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Application of machine learning and artificial intelligence in oil and gas industry

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A B S T R A C T

Oil and gas industries are facing several challenges and issues in data processing and handling. Large amount of data bank is generated with various techniques and processes. The proper technical analysis of this database is to be carried out to improve performance of oil and gas industries. This paper provides a comprehensive state-of-art review in the field of machine learning and artificial intelligence to solve oil and gas industry problems. It also narrates the various types of machine learning and artificial intelligence techniques which can be used for data processing and interpretation in different sectors of upstream oil and gas industries. The achievements and developments promise the benefits of machine learning and artificial intelligence techniques towards large data storage capabilities and high efficiency of numerical calculations. In this paper a summary of various researchers work on machine learning and artificial intelligence applications and limitations is showcased for upstream and sectors of oil and gas industry. The existence of this extensive intelligent system could really eliminate the risk factor and cost of maintenance. The development and progress using this emerging technologies have become smart and makes the judgement procedure easy and straightforward. The study is useful to access intelligence of different machine learning methods to declare its application for distinct task in oil and gas sector.

1. Introduction

The petroleum industry involves systems for oil field exploration, reservoir engineering, drilling and production engineering. Oil and gas is also the fuel source for other chemicals, including pharmaceutical drugs, solvents, fertilizers, pesticides, and plastics (Anderson, 2017). If prices of fossil fuels continues to rise, fossil fuel companies will need to develop new technology and strengthen operations to increase efficiency and build on their existing capabilities. However, the oil fields are now mature and are producing more water than oil because of water front arrival at shore, channelling, coning, or water breakthrough. This makes it impossible to produce petroleum from the formation economically. Moreover, because the price of oil has not yet been stable, fairly costly engineering or equipment is not at all of interest to any oil and gas firm. By using either Inflow Control Devices (ICD) or Inflow Control Valves (ICV) as well as downhole sensor systems, the easiest solution to save efficiency and productivity is to maximize cumulative extraction through effective and smart technologies. Improved control in major oilfields needs fast decision-making while taking into account ongoing challenges. The Smart Oilfield will do this by developing a comprehensive oilfield technology infrastructure by digitizing instrumentation systems and creating network-based knowledge exchange in order to optimize production process (Temizel et al., 2019).

It has been seen crystal clear that the digital technology has a tremendous influence on business and society. With time it has been seen that digital transformation is regarded as the "fourth industrial revolution", characterized by the convergence of technologies that blur the boundaries between the physical, digital and biological realms, such as artificial intelligence, robotics and autonomous vehicles. Artificial Intelligence (AI) technologies are gaining considerable attention because of their rapid response speeds and robust capacity for generalization (Evans, 2019). Machine learning demonstrates good potential for assisting and enhancing traditional reservoir engineering approaches in a wide range of reservoir engineering issues(Anifowose et al., 2017). Various studies employ advanced machine-learning algorithms such as Fuzzy Logic (FL), Artificial Neural Networks (ANN),

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Supporting Vector Machines (SVM), Response Surface Model (RSM), as classification and regression problems tools (Ani et al., 2016). Several of the machine-learning algorithms used in the reservoir field of engineering come under the supervised learning classification. Most reservoir engineering implementations often use evolutionary optimization techniques, such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO).

In order to estimate the accurate result of an inverse problems the aspect of the research should be to create analytical workflows by combining the forward and reverse-looking AI models. Rana et al., (2018), for example, organized AI-assisted common platform workflows using forward-looking Gaussian proxy designs, Bayesian optimization and numerical models of high fidelity procedures. The technology developed is implemented to solve a question of a coal seam degasification program that fits the past. Bayesian optimization. It can find numerous solutions of reservoir characteristics distributions to fit available information from the field (Esmaili and Shahab, 2016). The authors also built a specialist method based on ANN utilizing field data obtained from a portion of the Marcellus shale gas field, which is capable of assisting the history-matching method. It assessed multiple hydraulic fracturing designs. Costa et al. (2014), used ANN models and optimization programming to resolve an oilfield problem that suited the context. Throughout this process, forward-looking ANN expertise systems are equipped to mimic the quantitative high-fidelity simulations in order to forecast the output data during the historical field era. Indeed, machine learning in petroleum industry is used to investigate data related problems. The instructional program is developed to educate petroleum engineers by using algorithms of machine learning and artificial intelligence tools. This provides guidance for enhancing the productivity and minimizing the cost (Anderson, 2017).

Oil and gas industries in Gulf of Mexico has investigated the influence of technical transition in oil and natural gas inspection through specific collection of data type in micro structured grid. Findings suggest that the technical transition with adaptation of this technique has performed a substantial role throughout the offshore oil and gas sector in last 50 years, with rising deposits and reducing costs. Even though saturation impact remained influential in the very first 2 decades, its influence for technical progress had been able to compensate for the capital loss of over 50 years of investigation span (Managi et al., 2005). Improving knowledge for further changes in technology through experimentation as well as creation could consequently result to enhanced forecasting techniques for supplying oil and gas. Even though advancements could be done on substantial margins, developers are testing field as well as regional-level systems to know the implications of changes in exploration technology. Technology development influences the exploration of new deposits, that are commercially viable portions of established deposits, as well as the rental of capital, our analysis is essential for estimation of mineral resources throughout the government revenue accounts (Adelman et al., 1991). Besides technical advances, characteristic cases could have major effect upon cost efficiency of Clean Electricity Production from Offshore Natural Gas (CEPONG) framework (Roussanaly et al., 2019).

In order to forecast multiphase flowing bottom hole pressure Sami and Ibrahim (2021) looked at three alternative machine learning systems. The model is built and evaluated using real field data from such an open literature repository. A variety of datasets were used to assess the accuracy of the suggested models in order to validate the method accurately of the BHPs derived using ML models and verify the work's effectiveness. The precision and computational performance of machine learning algorithms for rate of penetration in directional well drilling were compared by Hazbeh et al. (2021). Hassanvand et al. (2018) used an artificial neural network to estimate the rock uniaxial strength properties for an Iranina carbonate oil resource. In the oil pipeline sensor network system, Priyanka et al. (2021) conducted a review analysis on cloud computing based smart grid technology.

The knowledge of block chain technology throughout oil and gas sector solves the possibilities, difficulties, threats and developments which are assessed in this sector. Block chain technology will offer several benefits to entire oil and gas sector, including declining payments and increasing accountability and performance. The advancement within block chain technology in oil and gas sector would then migrate to modified block chain network, cross-chain, modified smart contracts along with the additional multidisciplinary experts (Lu et al., 2019; Zheng et al., 2017). Technical changes with implementation of block chain method in this sector are showcased in: casing drilling technology; modern innovations, enhanced oil recovery; synthetic, thermic, physical and chemical techniques Microbial Enhanced Oil Recovery (MOER) and water alternating gas (WAG) processes.

This paper narrates the state-of-art research works related to application of Machine Learning and AI techniques in oil and gas upstream industry. The major objective of this paper is to unfold the merits of AI and machine learning techniques in various sectors of upstream. Based on the systematic understanding of this industry the paper presents the workflows that utilises the machine learning and AI for effective computation and decision making. This paper reviews that how a hand-shaking between petroleum industry and numerical simulator with intelligent system eases the work and advances the productivity.

2. Algorithms

Machine Learning is a subset of Artificial Intelligence. In oil and gas industries, various types of data are collected from surface and subsurface to understand the hydrocarbon potential. The sensors are found to be most prominent to collect these data in large number. It is required to plot and analyse these data with technical analysis and intervention. The machine learning methods provides relationship between input variables and predicts the output. In machine learning, the physical behaviour of the system is not interfered. The data associated with oil and gas industries are enormous and the process is very complicated for data correlations (Ali, 1994).

Several input and output signals with synaptic weights are associated in ANN. ANN model sums the product of inputs and their corresponding weights to pass through a transfer function to get the output of the layer. The convolution and non-linearity of the model are increased by increasing the number of hidden layers. Computation of hidden and output nodes consists of two calculations summation and transformation through active functions which may be linear or non-linear (Nyein et al., 2018).

The general relationship between input and output in an ANN model can be expressed as:

$$y_k = f_o\left[\sum_j w_{kj}.f_h\left(\sum_i w_{ji}x_i + b_j\right) + b_k\right] \tag{1}$$

Where

x = Input vector

W_{ji} = connection layer in the ith neuron to jth neuron in the hidden layer

b_j = Threshold value or bias of jth hidden neuron

w_{kj} = connection weight from the jth neuron in the hidden layer to the kth neuron in the output layer

b_k = bias of the kth output neuron
f_h and f_o are the activation functions for the hidden and output neuron.

Scaling of the data should be performed due to large& small input and output data.

The output data is normalized by

$$Y_{k,\ normalized} = \frac{Y_k - \ Minimum(Y_k)}{Maximum(Y_k) - \ Minimum(Y_k)} \quad (2)$$

Where.

Y_k = Original output value of the parameter
$Y_{k,\ normalized}$ = Normalized value of output

Minimum Y_k and Maximum Y_k are the Maximum and Minimum values of original output value.

Transfer function translates the input signals to output signals. There are four types of transfer functions such as unit step (Threshold), Sigmoid, Linear and Gaussian, Piecewise linear.

Example: sigmoid transfer function shown in equation (3)

$$Y = \frac{1}{1 + \exp(-x)} \quad (3)$$

In machine learning, the primary issue is identifying the mark of arriving new unlabelled input data providing the training collection of findings of recognized marks refers to classification. In this scenario, the grouping question will be focused on supervised learning where a group of correctly labelled and identified training information is possible (Tarrahi et al., 2015).

A framework and roadmap can be established to encourage the usage of data mining as well as for analytics, artificial intelligence, supervised and unsupervised learning, and other project administration methods as a supportive solution to conventional upstream frameworks in oil and gas industries (Fig. 1) (Pandey et al., 2021; Abou-Sayed, 2012).

Steps involved in Machine Learning are given in Fig. 2. Several algorithms used are summarized below:

2.1. Artificial neural network (ANN)

Deep Learning is a subset of Machine learning. In deep learning a structure called Artificial Neural Network learns and understands the concept of data. Neural Networks is one set of algorithm used in ML for modelling the data. A deep learning algorithm in Oil and gas industry helps to process huge amount of data and to achieve the best performance with large amount of data. Features are picked out without human Intervention. Deep learning algorithms perform complex operations where Machine learning algorithms cannot perform complex operations. Inputs are run through neural networks. ANN is used as effective machine learning method to solve complicated problems. In oil and gas industries, ANN is most widely used in nonlinear and complex problems which cannot be solved by linear relationship. Feed Forward-ANN (FF-ANN) transfers information in forward direction including hidden neurons (Ashena and Thonhauser, 2015). Areas of petroleum industry on which neural network can be applied are seismic pattern recognition, drill bit diagnosis, improvement of gas well production, identification of sandstone lithofacies, prediction and optimization of well performance (Ali, 1994). ANN model helps to predict pipeline conditions, it enables operators to assess and predicts the conditions of pipelines. Predicted pipe failure rate and mechanical reliability by using ANN and other methods are discussed in Tabesh et al., 2009). Machine learning model can be used to find percentage of sand in reservoir. Seismic Impedance, Instantaneous Amplitude and Frequency were used as input. The model predicted sand fraction in less program completion time and with enhanced visualization (Chaki et al., 2015). ANN- Generalized Auto Regressive Conditional Heteroscedasticity (ANN- GARCH) machine learning method is used to predict oil price volatility (Kristjanpoller and Minutolo, 2016). Example of simple Neural Network flowchart is shown in Fig. 3.

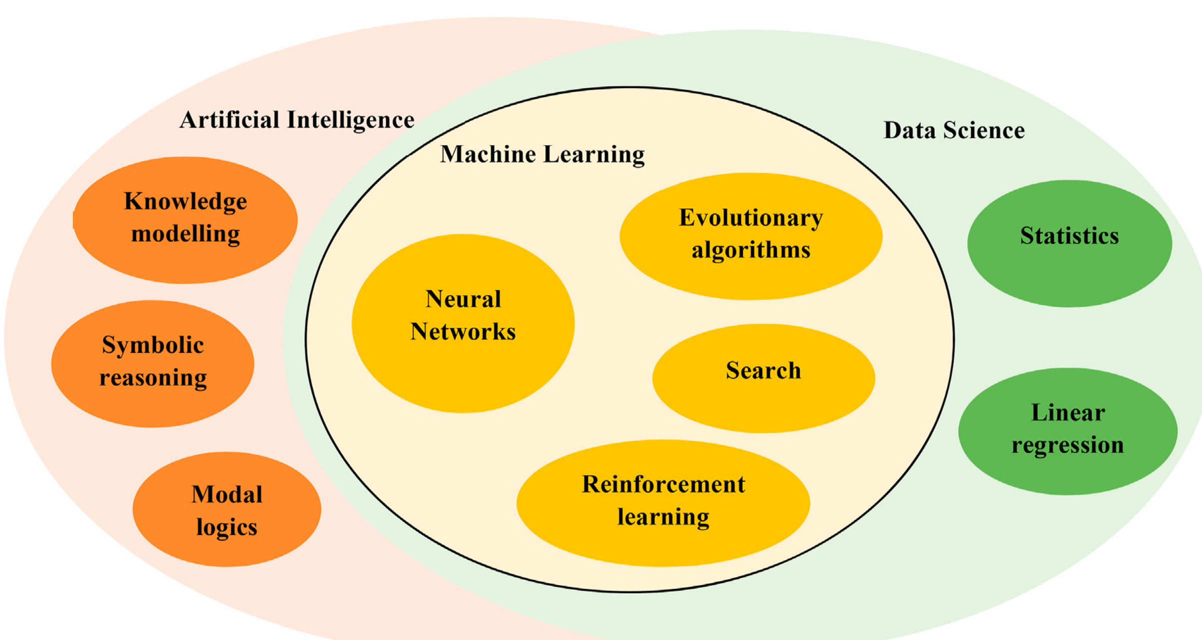

Fig. 1. Venn diagram showing the relationship between diversified fields of Artificial Intelligence (AI) and Machine Learning (ML), Deep Learning (DL) (Modified after Pandey et al., 2021).

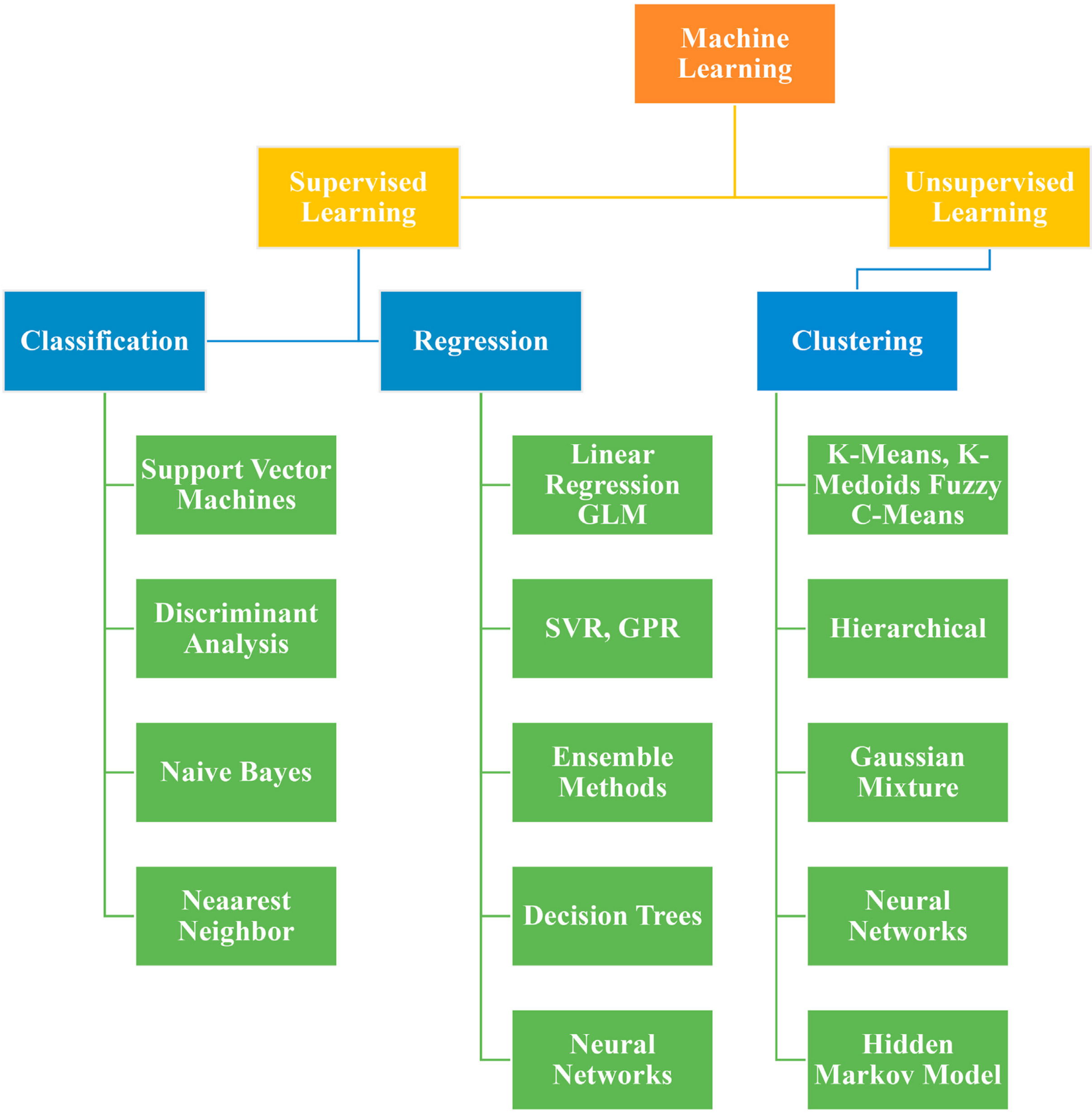

Fig. 2. Steps involved in Machine Learning Problems.

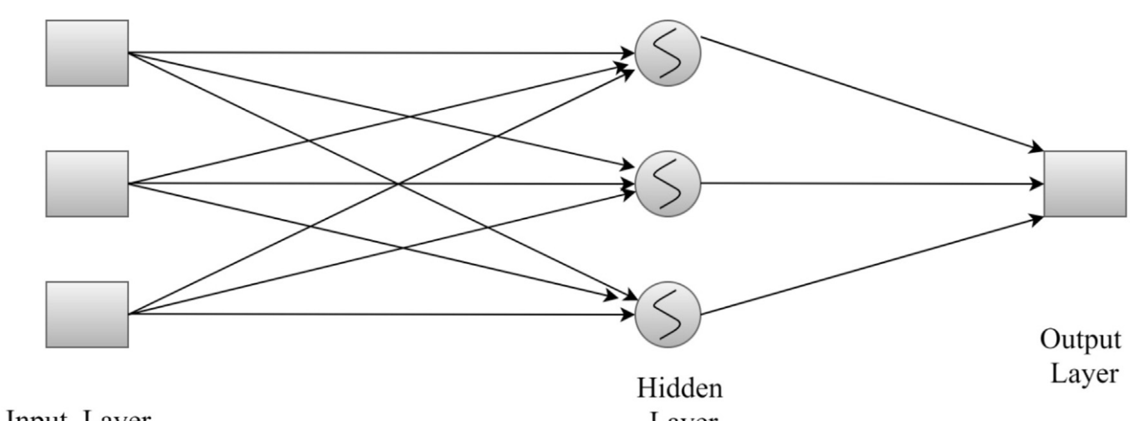

Fig. 3. Example of simple neural network.

2.2. Fuzzy logic

Neuro Fuzzy is generally used to study well placement optimization. It has been found that well placement has taken less time with Neuro-Fuzzy approach (Zarei et al., 2008). Ilkhchi et al. (2006) developed fuzzy logic model of reservoir for three wells of offshore gas in Iran. They predicted permeability of rock in gas reservoir. The method is useful for identifying pattern in data from large data. It represents behaviour of reservoir which will be cost effective and efficient recovery method for hydrocarbon exploitation.

2.3. Genetic algorithm

Genetic Algorithm (GA) is an inspired algorithm using the concept of natural evolution proposed by Charles Darwin. The algorithm uses the process of natural selection. The finest off-springs are considered for next generation population. Al-Mudhafer and Shaheed, 2011 used two genetic algorithm methods to identify optimal performance of reservoir regarding to infill drill. They obtained same results for both of the genetic algorithm methods. Genetic algorithm method is used to find optimum multilateral wells in 3D reservoir. They used well placement framework with genetic algorithm which handles variable numbers of producers and injectors (Yeten et al., 2003). The genetic algorithm (GA) is used for development of oil area, production scheduling, seismic inversion and characteristics of different reservoirs (Velez- Langas, 2005).

2.4. Linear regression

The linear regression is a statistical method. There is correlation between process variables in linear regression. Models based on linear and nonlinear regression is used to forecast global oil production. The inverse regression model shown superior performance compared to other methods. The global oil production is forecasted to be 4593 Mt in 2020 (Aydin, 2014) is an outcome of linear regression. Multiple linear regression models are used to interpret the real well logging data. The model was effective for pattern identifying the oil and gas layers (Peng et al., 2016). Wang and Liu, 2017 carried out regression analysis on influencing factors on the future economy of crude oil. Statistical software was used to build regression model.

2.5. Principal component analysis (PCA)

The principal component analysis use common patterns and trends from big data and uses it for production forecasting. Principal components methodology is generally used to forecast production from liquid rich shale reservoirs. Singular Value Decomposition (SVD) was used to calculate principal component. Makinde and Lee (2019) used these calculated principal component to forecast oil production. The model was useful to forecast production with reasonable accuracy. Cumulative Distribution Function based PCA (CDF-PCA) was used to map channelized reservoir. Their results showed that geological facies, reservoir properties and production forecast model with CDF-PCA were better and consistent (Chen et al., 2014). Principal component analysis was used to assess sustainability of the natural gas industry in china. The natural gas sustainability index was identified and evaluated by using PCA. The result suggested that sustainability kept rising from 2008 to 2013 because of increasing demand and supply (Dong et al., 2015).

3. Machine learning in upstream

The performance of electronic devices is enhanced due to increment in data processing capabilities. It is desirable for oil and gas industries to use computing power for production and exploration. Table 1 represents the upstream activities, tools and AI approach which can be used as per the activity.

3.1. Exploration

Hydrocarbon exploration is riddled with risk. The explorationist need to identify subsurface prospects accurately for drilling and exploitation of hydrocarbon. In the early 21st century limited 2D seismic data were considered to pinpoint the drilling locations based on subsurface mapping. Since it is riddled with risk the chance of success was 1:7. With time more data was acquired in each of the lease curved out for exploration. This large volume of data was termed as big data which was stored in Terabytes of memory space with the advancement in acquisition, processing and interpretation of seismic and well data. These big data was analysed using the machine learning concept. The objective behind use of big data and applicability of machine learning is to improve the signal to noise ratio during acquisition and processing. The clean data obtained were used to interpret 2D, 3D and 4D seismic using various robust algorithms. Mapping of various subsurface horizons accurately helped an interpreter to prepare subsurface volume maps and transform it into amplitude, porosity and saturation maps by integrating it with well logging. Inversion techniques were utilised to understand data parameters from the subsurface models (Zhang et al., 2020). With time machine learning algorithms helped to device horizon and window based attributes to understand the sweet spots. Recent attributes such as coherency, edge map, spectral decomposition, relief map are the outcomes of machine learning. Understanding the fault polygons, mapping complex fault structures and facies mapping using striatal slice improved the understanding of subsurface prospects. Machine learning algorithms were utilised to convert prospects into drillable prospects and improve the chance of success to 1:3. Use of 4D seismic or repeat seismic helped and interpreter to understand the hydrocarbon movement after the drilling activity (Kumar, 2019). Artificial neural network and heuristic methods are now commonly applied to refine the target prospects, its size and its volume of hydrocarbon (Fig. 4). Techniques like Monte Carlo simulation and Evolutionary programing are utilised to derive a stochastic range of hydrocarbon in the subsurface and how much can be exploited and bring to surface. In short machine learning brought a paradigm shift in the exploration and production regime in India and world.

The use of AI in the oil and gas industry is currently advancing rapidly, as the idea of AI increasingly infiltrates different stages of the sector, such as intelligent drilling, intelligent development, intelligent pipeline, intelligent processing, and so on, and it will become a potential research path. Developers have created a range of realistic application technologies in research and production using artificial intelligence algorithms. Developers have created a range of realistic application technologies in research and production using artificial intelligence algorithms. In the area of exploration, the use of the ANN approach has already yielded positive results in terms of lowering exploration risks and increasing exploration well success rates (Pandey et al., 2017). New drilling equipment, such as an automated drilling rig and an intelligent drill pipe, has greatly improved drilling quality and lowered costs (Holditch, 2013). The key application mode of AI technology in oilfield development is to refine the development plan based on historical data of oilfield production.

The field planning and well locations planning can be studied by

Table 1
Upstream activity, tool for the application and artificial intelligence approach.

Activity	Tool for the application	Artificial Intelligence Approach
Evaluation of the subsurface geology	• A tool for automatically mapping the characteristics of reservoir rock over an oil field. • A programme for collecting geological data from well logs. Boosting the gradient by 100 times or more accelerates the process. Based on photos of rock samples collected from wells, a tool for rock typing has been created.	• Interpolation techniques + none gradient optimization • Gradient boosting • Deep neural network
Drilling	Using real-time drilling telemetry, this tool can detect the drilled rock form and possible failure.	Algorithms for machine learning in combination
Reservoir engineering	Traditional reservoir simulations can be sped up with this tool.	Deep neural networks
Production optimization	A data-driven method for predicting the efficacy of well care campaigns objectively.	Gradient boosting + feature selection based on expert opinion

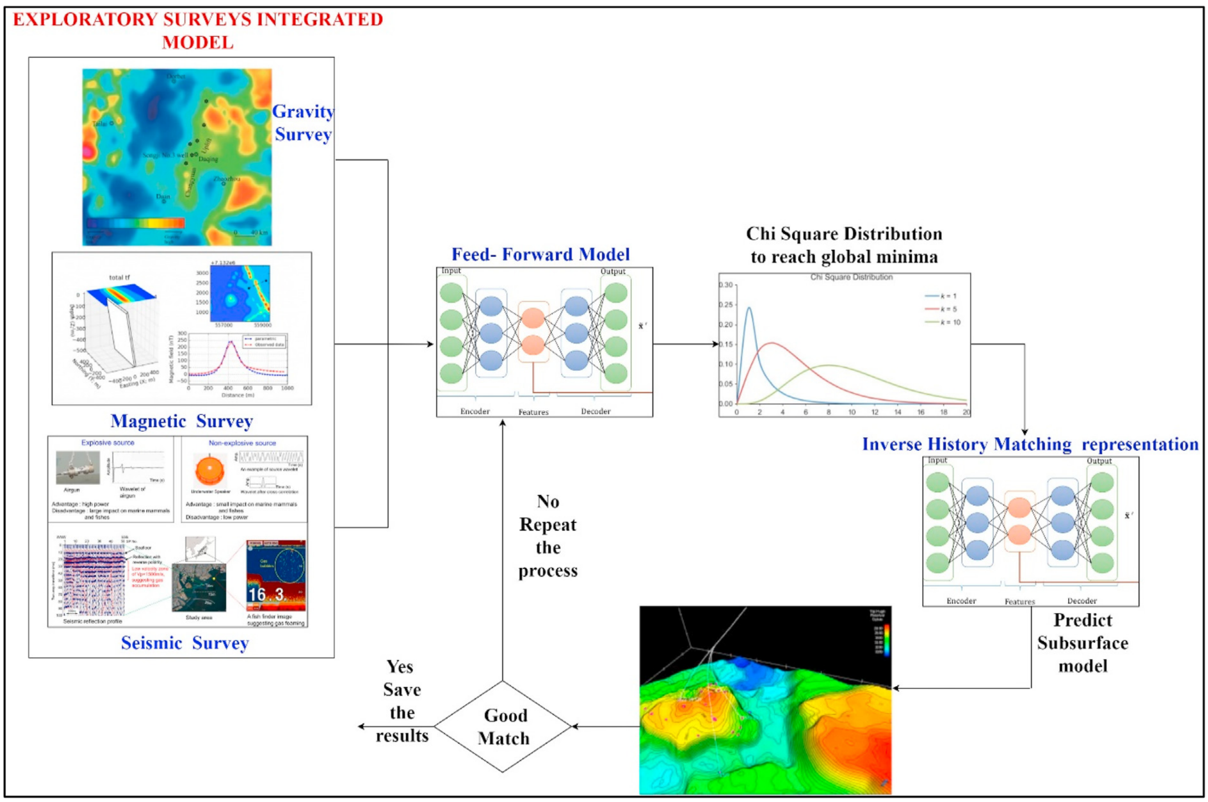

Fig. 4. Exploration outline for data processing and interpretation using machine learning technique.

using regression model. The characteristic of data can be understood with unsupervised learning. Kumar, 2019 proposed a framework which was found effective for shales because it can handle large data. The problem of rock physics can be solved with linearized rock physics inversion method. This model can provide accurate physical parameters but it cannot be useful for highly nonlinearized rock physics (Zhang et al., 2020). The recurrent neural network was proposed to obtain synthetic well log data from existing well logs data. It is concluded from Zhang et al. (2018) that the proposed machine learning approach can give accurate and cost effective well log generation. The Shift Window method can provide better pressure prediction compared with Long Short Term Memory Method (LSTM) (Heghedus et al., 2019).

Diersen et al. (2011) used artificial intelligence for reduction of the human efforts for processing and analysis of seismic full wave tomography. This is done by integrating artificial intelligence and Complex Wavelet Transform (CWT). CWT is a wavelet based transformation that helps one to study the time - frequency domains of waveforms. Artificial Neural Network and a Knowledge-based Artificial Neural Network can be used to select good seismic window fragments inside the full-wave tomography algorithm (Fig. 5).

3.2. Reservoir engineering

Reservoir engineering deals with fluid flow through porous media, production forecasting and field optimization. Numerical simulations modelling and experimentations are required for preparing subsurface property maps and PVT analysis. Modelling is done on huge volume of data to prepare static model and dynamic models. Data from seismic, well log, core analysis, past performance of the reservoir are integrated using machine learning algorithms for appraisal planning and stochastic field development plans. Complex pressure transient analysis and deconvolution of pressure data are carried out using algorithms pertaining to Artificial Neural Network, Genetic Algorithm, Response Surface Model (RSM), etc. These GA models are very helpful for reservoir history matching and preparation of P90. P50 and P10 production profiles

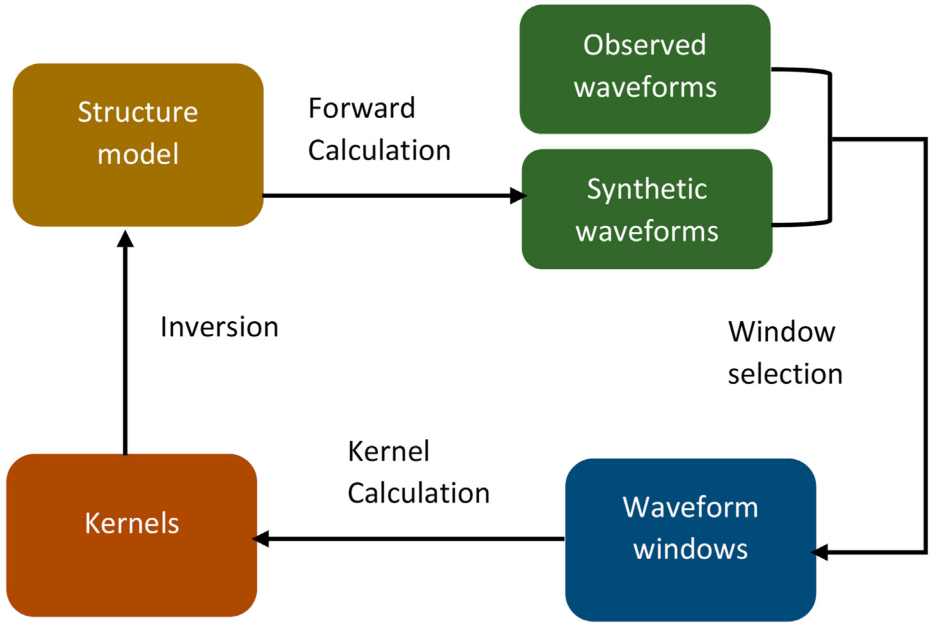

Fig. 5. Full wave tomography workflow (Modified after Diersen et al., 2011).

using the guidelines of Project Resource Management Systems (PRMS). Huge data volume is utilised to prepare reservoir maps which are refined iteratively based on new data up-gradation in database.

ANN is used for estimation of reservoir properties like permeability and porosity from many years. The study can be performed by applying different machine learning methods like K Nearest Neighbours (KNN), Support Vector Regression (SVR), Kernel Ridge Regression (KRR), Adaptive Boosting and Collaborative Filtering to predict reservoir fluid properties. Onwuchekwa (2018) found that collaborative filtering that was developed for consumer product recommendation system was utilised effectively for their reservoir study. The synthetic reservoir model can be used for numerical simulation for reservoir oil. Teixeira and Secchi (2019) used optimization algorithm to identify optimum control to maximize to total oil production. The parametric study can carried out by comparing various machine learning techniques to predict permeability and seismic attributes and wireline data. The performance of Superior Vector Mechanism (SVM) was superior compared to other methods for permeability prediction (Anifowose et al., 2019). Anifowose et al., 2019 created intelligent model with Extreme Gradient Boosting method to predict reservoir response based on injector wells. Nwachukwu et al. (2018) selected five cases like homogeneous reservoir water flood, channelized reservoir water flood, 20-model ensemble water flood, and CO_2 flood in heterogeneous reservoir with complex topography. Fig. 6 represents artificial intelligence assisted history matching workflow for reservoir properties tuning.

3.3. Drilling engineering

There are several problems in drilling like stick sleep vibrations, loss of circulation, bit wear, excessive torque, borehole instability etc. The machine learning has potential to solve these problems (Noshi and Schubert, 2018). The machine learning method was proposed by Aliouane and Ouadfeul (2014) to prepare poisson's ratio map which is useful to identify drilling direction and rock characteristics information. The machine learning method was applied by Castineria et al. (2018) to check quality of large drilling data, obtain crucial information and predict non-productive time. This method was helpful in reduction in labour cost to check quality of large drilling data. The Byesian network (BN) can be applied on deep water drilling for Managed Pressure Drilling operations (MPD) and Under Balanced Drilling (UBD) operations. Bhandari et al. (2015) suggested that the BN can be effectively used for risk analysis and failure prediction for offshore industry. The drilling parameters like Weight of Bit (WOB), Rotary Speed (RPM) and Rate of Penetration (ROP) were controlled by automation. The information like alternative bit or rig equipment up gradation, estimate abrasively and expected bit wear can be obtained by a machine learning algorithm (Dunlop et al., 2011).

3.4. Production engineering

The advance machine learning methods creates novel work flow which reduces load on engineers. There are several applications of machine learning in production engineering in oil and gas industries. The analysis of large data in short period of time for decision making is one of the challenging task. Machine learning methods can be used for production pattern data recognition. Subrahmanya et al. (2015) obtained the data point with highest information value with active learning. The information from wells was combined from labelled and unlabelled sources with semi supervised learning. The data was checked, verified and restored by using algorithms. The correction analysis of well logging data, quality control of physical and chemical fluid properties and separation among base production and well interventions were analysed by researcher (Andrianova et al., 2018). The ANN model can predict closure pressure with learning from patterns in data. The output data are generally compared with actual results to minimize error. Nande (2018) suggested that ANN model is capable to predict closure pressure efficiently. The Support Vector Regression Model was used by Shen et al. (2019) to predict wrinkling in mechanically lined pipelines. Saghir et al. (2018) explained the importance of edge analytics for oil and gas industries. The real time anomaly detection was carried out by edge analytics for electric submersible pump operated wells.

Continuous Integration/Continuous Deployment (CICD)

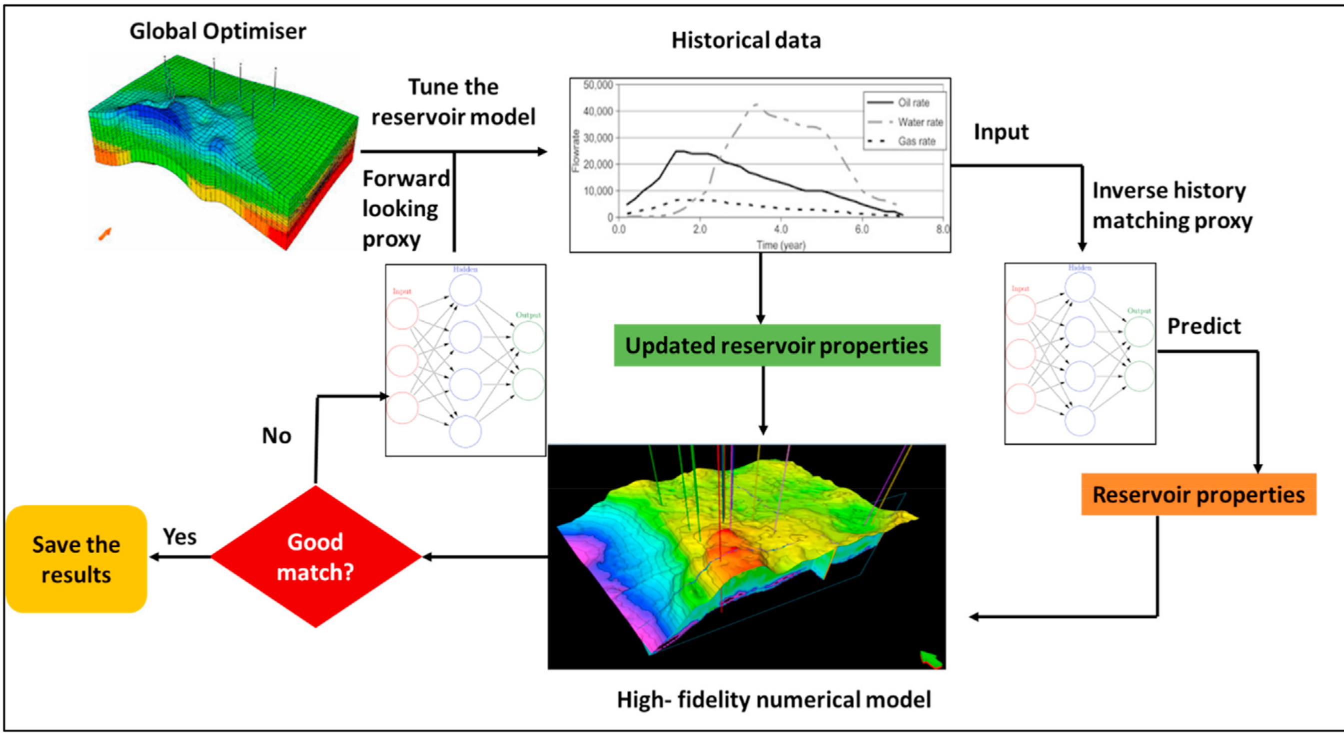

Fig. 6. Reservoir modelling outline using artificial neural network.

practices in ML are yet another important applications in oil and gas industry (Fig. 7). Advanced CICD should include an accurate and reproducible Machine Learning (ML) pipeline with the mechanisms for tracking, model lineage and version control. This is especially helpful in acknowledging conceptual drift where the performance of a statistical model deteriorates over time due to changes in data and input-output relationships modelled previously (Zliobaite et al., 2016).

Most of the offshore installations have already outlived their construction life expectancy. Their lower productivity isn't the only issue; they also have risk in aspects of social safety and environmental effects. The option is to deactivate them and lose the oil and gas they currently generate, or to invest heavily in upgrading or reinforcing them. The offshore energy sector has long relied on digital twins—or digital copies of a system —to track the health of tangible assets such as pipelines, drills, valves, and other machinery. Experts can anticipate the behaviour of a structure and determine its maintenance needs by using LiDAR to produce 3D point clouds and analytics for plant construction, extending its lifetime significantly. However, these simulations are quite "static," in that they do not account for all of the changes in an asset's actual, real-life physical conditions that could affect its performance over time. Novel control methods have been created to connect data from IIoT sensors about actual environmental loads with a virtual replica of the asset.

Table 2 represents some of the studies conducted with the help of artificial intelligence for production of oil and gas.

4. Recent advances in artificial intelligences in oil and gas industry

As the oil and gas industry becomes more competitive and unpredictable, companies are actively seeking innovative approaches to be more efficient through the streamlining of production, reducing costs, and improving worker safety, among other things. Many executives are looking to digitization to insulate themselves from market shocks, remain profitable at lower oil prices, and generate competitive advantage during recovery. The

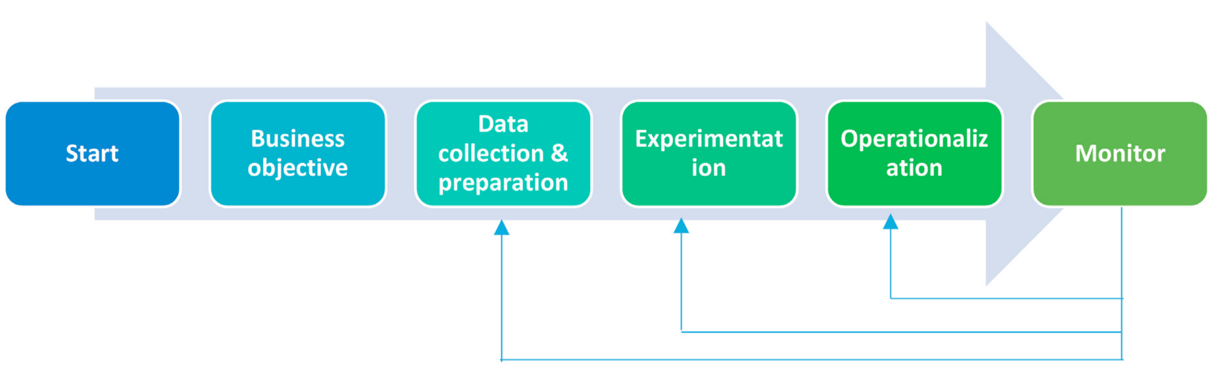

Fig. 7. Workflow of CICD modern Machine Learning pipeline (Hajizadeh, 2019).

Table 2
Use of Artificial intelligence in oil and gas production.

Method	Input parameters	Output parameters
Artificial neural network(Al- Fattah et al., 2001)	GDP growth rate, footage drilled, wells drilled, annual depletion, gas prices and other resources are all factors to consider.	Production of gas
Back propagation(Osman, 2001)	Temperature, heat, superficial gas velocity, and superficial liquid velocity are all factors to consider.	Liquid holdup
Graph neural network + Improved particle swami optimization(Yan et al., 2014)	capacity to produce liquids	Water content
Back propagation(Xu et al., 2015)	Number of open injection wells, newly opened production wells, and old wells with efficient treatment; remaining geological reserves; total number of production wells; monthly injection–production ratio; kernel function; number of open injection wells, newly opened production wells, and old wells with efficient treatment	Monthly oil and liquid producing capacity
Principal component analysis + Adaptive particle swarm optimization + Least squares support vector machine(Feng and Han, 2015)	Number of open wells, open injection wells, newly opened production wells, and old wells with efficient treatment; injection–production ratio; water content; number of open wells, open injection wells, newly opened production wells, and old wells with efficient treatment	Oil production
Artificial neural network(Gaurav, 2017)	horizontal permeability; porosity; velocity	Oil production
Back propagation(Salem et al., 2018)	diagenesis; deep; GR log; neutron log; density log; sonic log; deep resistivity log	Porosity; permeability
Multi-layer perceptron neural network(Ghahfarokhi et al., 2018)	regular flowing time; distributed temperature sensing; distributed acoustic sensing	Gas production
Artificial neural network + Adaptive network-based fuzzy inference system(Khan et al., 2018)	calliper; porosity; gamma ray; density; neutron; three separate resistivities; gamma ray; density; neutron	Water saturation

path forward lies in leveraging artificial intelligence (AI) and machine learning-based technologies that are maturing quickly and being adopted across the value chain. Countless industries have discovered the benefits of these emerging technologies, and thus we will continue to see more AI applications developed in the future.

Let's examine real-world AI applications in the oil and gas industry.

(a) Optimizing Subsurface Data Analysis – Total S.A. and Google Cloud

Oil and gas companies must collect and study a substantial amount of data before and after drilling into the Earth. To boost efficiency in day-to-day operations, they need to be able to solve complex exploration and production problems before they end up wasting loads of money on drilling into an unproductive well. Total S.A., an oil and gas company based in France, partnered with Google Cloud in 2018 to jointly develop AI solutions that optimize subsurface data analysis for exploration and production.

Wind the clock back a couple of decades and you'll learn that Total isn't new to implementing AI. The company started applying AI and machine learning algorithms to characterize oil and gas fields back in the 1990s. Jump forward to 2013 and you'll see that they implemented predictive maintenance technology for turbines, pumps, and compressors, resulting in savings of several hundred million dollars. Now they're taking it to the next level with Google Cloud. Together, their technologies will make it possible to interpret subsurface images from seismic studies using computer vision technology. In addition, their AI solutions will automate the analysis of technical documents using natural language processing. Altogether, these solutions will allow Total to explore and assess oil and gas fields much faster and more effectively.

(b) Detecting Oil Seeps With AI-Powered Robots – ExxonMobil and MIT

Everyone knows ExxonMobil as one of the leading oil and gas giants. They also invest their money into pretty cool AI projects. In 2016, the industry titan teamed up with the Massachusetts Institute of Technology (MIT) to design AI robots for ocean exploration. Brian Williams, an MIT professor and a core designer of the software for NASA's Mars Curiosity Rover, is one of the key members of this deep-sea initiative, further adding to the cool factor.

More specifically, ExxonMobil plans to use this deep-sea AI robot to boost its natural seep detection capabilities. According to the National Oceanic and Atmospheric Administration, naturally occurring oil seeps from the seafloor are the largest source of oil entering the world's oceans, accounting for nearly half of the oil released into the ocean environment every year. ExxonMobil's AI-powered robots will be able to detect these oil seeps in order to greatly reduce exploration risk and lessen harm to marine life.

ExxonMobil researcher and engineers are collaborating with MIT's Computer Science and Artificial Intelligence Laboratory (CSAIL) to develop self-learning, submersible artificial intelligence robots for exploration of ocean subsurface. The programming, or "intelligence," of the robots will enable them to work independently in conditions as extreme as those found on Mars, as well as adjust mission settings on their own to investigate unexpected abnormalities. The new technologies promising application would be to observe the oceans, charting deep areas and studying how they evolve over time and assessing their condition.

(c) Precision Drilling With Machine Learning Algorithms – Shell

Shell is yet another industry titan doing exciting things with AI applications. This time around, Shell is adopting reinforcement learning to control its drilling equipment, essentially using a reward system based on the AI's choices. For example, a machine learning model is trained on historical data from Shell's extensive drilling records, as well as simulations to steer the drill into the subsurface. It also takes into account data from seismic surveys, temperature, pressure, and other data points from the drill bit. Then the geosteerer, or the person operating the drilling machine can provide input via reward or penalty functions to help the machinery adapt to changing subsurface conditions. This helps the geosteerer to better understand the environment they're working in, leading to faster, more accurate results and less damage to machinery.

Innovation doesn't stop there, though. Shell is always looking for big ideas to push the boundaries of what's possible in the oil and gas industry. Through their Shell Game Changer initiative, the company regularly makes calls for AI proposals focused on machine learning from both individuals and start-ups all over the globe.

Whether it's investing in these ideas or straight up collaborating on a project, Shell is leading the way to help solve some of the industry's greatest challenges.

At each stage of the process, artificial intelligence is being implemented or tested. To manage its drill rigs, the company has recently adopted reinforcement learning, a type of "semi-supervised" machine learning. Whereas machine learning can function either with labelled or unlabelled data (supervised or unsupervised learning), reinforcement learning takes a middle path by including a reward system that is depending on the success of the AI's "choices." Algorithms that steer drills via the subsurface are developed using available information from Shell's drilling record as well as data acquired through simulated explorations. It includes mechanical data from the drill bit, such as pressures and temperatures, as well as data from seismic studies on the subsurface. As an outcome, a Shell geosteerer — the human programmer of the drilling machine—is capable of understanding the situation in which they are working, resulting in faster outcomes and less wear and tear on machinery.

(d) Boosting Productivity With Predictive Maintenance – Aker BP and Spark Cognition

Unplanned downtime can be a costly nightmare for offshore oil and gas platforms—to the tune of $2–3 million in a single day for catastrophic asset failures. Too many companies rely on outdated methods, prompting some to emphasize data and analytics to make maintenance decisions. Aker BP, an independent upstream oil and gas company in Norway, partnered with Spark Cognition to deploy an AI-powered predictive maintenance solution to their unmanned Tambar platform, where a significant amount of unplanned downtime is driven by problems with a critical multi-phase pump.

Spark Cognition developed and deployed a normal behaviour model of the multi-phase pump into its AI-powered predictive maintenance software, which then alerted deviations from normal subsystem behaviour. Over a period of six months, the AI software alerted Aker BP operators and SMEs to a potential multi-phase pump trip caused by a failing seal, of which previous failures resulted in over $10 million in lost production. Aker BP and Spark Cognition were able to prevent pump failure, increasing production by hundreds of thousands of dollars for each day of downtime avoided.

Aker BP is adopting SparkCognition's analytics tool SparkPredict® on offshore production facilities as part of a new transformation programme to boost productivity with superior predictive maintenance skills. Aker BP's complete fleet of production platforms will be supplemented by SparkCognition's AI systems, which will monitor all centerline and subsea systems for over 30 offshore structures. With powerful AI algorithms, SparkCognition is committed to promoting society's most essential interests," says the company. SparkPredict analyses sensor information using machine learning techniques to identify inefficient processes and impending faults before they happen. Aker BP will increase productivity and efficiency by installing SparkPredict on its offshore production platforms, accelerating its ambition to provide unrivalled value to its clients across the world.

5. Enablers and challenges in upstream oil and gas industry using artificial intelligence and machine learning

In order to minimize uncertainty, the primary step is to create system that can handle several hypotheses for achieving optimized solution. Efficient AI and machine learning approach was developed by Anifowose et al. (2017a) overcome this obstacle. To tackle this issue in machine learning hypothesis of Hybrid Intelligent System (HIS) was developed. It had been proved that the HIS has such tremendous capacity to boost the forecasts of oil field reserves leading to better discovery, much more effective extraction, expanded development and highly productive use of energy supplies (Anifowose et al., 2017b). Considering the present oil market situations, machine learning seems to have increasingly widespread over the last five years, especially in alleviating drilling issues even in actual time as well as in oil drilling automation and technology. Machine learning has also been most promising to enable this to achieve greater rate of penetration (ROP) and lesser CPF levels, and many other performance measures like 10k meter of well drilling per day (Noshi and Schubert, 2018).

Hawedi et al. (2011) suggested a data-driven methodology for evaluating well performance in two cases, predicting only for current well and predicting for a potential well that is expected to be drilled. The whole method is much more detailed relative to the step - wise regression evaluation in which it provides further data sources such as geological map details, output restriction such as tube head pressure as well as positions representing dynamic reservoir characterisation of non-traditional wells without providing a present model (Cao et al., 2016). Machine learning (ML) will greatly boost the exploration of oil and enhance the interpretation of seismic data, develop extraction techniques to make it more effective. The major problem confronting the oil sector nowadays is really the ecological risk that comes with both the extraction and production of oil. However the idea is, through advanced technical approaches, different systems will be created which is much more environmentally sustainable (Brekke, 2020). Artificial Neuro Fuzzy Inference System (ANFIS) produces marginally improved performance, but the prediction is really not necessarily influenced when ANN is being utilised, as well as the neural network is already capable of generating a realistic working formula (Khan et al., 2018).

While some oil and gas companies, like ONGC, OIL, Reliance, Shell are jump-starting their AI initiatives by investing aggressively in startups and R&D, several challenges are preventing them to massively and rapidly implement AI in the exploration and production of oil and gas. That is not an oil and gas specific problem, but a commonplace in applying AI at this stage of its development. Based on research, the critical challenges are related to the profile of people the industry requires, the central importance of data, and the need for open collaboration. These three issues are discussed below

5.1. People

The success of artificial intelligence critically depends on human intelligence. AI solutions are not generic – they cannot be just bought. Even when developed by third parties AI solutions have to be customized to the business context and database of a company. Thus, to actively use AI in processes and products, companies must grow in-house teams composed of data and AI specialists. These teams should be able to support development of AI infrastructure (algorithms and datasets) and, at least to customize tools that companies will later utilize in their operations. That means that oil and gas companies will become (partially) data-driven companies and, that AI specialists will become irreplaceable in supporting almost all innovation efforts in oil and gas companies in the next 10 years. However, finding and retaining AI talent is a very challenging task. There is a significant shortage of AI talent on the job market and with more and more companies getting into AI and forming their own AI groups, prospects are not good for the next decade. This is especially true for oil and gas companies. Next, to compete with tech giants like Google, Yandex, IBM, and Amazon, leading universities and cool startups worldwide over the same talent – oil and gas companies have to fight negative attitudes toward fossil fuel industries. That is not an easy neither a cheap task.

Although AI's entrance into the oil and gas industry announces "*the end of petroleum engineering as we know it*, petroleum engineers will not disappear. Just their role and required skillset will change. To successfully innovate in the AI-era, next to data scientists oil and gas companies will need petroleum engineers with a strong sense of data science and the ability to identify and design tasks to be solved by AI. Their role will be to ensure that the right problems are identified for applying AI, that the right data is collected and that solutions fit the physical and process reality. Over time, this will become a crucial role, as otherwise the wrong questions may be asked and existing human mistakes amplified, as it happened in the case of Google's breast cancer detection solution based on mammograms. So, it is not that just data science and AI skills are in demand due to the adoption of AI, but a new way of thinking about problems oil and gas companies face, rooted in deep understanding of the processes and the core logic of tasks. Thus, the new role of petroleum engineers will be more and more critical. To prepare the next generation of petroleum engineers for it, some universities like Skolkovo Institute of Science and Technology (Russia) and West Virginia University (US), already started implementing special educational programs that are a healthy mix of data science and petroleum studies.

Next to working more with data and data scientists, petroleum engineers will have to learn how to work with AI assistants – products similar to Alexa and Siri, but focused on industry applications. In these new partnerships, the challenge will be to combine best from the two sides – AI's ability to deal with a lot of data, find patterns and relations, and petroleum engineers' deep industry domain knowledge. Although AI is expected to be dominantly used by humans to augment their decision-making abilities rather than replace them [49], this will be a challenging task as many questions related to trust and fear of losing jobs may arise. There is an unsolved issue also related to people – the legal view on AI's recommendations. There could be cases when an AI tool recommends an action leading to a loss in money, production, or even severe health or environmental issues. In this case, we have no clear understanding of responsibility-sharing between the AI algorithm itself, the AI algorithm user, or the AI algorithm developer. With the development of AI tools, this question will rise more and more often. So the parallel establishment of the legal base is expected here. The practice says that the algorithms and their developers are not responsible, but the responsibility is still with the decision-makers getting the advice from the AI and AI users. Thus, to benefit from the opportunity to extend decision-making capabilities significantly, companies will have to create not only strategies *for AI*, but strategies *with AI* as well.

5.2. Data

AI tools need the good quality data of a suitable volume to be trained and then to work properly in the operational mode. While using smarter algorithms may help in getting better results from datasets of limited size, no manipulation can help with bad data. Thus, access to big and quality data is a crucial enabler and barrier for AI applications' successful development. Oil and gas fields generate large amounts of raw data. Still, it is not a guaranty for success as there are known issues with the quality and accuracy of field data and overall lack of large volumes of labelled data in the oil and gas industry. Training datasets have to be carefully collected through the well-planned workflow- and situation-specific multi-year procedure To enhance the value of data oil and gas companies possess or can access, they will have to redesign and adjust their organizational structures and processes. Data challenges (across industries, not only in the oil and gas) drive technical efforts in improving AI systems and their further practical usage in the exploration and production of oil and gas.

5.3. Open collaboration

Artificial intelligence is born in open and collaborative environment as a consequence of academia being a leading force in AI research for decades, almost without any business influences. This created culture of free sharing and open publishing which companies across industries (and across the globe) had to embrace as a standard to succeed in the era of AI] once they joined the race.

While open innovation is becoming standard in the tech sector, oil and gas companies are not famous for their joint industry projects, especially between competitors and especially not in strategic domains such as AI. Even though many companies announce bringing some of their data to the open-source and claim the necessity of cross-company and cross-border data sharing, the reality is rather pessimistic now. The UK's oil and gas National Data Repository is one of the first large oil and gas open data releases. It contains 130 terabytes of geophysical, infrastructure, field, and well data, covering more than 12,500 wellbores, 5000 seismic surveys, and 3000 pipelines (Oil and Gas Authority, 2019). The opportunities for machine learning and artificial intelligence applications based on available data are highlighted (offshoretechnology.com, 2019).

University labs are another important source of novel AI technology and AI talent, Thus, oil and gas companies should re-think strategies for collaborating and interacting with universities.

5.4. Impact of COVID-19 in oil and gas industry and AI as a solution

The oil and gas sector is entering a different normal of pandemic situation and, as a result, lower crude prices and geopolitical issues are leading to excess supply, and some main industry innovations. Although consumption is expected to grow as the world recovers from the pandemic normalises its relations and output quotas, industry players must be adaptable to the new reality. They must concentrate on improving their supply chain and activities, lowering manufacturing, distribution, and transportation costs. Artificial intelligence (AI) has the potential to change the oil and gas industry's value chain. AI models are often used as isolated point solutions with little overall benefit. Disappointment over performance influences future plans as benefits begin to plateau quickly.

The sector still concentrate on different across reservoir, geology, geophysics, engineering, and drilling as it integrates cross-domain data. These divisions were created to increase productivity across the company, with a single team in charge of all geotechnical needs. This operational division, which was created in the past to meet cost-cutting needs, prevents the oil and gas industry from adopting broader cross-functional AI use cases.

6. Conclusions

In this paper, we have gone through the recent advancements in the field of AI and machine learning and its applications in oil and gas industries. Representative cases using machine learning in exploration, reservoir, drilling and production are presented in this paper. The literature review of oil and gas industry is well-poised to take benefits of machine learning regarding their abilities of processing big data and fast computational speed. Many monitored learning methods have been defined and described throughout this paper. Machine learning has the potential of unequivocally changing the numerous critical actions made every day by administrators and engineers in the oil and gas sector. The future advantages of information can be achieved if appropriate techniques are used to implement different data types or structures and convert it into useful information that contributes to intelligent judgements. Many such solutions utilizing ANN, ALM, supervised learning, fuzzy logic, linear regression and PCA could be enforced to counteract various difficulties found in oil and gas industries and helps in maturing for profitable strategies. In the forthcoming years, the increase of machine learning utilization may begin to expand rapidly, as well as its value will also be significantly utilised throughout the oil and gas industries.

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