameters available — used for constructing the applications in the IA algorithm in drilling issues are as follows:

**Table 5** Digital technologies applications in drilling issues

Problem-challenge	Applications	Author
Mechanical and differential pressure stuck pipe	Neural network-based tools for stuck pipe and loss of circulation prediction	Moazzeni et al. [35]
	Neural network-based tools for stuck pipe prediction, results are better for differential pressure stuck pipe	Al-Baiyat and Heinze [36]
	Support vector machine (SVM) model associated to simulated annealing for probabilistic stuck pipe prediction	Chamkalani et al. [42]
	A Naïve Bayes probabilistic classifier for selection of attributes for stuck pipe predictive models	Dursun et al. [43]
	Real-time pipe sticking prediction tools based on data analysis	Salminen et al. [46]
	Neural network and support vector machine (SVM)-based tools for stuck pipe prediction	Miri et al. [33]
	Comparison between neural network and support vector machine (SVM) techniques for better stuck pipe prediction	Jahanbakhshi et al. [37]
	Real-time classifier system for detection and prediction of mechanical stuck pipe	Marques [47]
Loss of circulation	Neural network-based tools for stuck pipe and loss of circulation prediction	Moazzeni et al. [35]
	Monitoring real-time system for loss of circulation prevention	Johnson et al. [45]
Well instability	Support systems to knowledge sharing and communication between geologists and engineers to decide the best well trajectory and avoid instability	Beacom et al. [31]
	Real-time digital based sensor system for problems prevention	Veeningen et al. [39]
Widening of extended reach wells	Real-time data analysis system for support operations	Mason et al. [32]
Kick occurrences	Real-time data analysis tool for Kick alarm and prediction	Nybøet et al. [34]
Specific drilling operations monitoring	Real-time monitoring system for detecting problems during installation of liner tubing	Mason et al. [38]
	Real-time monitoring and alarm system for drilling operations based on comparison with historical data	Bardasz et al. [40]
Drilling data quality validation	Monitoring system based on Bayesian networks for real-time data quality validation	Ambrus et al. [41]
	Based rule system for real-time data quality validation in comparison with historical values. The study is applied to 70 wells drilled in the Santos basin and the Gulf of Mexico	Gandelman et al. [44]

- Drill string composition and well equipment configuration (bottom hole assembly);
- Operational drilling parameters (rate of penetration, rotation, vibration, torque, drag and weight, internal and external pressure of the casing);
- Drilling mud properties (weight, fluid flow, filtrate, solids content, gel strength);
- Formation parameters (lithology, pore pressure, fracture pressure, discontinuities, and faults), and;
- Well parameters and dimensions (shoe depth, well vertical depth, degree of inclination, well bottom pressure);
- Depth and position of sensors.

The literature review allows finding relationships among the inputs (data and parameters available) and the main problems. For mechanical and differential stuck pipe, the AI techniques used data from drilling string composition, operational drilling parameters, and drilling mud properties [36, 42, 43, 46, 47].

The applications of the digital transformation on drilling problems and challenges are shown in Table 5.

Results show that AI techniques can identify and distinguish mechanical from differential stuck pipe [36, 42, 43, 46].

IA-based tools for avoiding loss of circulation [35, 45] use formation parameters and drilling mud properties. Solutions for well instability issues and widening of extended reach wells are based mainly on formation parameters, operational drilling parameters, and mud density data [31, 32, 39]. Several historical parameters have been monitored by Nybøet et al. [34] for kick occurrences detection, including formation parameters (pore pressure, hydrostatic pressure), drilling fluids parameters (mud weight, mud fluid flow), and operational parameters (rate of penetration, internal and external pressure of the casing).

Digital technologies are also used in drilling for the development of real-time well monitoring systems [40, 41, 44]. In this case, the studies are based on the comparison between data obtained in real-time and historical data. Alarms work when real data exceed the historically accepted limits. The monitoring systems validate the quality of the data received from the sensors in the presence of real-time process variations.

Results of this literature review indicate growing trends in the use of AI techniques in drilling operations for classifying, detecting, and predicting problems and monitoring oil well behavior [40, 41, 44].

Adoption and implementation of AI techniques have been making changes in organizational culture, by increasing the communication between professionals, like geologists and engineers, to share information and knowledge [31]. Sensors and equipment have been installed for obtaining and interpreting data to the prevention of problems in real-time [38, 39], while efforts have been made to validate data quality [41], Gandelman et al. [44] and select the best parameters for the building of predictive models [43], avoiding complexity [34].

More recent studies show that oil companies are working to adopt a prevention problem culture in drilling by monitoring operations in real time, as shown by Gandelman et al. [44], Salminen et al. [46], and Marques [47].

## 6.2 Relevant results on production applications

The relevant results of the digital applications on production challenges and problems identified by this research are grouped in: production in hydrate zones and flow assurance, digital oil fields smart operations, oil production optimization and performance monitoring, failure detection and prediction in artificial lift systems, predictive maintenance

**Table 6** Production issues and main used AI techniques/digital technologies

Problem-challenge	Used AI techniques/digital technologies
Production in hydrate formation zones and flow assurance	Neural networks, support vector machine (SVM), decision trees, real-time data analytics, real-time smart monitoring and management systems, big data technologies, association of digital technologies, and multiphase flow tools
Digital oil field smart operations	Time series analysis, pattern recognition techniques, social networks analysis, texts contents extraction, knowledge discovery in databases, SCADA
Oil production optimization and performance monitoring	Neural networks, fuzzy logic, support vector machine (SVM), knowledge discovery in databases, real-time data analysis, Bayesian networks
Failure detection and prediction in artificial lift systems	Decision trees, support vector machines, Bayesian networks, times series analysis, random forest, knowledge discovery in databases
Predictive maintenance of equipment	Support vector machine (SVM); gradient boosting and Random Forest
Development of an academic and oil industry research system	Several digital technologies, genetic algorithm, real-time data analysis, and simulations

of equipment, and the development of an academic and oil industry research system.

These main problems and challenges are the basement reference for presenting the most used AI techniques and for describing the variables, parameters, and available data described in the papers. The results and applications implemented by oil companies in the context of digital transformation reveal the impact of AI techniques in the oil companies.

Table 6 shows the most used AI techniques/digital technologies associated to the production problems and challenges founded by the literature review.

Production in hydrate formation zones is a very important production problem where AI technologies are increasingly being used [52, 70]. Neural networks, support vector machine (SVM), decision trees, real-time data analytics, and real-time smart monitoring and management systems are the main used technologies for producing in the presence of hydrate.

The implantation and operation of digital oil fields is a strategic issue pursued by several companies. Digital oil fields allow companies to increase revenues and reduce costs by optimizing activities and anticipating operational questions. The companies are making efforts to construct several sensors web, communication systems, and data centers to collect, transmit and record data and information from the oil fields to implement intelligent strategies for rapid responses [65]. The path followed by companies to implement digital oil field operations encompasses the analysis and integration of heterogeneous data and information from various sources. AI techniques used include pattern recognition technologies, time series analysis, social networks analysis and content extraction from texts, knowledge discovery in databases, and supervisory control and acquisition systems (SCADA).

Oil field production optimization and performance monitoring, including production forecasting, is another issue that uses digital transformation. In general, oil companies include this challenge in the tasks needed to implement digital oil field operations. In our study, the papers related to this issue specifically address this question. The literature review shows that neural networks, fuzzy logic, support vector machine (SVM), knowledge discovery in databases, real-time data analysis, and Bayesian networks are the used AI techniques. Some works associate these techniques with multiphase flow metering for better production optimization, as shown by Alimonti and Falcone [48, 49].

Failure detection and prediction in artificial lift systems are being addressed with various AI techniques. Liu

et al. [51] applied decision trees, support vector machines, and Bayesian networks for understanding sucker rod pump production wells. Patri et al. [55] used decision trees and time series shapelets to monitor the behavior of electrical submersible pumps (ESPs). Pennel et al. [63] used random forest for studying rod pump artificial lift systems.

AI techniques have been used for predictive maintenance of equipment in the oil and gas sector. Carpenter [61] shows how a support vector machine (SVM) model works for predictive maintenance of compressor systems. Cadei et al. [69] present a tool based on random forest and gradient boosting trees for anticipating and detecting equipment failures in a gas field rich in hydrogen sulfide.

Applications build with AI technologies are data-driven-based methods. Oil companies need to collect, transmit, storage, treat, process, and interpret data in the digital context. Algorithms and models only learn a specific behavior associated with a phenomenon if there is enough data about this behavior. So, data must be distinct and diverse to include all possible phenomena and events in the circumstance under study. It is a relevant point for the efficiency of the IA algorithms and better application response.

In this study, data originate from the equipment and the associated processes are the main inputs used for constructing the applications. The results of the literature review show the following specifications and origins for the input data, for the problems listed in Table 6:

- Hydrate properties, properties of the fluids in flowline, salinity, flow rate, subsea structures, and architecture;
- Production and operational data, social networks, unstructured free texts, operational reports, equipment and facilities data, and historical data;
- Production data, oil and gas reserves, and fluid properties;
- Well parameters, artificial lift systems configurations, and pumps physical attributes (pumps, gas lift);
- Equipment data, variables and parameters, sensor data, maintenance reports, and chemical analysis;
- Studies and applied works, human resources formation, patents, and cultural changes.

The applications of the digital transformation on production problems and challenges (Table 7) are an emerging driver adding value and redefining the oil and gas sector boundary operations.

The hydrate formation and blockage is a substantial challenge in deepwater oil and gas production systems



**Table 7** Digital technology applications in production issues

<b>Problem-challenge</b>	<b>Applications</b>	<b>Author</b>
Production in hydrate formation zones	Systems integrations and simulation tools	Creek et al. [52]
	Monitoring system based on neural networks	Glénat et al. [58]
	Management system with association of engineering, hardware, and operational staff knowledge	Uribe et al. [60]
	Risk management tools based on neural networks, SVM, and decision tree	Qin et al. [68]
	Management system with combination of flow assurance modeling and data analytics methods	Vielliard et al. [70]
	Integration of digital technologies and flow assurance knowledge	Bomba et al. [66]
	Integration of neural networks and multiphase flow simulations	Bratland [67]
Digital oil field smart operations	Integrated digital technologies systems, well performance monitoring, and alarm systems	Danquigny et al. [50]
	A framework based on digital technologies for data analysis, event modeling and, linking heterogeneous data	Cheung et al. [57]
	Surveillance and alarm system for preventing and reducing response action in case of issues	Abdul-Aziz et al. [59]
	A local integrated data optimizes the organization of three oil fields with 700 wells	Jain et al. [62]
Oil production optimization and performance monitoring	Combination of AI techniques (neural networks and fuzzy logic) with fluid dynamic models for improving oil field performance monitoring	Alimonti and Falcone [48, 49]
	Smart workflows, prediction, and monitoring digital tools for production forecasting and issues management	Rebeschini et al. [54]
	A decline production warning model based on support vector machine (SVM)	Li et al. [56]
	Bayesian network model for the prediction of reservoir behavior and oil production in areas with limited data	Bassamzadeh and Ghanem [64]
Failure detection and prediction in artificial lift systems	Time series classifier algorithm for oil well pumps failure prediction	Liu et al. [51]
	Decision tree classifier, associated with time series shapelets, for electrical submerse pumps failure detection and prediction	Patri et al. [55]
	Random forest and cross-validation model for prediction failures in artificial lift system (rod pumps and gas lift) in 800 oil wells	Pennel et al. [63]
Predictive maintenance of equipment	Support vector machine (SVM) classifier for warning predictive maintenance in compressors, to avoid production deferments	Carpenter [61]
	Gradient boosting and random forest algorithm tool for hazard events prediction in gas-sweetening procedures and production operations	Cadei et al. [69]
Development of an academic and oil industry research system	Human resources formation for digital technologies; innovation and development of novel artificial intelligence tools	Siregar et al. [53]
	Culture change of the oil industry	Balaji et al. [65]

and constitutes a focal point of attention in flow assurance studies [70]. Traditional solutions for hydrate management involved avoiding entering the hydrate thermodynamic zone with the proposal of minimizing hydrate formation [58]. The conservative strategies are thermal insulation of subsea equipment and flowlines to retain heat, chemical injection of methanol or hydrate inhibitor, and pressure reduction [66]. These strategies are expensive and restrict the exploration and development of several oil reserves.

The solutions for production in hydrate zones based on AI techniques are novelties in the oil and gas sector. The production with care inside the hydrate zone, with the support of digital transformation tools and applications, is a new industry strategy [58]. Hydrate can form, but in a certain amount that does not block the flowline.

New offshore oil and gas reserves are in areas of extreme conditions [68]. Production in hydrate formation zones demands integrated management and accurate monitoring in subsea lines for avoiding blockage of flow lines and production losses. Digital transformation allows the production of oil and gas fields inside zones of hydrate formation [58] and with a high risk of blockage [60] and where prediction of hydrate plugging risks is necessary [68]. AI techniques allow detailed monitoring and management of the flow conditions in subsea lines in hydrate zones.

The main applications and strategies present in the literature review for this intent are systems integrations and simulation tools Creek et al. [52], monitoring systems based on Neural networks [58], management systems with the association of engineering, hardware, and operational staff knowledge [60], risk management tools based on neural networks, support vector machine (SVM), and decision tree [68], and management systems with the combination of flow assurance modeling and data analytics methods [70]

Besides hydrate formation and blockage, digital transformation and big-data technologies impact flow assurance engineering strategies and studies Bomba et al. [66]. The association of flow simulators and, for example, neural networks creates new possibilities for understanding complex multiphase flows Bratland [67].

Applications of digital technologies to oil fields allow real-time intelligent surveillance, automated linking of heterogeneous data sources, event modeling, and alarm systems. These modern and dynamic production operation techniques increase responsiveness and minimize production losses. Danquigny et al. [50], Cheung et al. [57], Abdul-Aziz et al. [59], and Jain et al. [62] present

cases of implementing digital oil field smart operations. Danquigny et al. [50] show strategies used by Total E&P for implementing integrated digital technologies systems and well performance monitoring for production optimization and costs reduction in wells with gas lift systems, using times series analysis and knowledge discovery in databases. Cheung et al. [57] present a framework based on digital technologies for data analysis, event modeling, and linking heterogeneous data. Abdul-Aziz et al. [59] show a smart field approach with a surveillance and alarm system for reducing response action and production optimization in a heavy oil project. The development of a management system for oil fields operation based on digital transformation tools is also proposed by Jain et al. [62] for three oil and gas fields with 700 wells in India.

Digital transformation applications in oil field production optimization and performance monitoring are related by Alimonti and Falcone [48, 49], Rebeschini et al. [54], Li et al. [56], and Bassamzadeh and Ghanem [64]. Alimonti and Falcone [48, 49] present a method for improving oil field performance monitoring based on the combination of AI techniques (neural networks and fuzzy logic) with fluid dynamic models. Rebeschini et al. [54] implement smart workflows, prediction, and monitoring digital tools for production forecasting and management. A decline production warning model based on support vector machine (SVM) is related by Li et al. [56]. Bassamzadeh and Ghanem [64] develop a Bayesian network model for the prediction of reservoir behavior and oil production in areas with limited data in sedimentary basins in the Gulf of Mexico region.

Artificial lift systems in oil wells use digital transformation applications for early warning against malfunction. Liu et al. [51] developed a time series classifier algorithm for pumps failure prediction in oil wells. Patri et al. [55] propose a Decision tree classifier, associated with time series shapelets, for electrical submerse pumps failure detection and prediction. Pennel et al. [63] developed a Random Forest and cross-validation model for prediction failures in an artificial lift system with rod pumps and gas lift in 800 operating wells in the Bakken formation, USA.

Predictive maintenance helps determine the condition of equipment, anticipating proactive measures to reduce maintenance costs. Carpenter [61] reports a support vector machine (SVM) model construction for predictive maintenance of compressor systems to avoid production deferrals. Cadei et al. [69] developed an integrated system, with gradient boosting and random forest algorithm tools,

for hazard events prediction and predictive maintenance in gas-sweetening procedures and production operations in a gas field in Italy.

Papers also show that oil industries and universities are creating research systems to understand the challenges and overcome the problems associated with the implementation and greater use of digital transformation technologies as pointed by Siregar et al. [53] and Balaji et al. [65].

## 7 Conclusions

The present study intended to analyze articles related to the application of AI techniques in oil wells, published over the current century, in various vehicles, accessed through the research base OnePetro. The goal of focusing on the twenty-first century has to do with the development of AI in the last 2 decades, when there is greater availability of field data in real time, which has stimulated the use of machine learning techniques. At the end of the previous century, the most studied area was Specialist Systems one, and Petrobras, the Brazilian oil state company, implanted a project to preserve and transfer the knowledge of experienced technicians (fishermen) who were about to retire [71].

Although the oil industry presents a large volume of technical and managerial studies and the same occurs with AI, the set of intersecting issues is limited. In our research, 142 articles were found, but after methodological scrutiny, only 39 were cited, a reasonably low number, 17 of which refer to the well drilling phase and 22 refer to the production one. This indicates that there is a demand for more exhaustive research and AI studies in energy and, specifically, in the oil and gas industry.

Another observation indicated by the sample is that the well is not monitored continuously, permanently, during its whole life; there are isolated studies on drilling phase and others on production one. This was also expected because the articles are generated either by large companies or research centers (mainly universities) or partnership with these types of institutions that produce the articles and research. Large companies employ a high number of professionals, specialized in specific technical activities: so, the group that works in the well drilling does not usually follow the well production and vice versa. Even in these two great activities, there is usually an even greater specialization: in drilling with well design, casing, cementing, special operations, directional and horizontal wells,

and safety, and in production with completion, reservoirs, elevation, and flow.

In smaller companies, engineers are more generic, following the well as a whole, but, due to financial and size restrictions, they are rarely able to dedicate more time to R&DI. Even universities have joint projects with larger companies, rarely with smaller ones.

In the Brazilian oil industry, investments in research are encouraged. In high-productivity fields (those that pay special participation) under the concession regime apply 1% of gross revenue in R&DI, the same percentage for all fields under the sharing production model (where it is assumed that they are all high potential fields, in the pre-salt polygon) and 0.5% in those under the transfer of rights regime.

Half of this amount can be allocated to the company's own research centers, and the rest should be invested in universities and external research centers accredited by the ANP, the Brazilian regulatory oil agency. From 2019 on, startups were also authorized, and, at the end of 2020, 1000 research units were accredited. The financial values are significant, around R \$ 17.3 billion between 1998 and 2019, 90% of which came from Petrobras, which was the only contributor until 2003 [72]. These resources changed the working and research conditions of several engineering and geology colleges in the country, generating 1429 projects by 2016, almost 30% in Rio de Janeiro (509 projects, R \$ 1.377 billion); the main participating educational institution was the Federal University of Rio de Janeiro (UFRJ), with 277 projects and R \$ 531.5 million [73].

Our sample was quite varied, with studies by companies/universities from different continents and presentations at events in different countries. In drilling stage, most studies were related to pipe sticking problems (almost half), although loss of circulation, reaming, kick, and casings were also addressed. Some works were real practical cases faced by companies in geographically dispersed fields: North Sea, Caspian Sea, Persian Gulf, Gulf of Mexico, Santos Basin, Congo, and Kuwait. Several AI techniques have been cited, with emphasis on neural networks.

The articles in the production stage were more numerous and focused mainly on combating the formation of hydrates, but also addressed fouling (scale), BSW, gas lift, and equipment failures (compressors, pumps, pumping rods). Likewise, there was a diversity of locations, with projects in fields located in England, France, Norway, Qatar, and the Mediterranean Sea. Among the data processing techniques, data mining and neural networks stood out.

## Appendix

**Table 2** Summary of literature on the application of digital technologies in drilling problems for selected articles

Author	Problem-challenge	Input variables and parameters	Used artificial intelligence technique/ digital technologies	Results and applications
Al-Baiyat and Heinze [36]	Mechanical and differential pressure stuck pipe prediction	Drilling string composition and mud parameters	Neural networks	The results achieved for pressure differential sticking were better than for mechanical reasons. Samples were divided for training and tests
Ambrus et al. [41]	Real-time well data monitoring system	Drilling and mud parameters	Bayesian networks	A monitoring system validates quality of the data received from the sensors in the presence of real-time process variations
Bardasz et al. [40]	Real-time well monitoring system	Drilling parameters, fluid properties, lithology properties	Real-time data acquisition and analysis, historical data analysis	Monitoring systems based on the comparison between real-time data and historical data to prevent problems. Alarms work when real data exceed the historical accepted limits
Beacom et al. [31]	Influence of geological faults in well trajectory, causing problems of instability and loss of circulation	Formation pressure, loss of circulation, geological faults, angle between failure and well trajectory, penetration rate and cost per interval drilled in the well	3D seismic data and geomechanical modeling to determine the ideal trajectory	Stimulate intense communication between geologists and engineers to share information and avoid isolation knowledge
Chamkalani et al. [42]	Prediction of stuck pipe and others problems during drilling	Drilling and mud parameters	Support vector machine (SVM), simulated annealing	AI techniques are associated to global optimization using local searches to decide between the current state of the variable and a change in the system, in a probabilistic way
Dursun et al. [43]	Identification and selection of main attributes for pipe sticking prediction models	85 different attributes	Naïve Bayes, attribute selection	A probabilistic classifier selects the best attributes for the building of pipe sticking predictive models for oil and gas data analytics
Gandelman et al. [44]	Real-time offshore drilling data diagnosis	Drilling and mud parameters	Real-time data acquisition, historical data analysis	A based rule system compares collected drilling data in real time with real historical values. The study is applied to 70 wells drilled in the Santos basin and the Gulf of Mexico
Jahanbakhshi et al. [37]	Differential pressure stuck pipe prediction	Drilling string composition and mud parameters	Neural networks, support vector machine (SVM), Gaussian kernel	Authors compare neural network and SVM techniques for obtaining the best performance of stuck pipe prediction in Iranian offshore fields



Table 2 (continued)

Author	Problem-challenge	Input variables and parameters	Used artificial intelligence technique/ digital technologies	Results and applications
Johnson et al. [45]	Determination of formation pressures in risky (loss of circulation or kick) areas	Pore pressure, fracture pressure, well bottom pressure, drilling mud properties	Managed pressure drilling (MPD), digital technologies, adjust the well bottom pressure	A system determines formation pressure during offshore MPD operations. Transmission of data through signals to the surface allows quickly pressures adjustment
Marques [47]	Mechanical sticking prevention, detection and classification	Drilling and mud parameters	Heat map algorithm, parameters selection, rule-based classifier, real-time data analysis	A real-time prediction and detection system points out the risk of mechanical sticking in a dynamic rating ranging
Mason et al. [38]	Monitor the descent of liner or liner tubing	Well dimensions, shoe depth, lithology, degree of inclination, drag and weight, internal and external pressure of the casing	Historical data analysis	A support system monitors the descent of a liner tubing for avoiding tripping in, reducing non-productive time, and detecting points at risk of sticking
Mason et al. [32]	Widening of extended reach wells, with a high inclination and large diameter	Well diameter, fluid flow rate, drilling mud density, penetration rate, rotation, vibration, torque	Real-time data acquisition, historical data analysis	This technique helps drilling in a study case in the Chirag field and in shallow waters in the Caspian Sea
Miri et al. [33]	Differential pressure sticking prediction	Filtrate, solids content, gel strength	Neural networks, support vector machine	Digital transformation was used to sticking prediction in a study with 63 wells drilled in the Persian Gulf. 61 sticking in 32 wells
Moazzeni et al. [35]	Prediction of stuck pipes and loss of circulation	Pore pressure, hydrostatic pressure, mud weight, mud fluid flow	Neural networks	Neural network-based tools were used for prediction of stuck pipe and loss of circulation in 32 wells drilled in the Iranian onshore field of Marun
Nybøet et al. [34]	Alarm problems in kick occurrences	Pore pressure, hydrostatic pressure, mud weight, mud fluid flow	Real-time data acquisition, historical data analysis	Many variables generate complexity and reduce kick alarm system performance. Authors use AI techniques to obtain better alarm prediction efficiency
Salminen et al. [46]	Pipe sticking prediction in real time	Drilling mud properties and drilling parameters	Real-time data analysis, historical data analysis, numerical and statistical analysis	Comparison between historical data and data being received allows real-time pipe sticking prediction; no false alert has occurred
Veeningen et al. [39]	High inclination wells with problems of instability, cleanliness and, drilling string vibration	Depth of sensors and well, pressure at different points in the column, pressure in the annular and logging	Real-time data acquisition from sensors in the well, digital transmission	Installation of acquisition equipment and transmission of data help prevention of problems

**Table 3** Summary of the literature on the application of digital technologies in production problems for selected articles

Author	Problem-challenge	Input variables and parameters	Used artificial intelligence technique/ digital technologies	Results and applications
Abdul-Aziz et al. [59]	Production optimization in sucker-rod pumping system in a heavy oil project	Variables associated with production process, sucker-rod pump facilities, flow line pressure	Smart field approach with SCADA (supervisory control and data acquisition) system; real-time wireless communications	Real-time intelligent surveillance and alarm systems prevent issues, identify required actions, and reduce response time
Alimonti and Falcone [48, 49]	Oil field performance monitoring, oil well diagnosis	Production data (flow rate) and fluid properties (pressure, temperature)	Knowledge discovery in databases, neural networks, fuzzy logic, and multiphase flow metering	Real data and fluid dynamic models are harmonized by artificial intelligence (neural networks and fuzzy logic) to improve integrated production systems in an oil field
Balaji et al. [65]	Evaluation of the status of data-driven methods in the oil industry	Review of applied works	Principal component analysis, decision trees, support vector machine, neural network, fuzzy rule-based systems, genetic algorithms, Bayesian networks	The adoption of data-driven methods improves decisions, increases productivity, reduces costs, and transforms the culture of the oil industry
Bassamzadeh and Ghanem [64]	Probabilistic prediction of oil production in wells located in areas with little data	Reservoir properties: permeability, average thickness, subsea depth, pressure, oil produced, oil area, spatial coordinate, and porosity	Bayesian network is used for uncertainty quantification and for reducing dimensionality	A Bayesian network data-driven model approach uses available data in the oil field for predict petroleum-reservoir behavior and oil production in areas with limited data
Bomba et al. [66]	Impacts of digital transformation and big-data technologies on flow assurance engineering	Theoretical and historical approach	Digital transformation and big data technologies	Integration of digital technologies and flow assurance engineering helps to understand hydrate events in deeper tiebacks, allowing to unlock new reserves
Bratland [67]	Multiphase pipe flow assurance simulations using dimensional analysis and digital technologies	Pipe parameters and fluid properties (densities, viscosities, and surface tensions)	Neural network	Integration of dimensional analysis, mechanistic theory, and neural networks improves the accuracy of multiphase flow assurance simulations
Cadei et al. [69]	Optimization of gas production in a field with hydrogen sulfide and carbon dioxide	Time series from 420 different equipment's sensors, network, maintenance reports, and chemical analyses	Big data environment with machine learning algorithms: deep learning, random forest, gradient boosting trees	A gradient boosting algorithm predicts the risk of excess of hydrogen sulfide and allows to optimize production parameters
Carpenter [61]	Predictive maintenance of compressor systems	Historical data from variables associated with compressor systems behavior	Support vector machine (SVM)	A support vector machine (SVM) classifier warns need for intervention caused by anomalous behavior, avoiding production deferrals
Cheung et al. [57]	Analysis and integration of heterogeneous data sources for digital oil field operations	Operational databases, time series, social networks, unstructured free texts, and operational reports	Pattern recognition techniques; time series analysis; social networks analysis, texts contents extraction	Digital technologies allow the implementation of a framework for automated linking of heterogeneous data sources, integrated data analysis, and event modeling

Table 3 (continued)

Author	Problem-challenge	Input variables and parameters	Used artificial intelligence technique/digital technologies	Results and applications
Creek et al. [52]	Management of hydrate formation and blockage in subsea lines	Laboratory and large-scale experiments data: reservoir fluid properties, hydrate properties, subsea structures dimensions, and architecture	Systems integration and multiphase flow tools (Oiga, FlowAsta)	Systems integration and simulation tools allow the operation of production systems in the presence and formation of hydrates
Danquigny et al. [50]	Production optimization and costs reduction in wells with gas lift	Production data, operational data from gas lift systems	Times series analysis, knowledge discovery in databases, statistical data analysis	Integrated digital technologies systems, well performance monitoring, and alarm systems allow productivity gains and cost savings
Glénat et al. [58]	Production inside hydrate zone	Pressure, temperature, water salinity, electrical conductivity, and acoustic velocity in produced water	Neural network	Monitoring instruments based on neural networks avoid hydrate plugging risks and ascertain safe production
Jain et al. [62]	Development of a smart management system for oil fields operation	Historical data related to oil field operations (drilling, completions, production, facilities, operational data, spreadsheets)	Several digital transformation tools used to develop a smart system	Integrating multiple and different data sources in one place brings several advantages to the organization of three oil fields with 700 wells
Li et al. [56]	Abnormal oil field decline production prediction	Oil production, oil reserves, water production	Support vector machine (SVM), data mining, and neural network	A decline production warning model developed with SVM identifies problems and deploys adjustment measures
Liu et al. [51]	Failure prediction for sucker rod pump production wells (artificial lift systems)	Real-time data from sucker rod pump lift systems	Decision trees, support vector machines, Bayesian networks, times series analysis, knowledge discovery in databases	A data mining framework supported in a classifier algorithm in a time series anticipates oil well failure
Patri et al. [55]	Failure detection and prediction in electrical submersible pumps (artificial lift systems)	Physical attributes (current, voltage, and intake pressure) of electrical submersible pumps (ESP)	Decision trees, time series shapelets	A decision tree classifier, associated with time series shapelets, is used for failure detection and prediction in the streams of real-time sensor data
Pennel et al. [63]	Failure detection and prediction in rod pumps artificial lift systems	Variables associated with artificial lift systems process, fluid load, tubing pressure, casing pressure	Random forest model, cross validation	The application of data science for prediction failures in artificial lift system composed of 800 wells increases revenue and reduce costs
Qin et al. [68]	Prediction of hydrate plugging risks	Water cut, gas/oil ratio, flow rate, PVT properties	Neural networks, support vector machine (SVM), decision trees	Risk management technologies based upon neural networks, SVM, and decision trees help to operate in areas favorable to hydrate formation
Rebeschini et al. [54]	Production forecasting of a digital oil field	Well parameters and variables related to electronic submersible pumps (ESP) and gas lift (GL) systems	Neural networks, real-time data analysis	Smart workflows, prediction methods, and well monitoring digital tools enable production forecasting and rapid reaction to production issues

Table 3 (continued)

Author	Problem-challenge	Input variables and parameters	Used artificial intelligence technique/ digital technologies	Results and applications
Siregar et al. [53]	Development of an academic and oil industry research system	Several projects with specific variables and parameters	Digital technologies, genetic algorithm, real-time data analysis, and simulations	Academic and oil industry integrated researches allow training of human resources and the development of novel artificial intelligence tools
Uribe et al. [60]	Production line (length over 10,000 ft) with high risk of hydrate formation	Temperature, pressure, gas oil ratio, line sizing, pipeline design, and process control design	Smart monitoring real-time management system	A novel and successful smart hydrate management strategy was developed by the association engineering and hardware teams, and operational staff
Vielliard et al. [70]	Real-time hydrate management in an offshore, subsea gas field	Salt concentration, process temperature, hydrate inhibitor concentration in the aqueous phase, and chemical injection flow rate in each well	Real-time data analytics methods	A successful real-time hydrate management system was developed using a combination of flow assurance modeling and data analytics methods

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## Declarations

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