Palacký University of Olomouc
Faculty of Science
Department of Geology

A Critical Review on the application of Artificial intelligence (machine learning) in the Oil and Gas industry

Bachelor thesis

Shad Kamal Qadir

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Supervisor: Jagar A. Ali, PhD

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Abstract

The oil and gas industries are encountering various challenges and concerns pertaining to the processing and management of data. A substantial quantity of data is generated through a variety of techniques and processes. The implementation of a comprehensive technical analysis of this database is necessary in order to enhance the operational efficiency of the oil and gas sectors. This paper presents a thorough and up-to-date review of the current state of machine learning and artificial intelligence research as applied to addressing challenges within the oil and gas industry. This extensively researched and thorough study can serve as a definitive resource for machine learning applications in the industry. The conducted review revealed that machine learning techniques possess significant potential for addressing challenges across various domains within the oil and gas industry, encompassing prediction, classification, and clustering tasks. The oil and gas industry are currently generating vast amounts of data on a daily basis. As a result, there is a growing need for the implementation of machine learning and big data handling techniques in order to enhance the efficiency of the industry. This study offers a comprehensive analysis of the various applications and use cases of artificial intelligence (AI) and machine learning (ML) techniques within the petroleum industry. Specifically, it focuses on how these techniques can be utilized to optimize upstream processes, including reservoir studies, drilling, and production engineering.

Anotace

Ropný a plynárenský průmysl se setkává s různými problémy týkajícími se zpracování a správy dat. Podstatné množství dat je generováno prostřednictvím různých technik a procesů. Zavedení komplexní technické analýzy této databáze je nezbytné pro zvýšení provozní účinnosti ropného a plynárenského sektoru. Tato práce představuje aktuální přehled současného stavu výzkumu v oblasti strojového učení a využití umělé inteligence při řešení problémů v ropném a plynárenském průmyslu. Tato rozsáhlá a důkladná studie může sloužit jako zdroj pro využívání strojového učení v průmyslu. Provedený výzkum odhalil, že techniky strojového učení mají významný potenciál pro řešení problémů napříč různými oblastmi v rámci ropného a plynárenského průmyslu, včetně úloh predikce, klasifikace a shlukování. Ropný a plynárenský průmysl v současné době denně generuje obrovské množství dat. V důsledku toho roste potřeba implementace technik strojového učení a zpracování velkých dat, což bude mít za následek zvýšení efektivity tohoto odvětví. Tato studie nabízí komplexní analýzu různých případů využití technik umělé inteligence (AI) a strojového učení (ML) v ropném průmyslu. Konkrétně se zaměřuje na to, jak lze tyto techniky využít k optimalizaci předřazených procesů, včetně studií nádrží, vrtání a výrobního inženýrství.

Keywords: Artificial intelligence; Oil and gas industry; production; Reservoir; Exploration; Drilling.

Klíčová slova: Umělá inteligence; Ropný a plynárenský průmysl; Výroba; Nádrž; Průzkum; Vrtání.

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Declaration

I hereby declare that I have independently authored the bachelor's thesis and have duly acknowledged all sources of information utilized therein.

In Olomouc, July 29, 2023

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Shad Kamal

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List of abbreviations

Abbreviation	Description	Abbreviation	Description
PPM-M	Parts Per Million Multiplied by Meters	MP	megapixels
ROP	Rates of Penetration	SVD	Singular Value Decomposition
PDC	Polycrystalline Diamond Compact	UAV	Unmanned Aerial Vehicle
GRNN	Generalized Regression Neural Networks	RBF-NN	Radial Basis Function Neural Networks
DRIFT	Diffuse Reflectance Infrared Fourier Transform	MSE	Mean Square Error
WOB	Weight on Bit	BP	Back Propagation
RPM	Revolutions Per Minute	RBF	Radial Basis Function
DT	Decision Tree	MLP	multilayer perceptron
FL	Fluid Level	PVT	Pressure-Volume-Temperature
SVM	Support Vector Machine	CDF-PCA	Cumulative Distribution Function based Principal Component Analysis
LSSVM	Least Squares Support Vector Machine	RADAR	Radio/Light Detection and Ranging
ANFIS	Adaptive Neuro-Fuzzy Inference System	PCA	Principal Component Analysis
PSO	Particle Swarm Optimization	GA	Genetic Algorithm
CSA	Cuckoo Search Algorithm	FL	Fuzzy Logic
ASR	Anelastic Strain Recovery	FF-ANN	Feed Forward Artificial Neural Network
DSCA	Differential Strain Curve Analysis	ANN	Artificial Neural Network
E&D	Exploration and Development	AI	Artificial Intelligence
ALM	Additive Layer Manufacturing	ML	Machine Learning
VOC	Volatile Organic Compounds	IR	Thermal Infrared
MWIR	Mid-Wave Infrared	SAR	Synthetic Aperture Radar
LWIR	Longwave Infrared		

1. Introduction

Artificial intelligence (AI) is the study of how to combine human intelligence and computing capacity to tackle extremely complex, highly nonlinear problems. Artificial intelligence (AI) enables computers to independently reason and make decisions. Machine learning (ML) is a subfield of AI that provides statistical methods for investigating and analyzing large data sets. ML also includes supervised, unsupervised, and reinforced learning as subgroups. When historical or labelled data is available for function approximation-based forecasting of the future, supervised learning is the data learning strategy employed. In the absence of labelled historical data, machine learning techniques such as unsupervised learning are frequently used for clustering. Combining supervised and unsupervised learning methods to provide reinforcement learning when some data is labelled, and some is not.

Hydrocarbon reservoirs have been discovered at greater depths and in more remote locations. The daily demand for materials derived from petroleum is increasing (Lantham, 2019). Companies must therefore implement measures aimed at optimizing production, reducing costs, and mitigating the environmental effects of hydrocarbon production. Traditional methods for the exploration, production, and management of hydrocarbon resources cannot be utilized to achieve these objectives. Nonetheless, organizations have the potential to increase their profitability through the efficient application of data-driven technologies if they utilize cutting-edge strategies and advanced modelling techniques. The mathematical methods utilized in this context are founded on the conservation of mass, momentum, and energy. In contrast, empirical approaches are founded on prior observations and experimental information. The limitations of mathematical methods in various operational scenarios and the imprecision of empirical methods necessitate the use of a number of simplifying assumptions when employing these approaches. As a result, their ability to manage complex relationships, noise, and incomplete data is diminished.

In the context of exploration and production activities, a multiplicity of daily operational processes generates vast quantities of data. These databases have the potential to be utilized in data-driven methodologies and the interpretation of massive amounts of data, thereby facilitating the development of effective decision-making strategies. Using these models improves and optimizes the production of hydrocarbons (Hamzeh, 2016).

1.1. Objective

This research will primarily focus on analyzing and shedding light on AI-derived technologies so that future applications of these technologies can be better understood. This paper will focus primarily on the following aspects of petroleum operations: reservoir engineering, exploration, production, and drilling. Following a review of these topics, we will then examine the potential future applications of the technology before concluding.

2. AL and ML (background)

The technology of artificial neural networks (ANN) possesses a variety of desirable characteristics, including adaptive learning, self-organization, defect tolerance, real-time operation, and seamless integration with existing systems. Neural networks are capable of adapting and learning from input stimuli, enabling them to recognize patterns without prior knowledge of the underlying models or functional relationships. Neural networks can independently organize or generate a unique representation of the data they are presented with. Machine Learning is considered a subfield of Artificial Intelligence as a whole. To obtain insight into the potential for hydrocarbon extraction, the oil and gas industries collect a vast amount of data from both surface and subsurface sources. The sensors are widely acknowledged as the primary method for collecting voluminous amounts of data. In order to plot and analyze the data, technical analysis and intervention are required. Methods of machine learning establish a correlation between input variables and predict the output. In the discipline of machine learning, the tangible behavior of the system remains unchanged and unaltered. The oil and gas industries generate a vast amount of data, and establishing correlations between these data is a complex process. Multiple input and output signals connected by synaptic weights are incorporated into artificial neural networks (ANNs). The artificial neural network (ANN) model computes the weighted sum of inputs and their respective weights, which is then transmitted through a transfer function to generate the layer's output. Increasing the model's number of hidden layers improves its convolutional and nonlinear properties. There are two distinct calculations involved in the computation of concealed and output nodes: summation and transformation. These calculations are carried out using active functions, which may be linear or non-linear (Nyein et al., 2018). Several AI algorithms are listed below:

2.1. Artificial Neural Network (ANN)

Deep Learning is widely acknowledged as a subfield encompassed within the broader domain of Machine Learning. Deep learning encompasses the utilization of a computational framework referred to as an Artificial Neural Network (ANN) to acquire knowledge and comprehension of patterns and concepts within data. Neural networks represent a category of algorithms that are frequently utilized in the field of machine learning for the purpose of data modelling. The application of deep learning algorithms in the oil and gas sector enables the effective handling of large datasets, leading to enhanced performance in the presence of significant data volumes. Deep learning algorithms possess the ability to perform complex operations that exceed the capabilities of conventional machine learning algorithms. The inputs are subject to processing within neural networks. Artificial Neural Networks (ANNs) have demonstrated significant efficacy as a machine learning methodology for tackling intricate problems. Artificial Neural Networks (ANN) are widely utilized in the oil and gas industries to tackle complex and nonlinear problems that cannot be adequately addressed through linear relationships. The Feed Forward Artificial Neural Network (FF-ANN) is a neural network architecture that facilitates the transmission of information in a unidirectional manner, specifically in the forward direction. This type of network incorporates hidden neurons (Ashena and Thonhauser, 2015). The utilization of neural networks in the petroleum sector encompasses a range of domains, such as seismic pattern recognition, drill bit diagnosis, improvement of gas well production, identification of sandstone lithofacies, and prediction and optimization of well performance (Ali, 1994).

The utilization of artificial neural network (ANN) models facilitates the prediction of pipeline conditions, thereby empowering operators to evaluate and forecast the state of pipelines (Tabesh et al., 2009). The application of a machine learning model facilitates the estimation of the percentage of sand content within a reservoir. The seismic impedance, instantaneous amplitude, and frequency were the input parameters employed in this study. The schematic representation of a neural network is depicted in Figure 1.

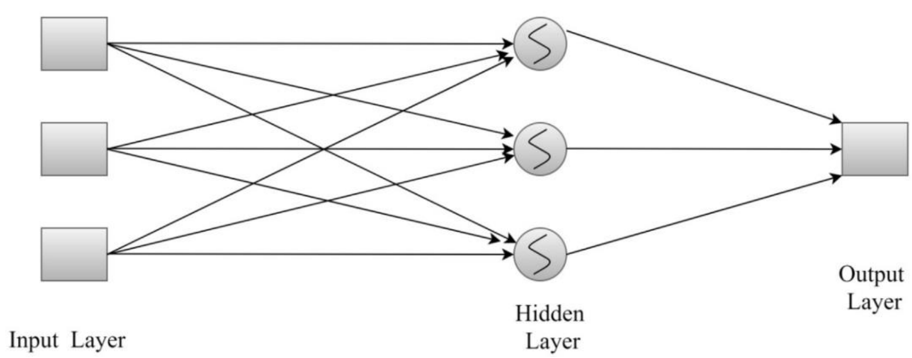


Figure 1. Flowchart of neural network (Sircar et al., 2021).

2.2. Fuzzy logic

Neuro-Fuzzy techniques are frequently utilized in research pertaining to the optimization of well placement in various fields. The application of the Neuro-Fuzzy methodology has led to a decrease in the duration needed for achieving satisfactory placement (Zarei et al., 2008). A fuzzy logic model may be developed to assess the reservoir characteristics of three offshore gas wells situated in Iran (Ilkhchi et al., 2006). The researchers conducted a prediction concerning the permeability of rock within a gas reservoir. The approach is beneficial for identifying patterns within datasets of considerable magnitude. The present study investigates the behavior of a reservoir as a means of cost-effectively and efficiently recovering hydrocarbon resources.

2.3. Genetic algorithm

The Genetic Algorithm (GA) is an algorithm that is derived from Charles Darwin's theory of natural evolution. The algorithm utilizes the process of natural selection. The offspring with the highest level of excellence are chosen to contribute to the population of the succeeding generation. The researchers obtained similar results for both of the genetic algorithm methodologies. The utilization of the genetic algorithm methodology is implemented in order to ascertain the most advantageous arrangement of multilateral wells within a reservoir that exists in three dimensions. A well placement framework in combination with a genetic algorithm was employed to proficiently handle diverse numbers of producers and injectors (Yeten et al., 2003). The utilization of the genetic algorithm (GA) has been observed in the domains of oil field growth, production scheduling, seismic inversion, and the analysis of reservoir characteristics (Velez-Langas, 2005).

2.4. Linear regression

Linear regression is a commonly employed method for conducting statistical analysis. Linear regression involves the examination of the correlation between process variables. Projections regarding global oil production are formulated through the utilization of models that rely on both linear and nonlinear regression techniques. In comparison to alternative methodologies, the inverse regression model exhibited superior performance. It is projected that the global oil production will attain a volume of 4593 Mt by the year 2020 (Aydin, 2014). The analysis of authentic well logging data involves the utilization of multiple linear regression models. The utility of the model has been demonstrated to identify and analyze patterns within oil and gas layers (Peng et al., 2016). Regression analysis on the variables have the potential to influence the future economic aspects of crude oil (Wang and Liu, 2017). Regression modelling was developed utilizing statistical methodologies.

2.5. Principal component analysis (PCA)

Principal Component Analysis (PCA) is a statistical methodology that utilizes prominent patterns and trends present in extensive datasets to aid in the prediction of production outcomes. The application of principal components methodology is frequently utilized in forecasting production from reservoirs that contain substantial quantities of liquid-rich shale. The principal component was computed utilizing the Singular Value Decomposition (SVD) method. Makinde and Lee (2019) conducted a study wherein they utilized derived principal components to generate predictions pertaining to oil production. The application of the model demonstrated its effectiveness in accurately forecasting production results.

The methodology utilized for the mapping of channelized reservoirs involved the application of Cumulative Distribution Function based Principal Component Analysis (CDF-PCA). Findings have been presented that showcased the enhanced and consistent outcomes achieved through the utilization of CDF-PCA in combination with geological facies, reservoir properties, and production forecast model (Chen et al., 2014). Principal component analysis was utilized to assess the sustainability of the natural gas industry in China. The process of identifying and assessing the sustainability index of natural gas was carried out using Principal Component Analysis (PCA). This can be attributed to the concurrent expansion in both demand and supply.

3. Application of AI and ML in oil and gas industry

3.1. Reservoir engineering

The process of reservoir characterization is of utmost importance as it involves the quantitative determination of several parameters, including porosity, permeability, fluid properties, and other pertinent characteristics, for the reservoir. The objective of this practice is to improve the understanding of the characteristics and dynamics of the reservoir. The exact measurement of the Pressure-Volume-Temperature (PVT) properties of reservoir oils is crucial for performing reservoir estimations, forecasting reservoir performance, and optimizing production conditions. The objective of this study is to develop resilient and sophisticated models utilizing Multilayer Perceptron (MLP) and Radial Basis Function (RBF) neural networks. The purpose of utilizing these models is to estimate the solution gas-oil ratio, while considering various factors including bubble point pressure, reservoir temperature, oil gravity (API), and gas specific gravity.

The evaluation and analysis of the performance of the multilayer perceptron (MLP) and radial basis function (RBF) models were conducted by means of a comparative assessment with various established empirical correlations. The evaluation was performed by employing statistical and graphical error analyses. The results of this study indicate that the suggested models demonstrate enhanced performance in comparison to the empirical correlations that were examined. The models exhibit a notable degree of concurrence between the projected values and the empirical values. Nevertheless, it is important to acknowledge that the developed radial basis function (RBF) model exhibited superior accuracy and efficiency in comparison to the proposed multilayer perceptron (MLP) model.

3.1.1. Artificial Neural Network (ANN)

The origins of the study on artificial neural networks (ANNs) can be attributed to the year 1943, when McCulloch and Pitts developed a basic computational model for neural networks (McCulloch and Pitts, 1943). In 1954, Hebb introduced learning rules for neural networks. Subsequent to that, artificial neural networks (ANNs) have experienced substantial growth and have been widely employed in various fields (Hebb, 1949). Artificial neural networks (ANNs) are computational algorithms employed to identify and analyze both linear and non-linear relationships between input and output variables in a given dataset. The main goal of an Artificial Neural Network (ANN) is to establish a functional relationship between a specified set of input patterns and their corresponding set of output patterns (Oludolapo et al., 2012). MLP-NNs basically include three sets of layers, input layer, hidden layer(s), and also output layer (Figure 2). The networks under consideration can be characterized as a configuration comprising of neurons, biases allocated to each neuron, interconnections or links connecting the neurons, and weights assigned to these interconnections. The learning process is conducted through the utilization of input and target datasets, and is facilitated by the implementation of training algorithms.

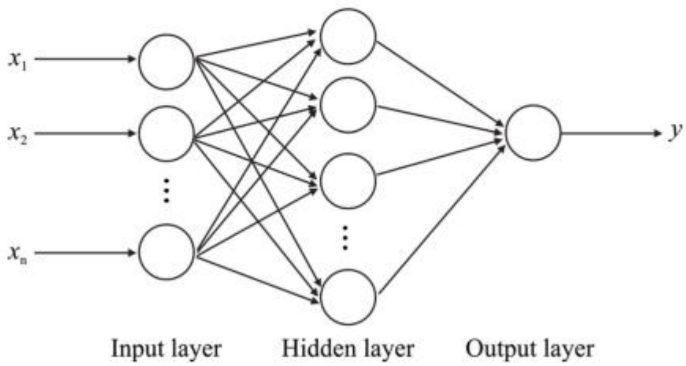


Figure 2. Model of MLP-NNs (Hashemi Fath et al., 2020).

3.1.2. Multilayer perceptron neural networks (MLP -NNs)

Multi-layer perceptron neural networks (MLP-NNs) are instructed through the utilization of the Back Propagation (BP) technique, which incorporates an error-correction mechanism as an integral component of its learning process. This procedure is consistently implemented during the entirety of the training process. The network effectively produces network outputs through the processing of input data that is transmitted into the network. Subsequently, the error value is ascertained through a process of comparing the goal values with the output generated by the network. Subsequently, the weights and biases undergo adjustments in order to minimize the error, and the training procedure persists until the neural network attains a predetermined threshold of acceptable error. The error function commonly employed for this purpose is known as Mean Square Error (MSE).

3.1.3. Radial basis function neural networks (RBF-NNs)

Radial Basis Function Neural Networks (RBF-NNs) are widely employed across various domains, such as function approximation, pattern classification, and other related areas. These networks have gained significant popularity due to their ease of construction, robustness against input noise, rapid training capabilities, and extensive coverage (Fu and Wang, 2003). The network exhibits a favorable response, even towards patterns that have not been employed for the purpose of learning (Yu et al., 2011).

The structural composition of a radial basis function neural network (RBF-NN) encompasses three distinct layers, namely the input layer, the hidden layer, and the output layer, as visually depicted in Figure 3. The primary role of the input layer is to facilitate the distribution of input signals to the subsequent hidden layer. The concealed layer of the neural network is comprised of radial basis functions, whereas the output layer produces the network's output by linearly amalgamating the outputs of the concealed neurons. The primary function of the input layer is to serve as a channel for transmitting input signals to the hidden layer. The hidden layer of the neural network contains radial basis functions, which are responsible for processing the input data. On the other hand, the output layer combines the outputs of the hidden neurons in a linear manner to generate the final output of the network.

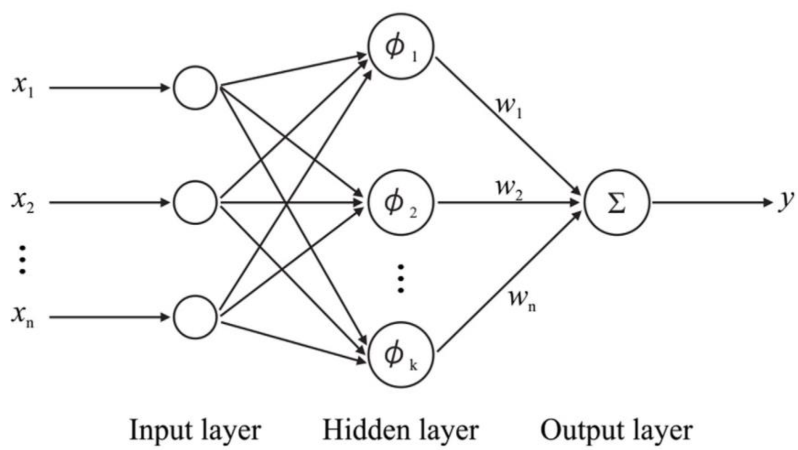


Figure 3. Model of RBF-NN (Fath et al., (2020).

3.1.4. Comparison of MLP and RBF neural networks

The Multilayer Perceptron (MLP) and Radial Basis Function (RBF) neural networks are both classified as feed-forward neural networks. This categorization indicates that the transmission of information within the network architecture is unidirectional, specifically from the input neurons to the output neurons. Several fundamental distinctions have been identified between Multilayer Perceptron (MLP) and Radial Basis Function (RBF) neural networks (Yu et al., 2011). Firstly, one could argue that Radial Basis Function Neural Networks (RBF-NNs) demonstrate a greater degree of simplicity when compared to Multi-Layer Perceptron Neural Networks (MLP-NNs). Moreover, it is widely acknowledged that Radial Basis Function Neural Networks (RBF-NNs) are generally more conducive to training when compared to Multilayer Perceptron Neural Networks (MLP-NNs), primarily because of their uncomplicated and consistent three-layer architecture. Furthermore, Radial Basis Function Neural Networks (RBF-NNs) operate as networks that approximate local functions. In these networks, the outputs are determined by specific hidden neurons located within distinct local accessible fields. In contrast, Multilayer Perceptron Neural Networks (MLP-NNs) exhibit a global operation characteristic, wherein the network outputs are subject to the influence exerted by all neurons within the network. The Multilayer Perceptron (MLP) and Radial Basis Function (RBF) neural networks utilize different classification methodologies. Radial Basis Function Neural Networks (RBF-NNs) utilize hyper spheres as a means to effectively separate clusters, while Multilayer Perceptron Neural Networks (MLP-NNs) employ hyper surfaces for the purpose of cluster separation.

3.2. Exploration

The hydrocarbon exploration process is inherently associated with various risks. The explorationist plays a crucial role in the identification of subsurface prospects with precision, aiming to facilitate the subsequent drilling and exploitation of hydrocarbon resources. In the early years of the 21st century, the utilization of limited two-dimensional seismic data was considered crucial for the precise identification of drilling sites through subsurface mapping. Owing to the existence of multiple hazards, the likelihood of attaining success was estimated to be 1 in 7. Over the course of time, a progressive accumulation of data was acquired within each of the designated leased areas for exploration. The substantial quantity of data discussed in this context is commonly known as big data. The storage of this data is facilitated by memory space with a capacity of Terabytes, which has been made possible by advancements in the acquisition, processing, and interpretation of seismic and well data. The extensive dataset was subjected to analysis using the machine learning framework. The main objective of employing big data and integrating machine learning methods is to improve the signal to noise ratio within the realm of data acquisition and processing. The clean data that was acquired was employed in the analysis of 2D, 3D, and 4D seismic data using various robust algorithms. The accurate delineation of various subsurface layers enabled the interpreter to produce volumetric maps of the subsurface. Subsequently, the maps underwent a conversion process utilizing well-logging data, resulting in the generation of amplitude, porosity, and saturation maps. The researchers employed inversion techniques to enhance their comprehension of the data parameters obtained from the subsurface models (Zhang et al., 2020).

3.2.1. Unmanned Aerial Vehicle (UAV)

An aircraft lacking a human pilot on board is commonly denoted as an Unmanned Aerial Vehicle (UAV), alternatively known as a drone or a remotely piloted aircraft system (RPAS). In contemporary times, there has been a significant surge in the utilization of unmanned aerial vehicles (UAVs), commonly known as drones, within the realms of civil and business domains. This technological advancement has witnessed its widespread integration across diverse fields, encompassing but not limited to agriculture, archaeology, land surveying, mining, and the petroleum industry. The utilization of remote sensing has been significantly employed within the oil and gas industry. The industry currently employs a diverse range of aerial remote sensing instruments to investigate natural oil seepages and detect instances of oil spill disasters in the marine ecosystem.

Drones are now extensively utilized in various industrial sectors, including farming, archaeology, surveying, mining, and the energy industry, in both civil and commercial contexts (Yao et al., 2019). The ability of drones to effortlessly transport sensors is significantly transforming various processes, pushing the boundaries of traditional approaches, and offering unique and innovative perspectives. According to Mordor Intelligence, drones have the potential to significantly impact the oil and gas industry as a disruptive force. This is due to their ability to fulfil various essential services within the sector, such as emergency response, monitoring of pipelines and infrastructure, inspections of oil derricks, mapping of oil spills, and detection of fugitive gas emissions, among other applications. Unmanned Aerial Vehicle (UAV) drones exhibit a wide range of physical configurations and dimensions, accompanied by diverse attributes and functionalities. Drones possess a diverse range of technologies that offer potential utility within the oil and gas sector. These technologies encompass various components such as platforms, sensors (both passive and active), and cameras. The subsequent section will provide a comprehensive examination of the methodologies and practical implementation of these various tools, elucidating their potential applications in real-time scenarios.

3.2.2. UAV petroleum exploration

Prior research has employed high-resolution three-dimensional orthomosaic images acquired from unmanned aerial vehicles (UAVs) for the purpose of producing sophisticated geologic maps, with a specific emphasis on lithofacies and structural attributes (Vollgger and Cruden, 2016; Bemis et al., 2014). In a more advanced version, unmanned aerial vehicles (UAVs), colloquially referred to as drones, possess the capacity to be employed in order to facilitate entry into geographically arduous areas, such as vertical or overhanging rock formations. This proposed application aims to enhance the accuracy of spatial mapping by incorporating remote orientation measurements in addition to on-site observations. By doing so, it seeks to bridge the gap between traditional field techniques and satellite-based remote sensing methods, (Pavlis and Mason, 2017; Madjid et al., 2018; Vasuki et al., 2014; Chesley et al., 2017). The researchers utilized an unmanned aerial vehicle (UAV) equipped with a digital camera to acquire multiple high-resolution images of a geological formation located in Spain. The aforementioned images were subsequently employed to create a three-dimensional (3D) virtual depiction of the outcrop. The utilization of the model served as a method for depicting underground formations with the purpose of simulating the fluid dynamics taking place within a reservoir (Jacobs, 2013). Outcrop analogs, like the one presented, are highly beneficial tools for geologists and petroleum engineers as they enable the examination of sedimentary and structural characteristics that may not be easily identifiable through seismic surveys. The utilization of these analogs facilitates the understanding of the dynamics exhibited by actual reservoirs and provides additional perspectives to subsurface models. In the given context, the utilization of hyperspectral remote sensing data can effectively highlight the mineralogical distinctions present in comparable outcrops. This, in turn, enhances the understanding of the variations in porosity and permeability within the subsurface reservoir. In order to generate a 3D/virtual/digital representation of an outcrop, the researchers employed a drone equipped with a digital camera to capture a multitude of high-resolution photographs of a specific geological formation located in Spain. The development of the model aimed to investigate the dynamics of fluid within a reservoir by employing an analogy to subsurface formations. Geologists and petroleum engineers have the capability to examine sedimentary and structural attributes that are below the resolution of seismic surveys. This enables a more comprehensive understanding of reservoir behavior and enhances the data available for subsurface model simulations. Detailed outcrop analogs, such as the one mentioned, play a crucial role in facilitating this investigation. In this scenario, the utilization of hyperspectral remote sensing data could be employed to enhance the understanding of the diverse variations in porosity and permeability of subsurface reservoirs. The provided figure is displayed as (Figure 4).

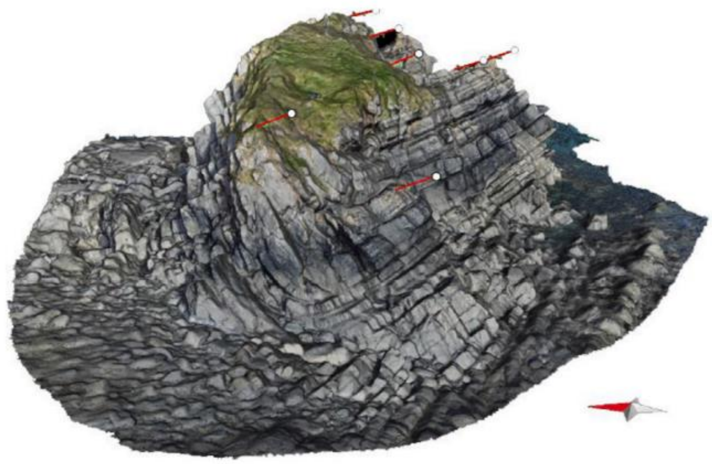


Figure 4. A detailed virtual outcrop constructed by mosaicking close-up images (Cawood et al., 2017).

3.2.3. UAV platforms

Unmanned Aerial Vehicles (UAVs) display a broad spectrum of physical structures, incorporating various sizes and proportions, ranging from large, long-endurance models to small counterparts. Drones have been classified based on various performance attributes, such as flight altitude and range, dimensions (specifically wingspan), velocity, duration, landing mechanism, and weight (specifically take-off weight). Drones can be categorized into distinct classifications based on their weight. The classification of Class I can be delineated into four discrete categories (Hassanalian and Abdelkefi, 2017). Table 1 presents different classifications of drones.

Class	Type	Weight range
Class I(A)	Nano drones	W ≤ 200 g
Class I(B)	Micro drones	200 g < W≤ 2Kg
Class I(C)	Mini drones	2 Kg <W ≤ 20 Kg
Class I(D)	Small drones	20 Kg < W ≤ 150 Kg
Class II	Tactical drones	150 Kg < W ≤ 600 kg
Class III	Strike drones	W > 600 Kg

Table 1. Drones' categorization based on their weight (Asadzadeh et al., 2017).

Drones can be categorized into two separate categories according to their airframe design: fixed-wing vehicles (as shown in Figure 5) and rotary-wing vehicles (as depicted in Figure 6).

Figure 5. Examples of lightweight fix-wing commercial drones (Asadzadeh et al., 2017).

Figure 6. Examples of lightweight rotary-wing commercial drones (Asadzadeh et al., 2022).

3.2.4. UAV sensors

The domain of drone technology embodies the amalgamation of conventional aerial and space-based remote sensing techniques with the utilization of portable, handheld sensors and detectors. A diverse range of commercial sensors has been developed for drones, with the intention of meeting specific requirements. The sensors mentioned in the text include a range of capabilities, including high-resolution photography, Thermal Infrared (IR) cameras, hyperspectral imaging systems, Radio/Light Detection and Ranging (RADAR/LiDAR), and gas detectors known as sniffers or imagers (Colomina and Molina, 2014). In this section, we provide a succinct overview of the passive and active sensors currently available in the market, as well as those under development, which are specifically intended for integration with unmanned aerial vehicle (UAV) platforms.

3.2.5. Passive sensors

Passive sensors are employed to measure the intrinsic radiation that is either reflected or emitted by the materials under observation. At present, drones predominantly employ passive sensors in the form of visible-light digital cameras. The current market for drone cameras is characterized by a wide array of options, with a notable abundance of choices. This trend is anticipated to persist and even intensify as the market further evolves and matures. The selection of a suitable camera model depends on several factors, including the particular domain of application, financial limitations, project scale, and compatibility with the designated vehicle, while also considering constraints such as weight restrictions. In the field of surveying, it is crucial to employ a high-resolution camera that is equipped with a large sensor size and a fast shutter speed, particularly utilizing a global shutter mechanism. The determination of a camera's spatial resolution is contingent upon the size of its sensor. Typically, cameras equipped with larger sensors provide a wider imaging range and increased coverage area during a single operation. In general, it is recommended that the cameras mounted on unmanned aerial vehicles (UAVs) possess a minimum resolution of 10 megapixels (MP) or higher. Some examples of cameras with different megapixel counts include the Canon 5D Mark III (20 MP), DJI Zenmuse (20 MP), Sony RX100 (20 MP), GoPro series (12 MP), iLook (13 MP), Ricoh GR2 (16 MP), DJI Phantom4 (12 MP), Canon 5Ds (50 MP), and Hasselblad X1D (50 MP), among others. The majority of these cameras could be utilized for capturing still or video footage in daylight conditions. Thermal infrared (IR) cameras are also available, which possess the capability to capture radiations in the Longwave Infrared (LWIR) spectrum, specifically within the wavelength range of 7.5 to 14 m. These cameras have the ability to convert these captured radiations into temperature images and video, which are calibrated for accuracy. In Table 2, a compilation of thermal imaging cameras commonly employed in conjunction with drone platforms is presented, along with their respective features.

Manufacturer	sensor	Resolution (px)	Temperature range (°C)	Sensitivity (mK)	Weight (g)
DRS technology	Tamarisk	640 x 480	-40-80	50	90
FLIR	Quark 640	640 x 512	-40-160	50	23
	Lepton	80 x 60	-40-80	<50	0.55
	Vue pro	640 x 512	-25-350	?	113
Optris	PI 450	382 x 288	-20-900	40	320
Polaris	Pyxis (polarimetric)	640 x 512	0-45	<70	<140
PRLOG	EYE-R	640 x 480	-40-75	<50	<380
Workswell	WIRIS	640 x 512	-25-150	30	<390
Yuneec	CGOETUS	160 x 120	-10-180	<50	278

Table 2. Common thermal IR imaging cameras for drones (Asadzadeh et al., 2017).

The acquisition of data can be enhanced through the utilization of this configuration, which additionally enables the seamless integration of temperature data onto visible footage for subsequent analyses. The thermal drones are commercially promoted as a comprehensive unit, which encompasses a thermal camera as an integral component. The technique of trace gas imaging is facilitated through the utilization of a distinct category of specialized thermal infrared cameras. These cameras are designed to measure a narrow spectral range that aligns with the distinctive absorption characteristics of a specific gas molecule, enabling the detection and visualization of said gas. The camera in question is equipped with a sensor array operating in the mid-wave infrared (MWIR) range, specifically between 3 and 5 micrometers. This sensor array captures comprehensive imagery of the scanned object. The presence of gas leaks and plumes in the image is discernible due to fluctuations in the intensity of the detected radiation. Recently, there has been a development of a novel cohort of compact gas imaging cameras that can be integrated with unmanned aerial vehicles (UAVs). These cameras utilize advanced technologies that are currently undergoing active development. Thermographic cameras demonstrate exceptional sensitivity in detecting trace gases such as ethylene, ethanol, and methanol, even at extremely low concentrations. Additionally, these cameras are capable of detecting lightweight hydrocarbons (C1-C8), Volatile Organic Compounds (VOCs), and various other gases. Table 3 presents a comprehensive compilation of the characteristics pertaining to a selection of optical imaging cameras currently available in the market, which possess the potential to be employed in the detection of gas leaks through the utilization of unmanned aerial vehicles. Figure 7 displays illustrations of the aforementioned cameras.

Examples of optical gas imaging cameras available for drones.

Manufacturer	Sensor	Spectral range (μm)	Resolution (px)	Weight (g)
FLIR	G300a	3.2–3.4	320 × 240	1400
ICI	Mirage HC	3.2–3.4	640 × 512	<800
IRCameras	Niatros HD Niatros SD	3.2–3.4	1280 × 1024 640 × 512	<900
Sierra Olympic	Ventus OGI	3.2–3.4	640 × 512	475
Workswell	GIS-320	3.2–3.4	320 × 240	<1700

Table 3. Examples of optical gas imaging cameras available for drones (Asadzadeh et al., 2017).

Figure 7. Optical gas imaging cameras used in drones (Asadzadeh et al., 2017).

3.2.6. Active sensors

Active sensors are characterized by the presence of an integrated light or illumination source. In comparison, active systems exhibit greater weight than passive systems as a result of the necessity for a power supply to generate the signal. As a consequence, the available selection of active sensors for the integration of drones is comparatively narrower in scope when compared to their passive counterparts. Active sensors that are currently utilized for drones include Lidar (Laser imaging detection and ranging), Synthetic Aperture Radar (SAR), laser fluorosensors, and laser gas detectors. The deployment of an Unmanned Aerial Vehicle (UAV) integrated with a Light Detection and Ranging (LIDAR) system necessitates the attachment of a laser scanner to the drone, which has the ability to emit ultraviolet, visible, or near-infrared light. The aforementioned system is utilized for the purpose of ascertaining the diverse distances to a particular target. This is achieved by illuminating the said target with a laser that emits pulsed light, and subsequently examining the duration it takes for the reflected light to travel back. Laser detectors commonly report gas concentrations as parts per million multiplied by meters (PPM-M), representing the concentration of gases over the vertical air column between the measuring platform and the desired location.

Another laser-based sensor that warrants mention is the laser fluorosensor. The sensors' function based on the principle that aromatic compounds found in oil demonstrate interaction with ultraviolet light, leading to the absorption of energy. Consequently, these compounds emit the surplus energy in the form of observable fluorescence emission. By employing spectral analysis and measuring fluorescence decay rate, the system demonstrates the ability to detect the presence of oil and differentiate between different types of oil, such as light, heavy, or medium (Fingas and Brown, 2018). Synthetic Aperture Radar (SAR) is a frequently utilized active sensor for the identification of oil spills and seepage in the offshore regions adjacent to satellite platforms. The observation of oil on the water surface has been found to have a suppressive impact on capillary waves, primarily attributed to the phenomenon of Bragg scattering. The aforementioned dampening effect subsequently results in a reduction in the radar backscatter. As a result, synthetic aperture radar (SAR) imagery reveals a discernibly darker appearance when depicting oil slicks.

Figure 8. An example of UAV-SAR equipped with P-, C-, and L-band antennas (Asadzadeh et al., 2017).

3.2.7. Applications of drones in oil and gas industries

As previously stated, the implementation of drone technology is expected to have a substantial influence on the detection and monitoring operations across different sectors of the petroleum industry. The examination and interpretation of unmanned aerial vehicles, more commonly referred to as drones, can be approached and analyzed from multiple perspectives. To enhance the discussion, a comprehensive methodology was utilized to analyze the present state of drone remote sensing in the petroleum industry. There exist six primary categories that encompass the detection of offshore oil spills, detection of oil leakage and monitoring of pipelines, sensing of gas emissions, inspection of remote facilities, petroleum exploration (specifically, land surveying, geologic mapping, and petroleum exploration), and environmental monitoring. Due to the significant significance of pipeline monitoring in the midstream industry, a dedicated section has been designated to discuss this topic. Our research has primarily centered on the identification of terrestrial oil seepage within the specified area.

3.2.8. Oil leakage detection and pipeline monitoring

The worldwide network of pipelines for the transportation of oil and gas extends across a distance exceeding 3 million kilometers (Gomez and Green, 2017). Pipeline integrity failure is a commonly observed phenomenon that frequently results in the loss of human lives and substantial environmental damage. Within the Russian context, it has been noted that there exists an average frequency of (1.1 - 1.4) pipeline ruptures per every 10 kilometers annually (Gomez and Green, 2017). The growing prevalence of worldwide networks has led to an urgent requirement for ongoing monitoring systems in order to improve the safety and reliability of petroleum pipelines, regardless of their location above or below ground. The conventional approach to pipeline monitoring entails conducting visual inspections of the pipeline structure or evaluating the ecological impacts, such as vegetation and soil conditions, in order to detect subterranean oil leaks. The identification of minor yet persistent petroleum losses, which constitute less than 1% of the pipeline's flow capacity, can present difficulties when exclusively relying on visual examination, especially in regions characterized by damp soil conditions (Correa Pabon ´ and Souza Filho, 2016). At present, drones are being acknowledged as highly effective tools for fulfilling the need for pipeline monitoring.

The identification of minute quantities of oil seepage on the surface can be accomplished by employing hyperspectral remote sensing techniques. the identification of oil can be accomplished by observing its occurrence within a pixel's surface area, which typically falls within the range of 2.5-25% (Asadzadeh and Souza Filho, 2017). This determination is made through the analysis of SWIR spectral data. The feasibility of detecting small oil leaks using drone-mounted hyperspectral systems, which provide a ground sampling distance between 5 and 50 cm, is enhanced. This technology enables the identification of even the slightest amount of oil leaks that are detectable by the sensor. This capability demonstrates significant efficacy in the detection of oil leaks within soil conditions that are both bare and uniform. One instance demonstrating the effective utilization of airborne hyperspectral remote sensing data is its capacity to detect hydrocarbon spills originating from a pipeline, exhibiting a detection threshold of approximately 20 barrels (Taylor, 2000). The most formidable situation, nonetheless, occurs when the leakage is in its nascent stage, resulting in the gradual permeation of hydrocarbon fluid into the soil without reaching the surface.

In the provided scenario, it is recommended to employ thermal imaging technology as a method to precisely detect the underground leakage, which is estimated to be located at a depth of approximately 3 meters. The objective can be accomplished through the development of a cartographic representation illustrating the variations in temperature across the surface. The methodology is based on the discrepancies in heat capacity between soils that have been contaminated with petroleum and their adjacent areas (or in comparison to previous images). This leads to discernible fluctuations in surface temperature at the location of the leakage. The thermographic map illustrates that the soils containing oil in close proximity to oil pipelines exhibit elevated temperatures, as depicted in Figure 9a. In contrast, the emissions of natural gas from gas pipelines give rise to cooler anomalies, as depicted in Figure 9b. The occurrence of this phenomenon can be ascribed to the adiabatic expansion of the gas that is being released (Mucsi et al., 2004).

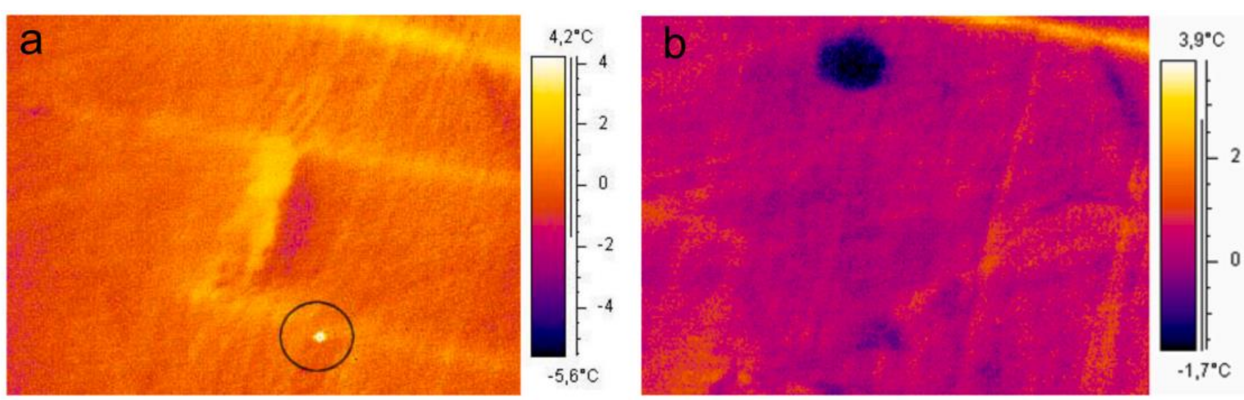


Figure 9. Evidence of petroleum leaking points in temperature data from remote sensing: a) a heated oil leakage-related location (circled). b) a cool anomaly (dark blue) brought on by a gas leak (Mucsi et al., 2004).

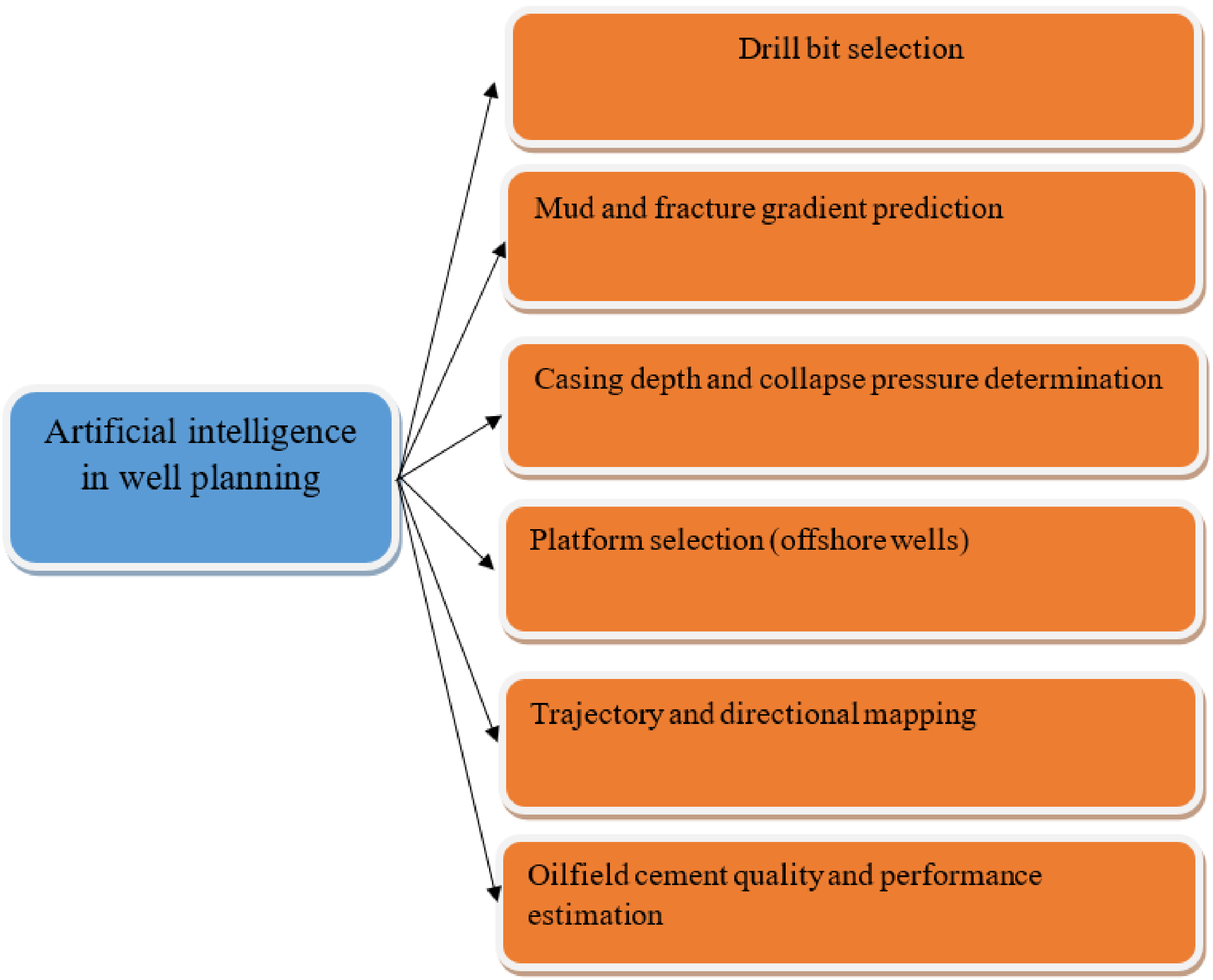
It is expected that conducting surveys during nighttime will result in the most favorable outcomes when employing this technique. The acquisition of nocturnal temperature data, with a spatial resolution ranging from 10 to 20 cm and collected at regular intervals, holds the capability to identify subtle fluctuations in the thermal properties of the backfill material surrounding pipelines resulting from petroleum leakage (Guozhong et al., 2009). The utilization of fixed-wing unmanned aerial vehicles (UAVs) emerges as the most suitable approach for systematic and timely monitoring of pipelines due to their extensive coverage capabilities. As an example, a compact aircraft equipped with appropriate sensors, travelling at a velocity of 80 kilometers per hour, has the capability to traverse a distance of 200 kilometers in a time frame of less than 3 hours. Thus, through the utilization of a fleet of unmanned aerial vehicles, the inspection of an extensive pipeline could be expeditiously conducted within a span of a few hours. On the other hand, the inherent adaptability and agility offered by rotary wing vehicles render them a viable option for shorter and geographically limited inspection missions.

3.3. Drilling engineering

The petroleum industry encounters several challenges in the drilling process, including issues such as loss of circulation, bit wear, borehole stability, excessive torque, and stick slip vibration, among others. These aforementioned issues possess the potential for resolution through the utilization of machine learning techniques (Noshi and Schubert, 2018). The process of drilling a well presents significant challenges due to the limited availability of information regarding subsurface conditions. These challenges become more pronounced as drilling depths increase or when the trajectory of the well deviates from a strictly vertical path. Furthermore, the operational process becomes increasingly intricate and challenging as a result of various drilling phenomena, including differential pipe sticking, lost circulation, and severe doglegs, among others. Artificial intelligence methodologies have gained significant traction in addressing these challenges in recent times.

3.3.1. Well planning

The process of constructing a well for the purpose of achieving faster and safer operations, as well as managing economic budgets, requires the implementation of sophisticated decision-making strategies that are informed by relevant experiences. AI has been subjected to rigorous testing by experts from diverse geographical locations to evaluate its efficacy in different stages of effective planning. The diagram presented below illustrates several potential outcomes in relation to the meticulous preparation for effective well planning.



3.3.1.1. Drill bit selection

Based on the attributes pertaining to formation, the following industries are anticipated to derive the greatest benefits from the implementation of artificial intelligence (AI). The trained artificial neural network (ANN) has emerged as a crucial instrument for deciphering data, categorizing empirical correlations, and determining the optimal drill bit by leveraging user-defined information databases. Possible inclusions in the database may encompass IADC bit codes pertaining to common rock formations, rock strength data, geological characteristics, compaction properties, and traditional rates of penetration (ROP) values associated with the rocks. Therefore, based on user input, artificial neural networks (ANNs) possess the capability to effectively acquire knowledge of codes and numerical values, enabling them to make informed decisions regarding the suitable bit for a given drilling environment, such as a polycrystalline diamond compact (PDC), roller cone, diamond insert, or hybrid bit. The layout of the drill bit selection is depicted in Figure 10, which illustrates the Artificial Neural Network (ANN) configuration.

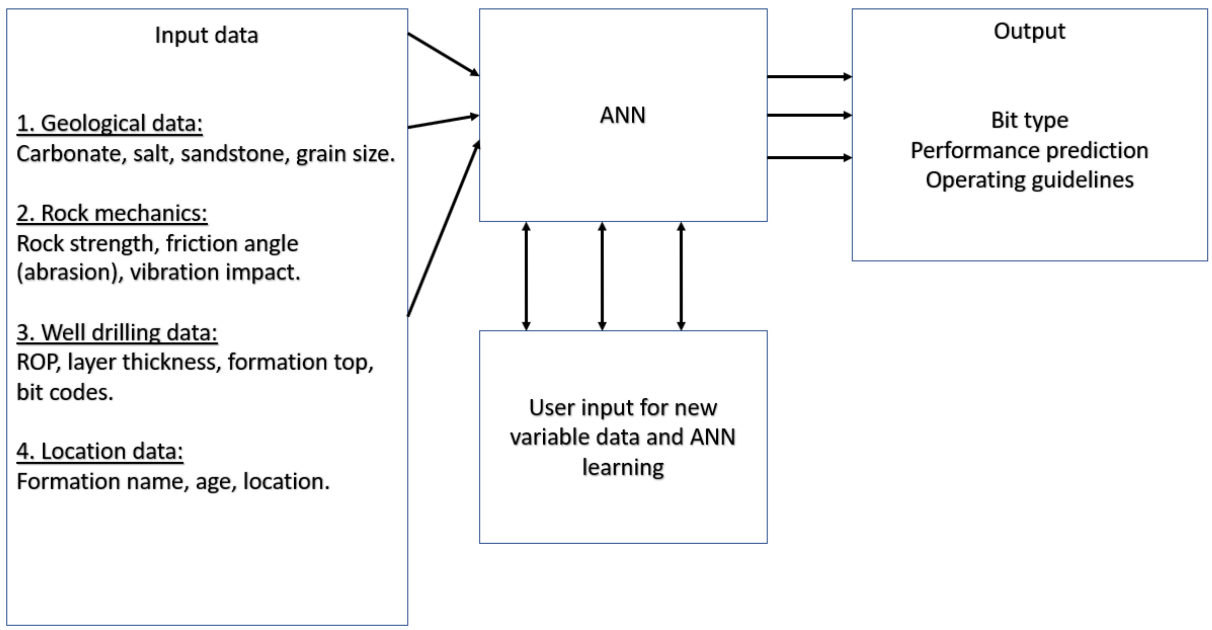


Figure 10. Layout for drill bit selection by ANNs (national Oilwell Varco, 2013).

3.3.1.2. Mud and fracture gradient prediction

In the last decade, the utilization of neural network systems, specifically Generalized Regression Neural Networks (GRNNs), in conjunction with the identification of proximate oil and water-bearing formations, as well as the implementation of highly discerning production and injection techniques, has yielded accurate results. Indeed, several experts consider Generalized Regression Neural Networks (GRNNs) to exhibit higher levels of accuracy and reliability compared to conventional methodologies like D-exponent, Comb, Ben Eaton, and others. Gaussian Radial Basis Function Neural Networks (GRNNs) are frequently utilized for the purpose of predicting the estimations of gradients, specifically in relation to depth, overburden gradient, and Poisson ratio. The neural network model illustrates the anticipated mud and/or fracture gradient for the given dataset by utilizing all of the input data, which may consist of authentic field data or estimations derived from alternative methodologies. It is imperative to employ the forecast solely within the provided data range. Extrapolations conducted at greater depths may yield substantial errors and inaccuracies due to their heavy dependence on the extent of the provided data (Sadiq and Nashwi, 2000).

3.3.1.3. Casing collapse and depth determination

Casing collapse poses a significant challenge within the oil and gas industry, making it highly advantageous to develop strategies for its prevention. The utilization and training of the back-propagating neural network (BPNN) technique can be employed. A neural network utilizing back-propagation, featuring a customizable quantity of internal (hidden) layers interconnected with the input and output layers, as previously demonstrated in the Middle East and Asia, has the capability to provide a "knowledgeable" prediction of the depth at which the casing of newly drilled wells will experience collapse. In order to evaluate and provide insights regarding the anticipated depth and probability of casing collapse, expressed in terms of time, the data layer has the capability to incorporate diverse inputs such as location, depth, pore pressure, corrosion rate, and casing strength, among others. Figure 11 presents a schematic representation of the methodology employed in this particular case. The method, currently undergoing refinement in terms of result accuracy and input data generalization, is of recent origin.

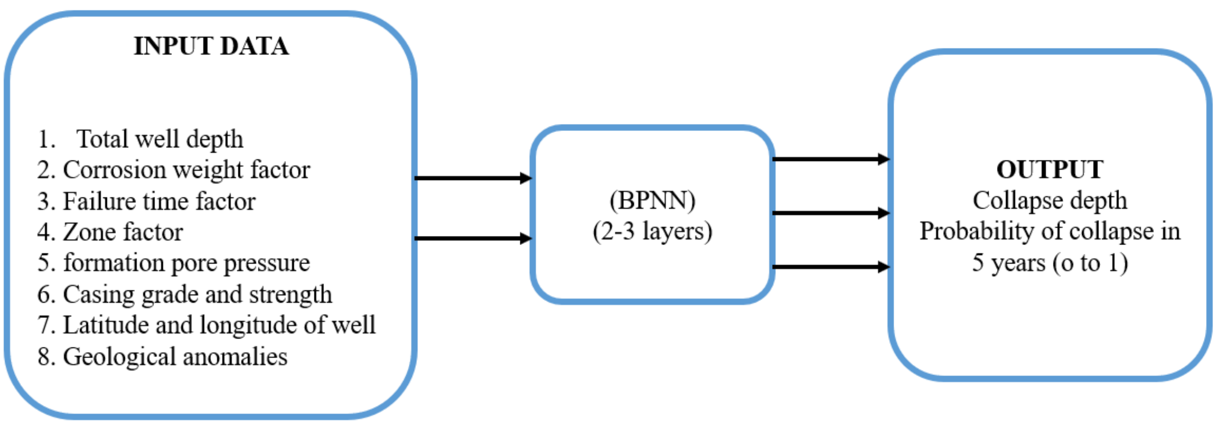


Figure 11. layout for casing collapse occurrence and depth determination using BPNN (Bello et al., 2016).

3.3.1.4. Quality and performance of oilfield cement slurries

The prediction of composition, particle size distribution, and thickening time (neat and retarded) can be achieved by utilizing the Diffuse Reflectance Infrared Fourier Transform (DRIFT) spectra of cement powders. The technique utilizes Artificial Neural Networks (ANNs) to generate predictions for the performance of slurry. The primary objective is to establish a database that characterizes the behavioral attribute of cement particles through the identification of their infrared spectrum. The presence of impurities, variations in particle size distribution, the effects of cement ageing, and the utilization of non-API cements can provide the opportunity to obtain highly detailed and precise information about the inherent characteristics of cement through spectral analysis. This level of data cannot be accessed through the use of API tables.

In 1994, Schlumberger developed the initial database pertaining to the evaluation of quality and performance of oilfield cement slurries. This database encompassed information from 158 distinct cements across the globe, incorporating empirical data on various characteristics such as oxide composition, lime content, insoluble residue content, particle size distribution and diameter, general composition, loss of ignition, and surface area. Subsequently, Fletcher et al. (1994) developed models for predicting cement properties and quality by utilizing the complete diffuse spectra as input variables.

3.3.1.5. Selection of offshore platform

The process of selecting an offshore platform necessitates the application of specialized expertise, taking into account a range of distinct factors such as the characteristics of the site, water and well depth, projected production rates, cost considerations, operator proficiency, and anticipated weather and tidal conditions. In their study, Wang et al. (2011) developed a selection model for Deepwater floating platforms utilizing artificial neural networks from BP. This study proposes a methodology for the case-specific determination of the most appropriate offshore units (SPAR, TLP, FPSO, or semi-submersible) through the utilization of non-linear Backpropagation Neural Networks (BPNNs). The BPNNs consist of nine input nodes and one hidden layer, which incorporates five model functions: technology maturity, field development time, cost, operator experience, and risk assessment. The layout of the offshore platform selection is depicted in Figure 12, which illustrates the BPNN configuration.

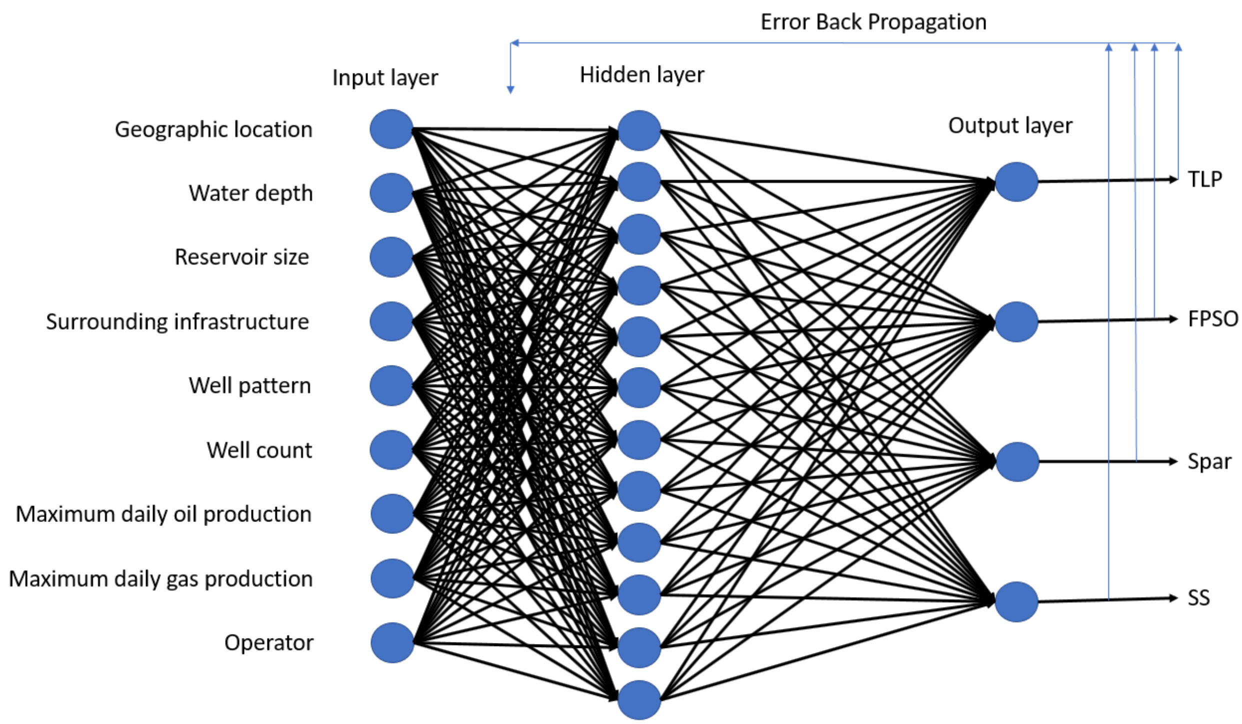


Figure 12. BPNN layout of the offshore platform selection (wang et al., 2011).

3.3.1.6. Trajectory and directional planning

The application of fuzzy theory and the development of general algorithms have yielded significant benefits in the domains of trajectory and directional planning, specifically in the context of offshore well design. Fuzzy reasoning techniques can be employed to develop a comprehensive dataset specific to offshore drilling. Following the retrieval of comparable events from the dataset, a general method was devised to predict feasible trajectories and relevant directional information. Nevertheless, it is imperative to validate the forecasts by means of computer simulations to ascertain their accuracy.

3.3.2. AI in pattern recognition

The evaluation of parameters in intelligent technologies, irrespective of the specific technique employed (such as Case-Based Reasoning, Artificial Neural Networks, or generic algorithms), relies on a substantial dataset comprising relevant information from numerous past instances. This suggests that a methodical case study is generated and uploaded to the database alongside previous incidents whenever a novel problem arises in a specific drilling region. An intelligent system has the capability to compare an input feed with a specific range of data and disregard any other information stored in the database. This functionality serves to reduce the likelihood of errors and enhance the precision of decision-making. This capability is facilitated by a consecutive stream of data that is systematically arranged based on criteria such as well depths, dates, areas, costs, or selected processes. The utilization of data obtained from shallow wells will be limited to the analysis of input feed for a well with a depth of 900 meters. Conversely, the data collected from mid-range and deep wells will not be employed in the processing of the input feed. The aforementioned prediction methodology has undergone refinement and augmentation in order to effectively identify and evaluate input streams at a cognitive level within specific datasets. Several modelling systems and inspection techniques have been developed and implemented in the drilling industry over the years, as shown in Figure 13.

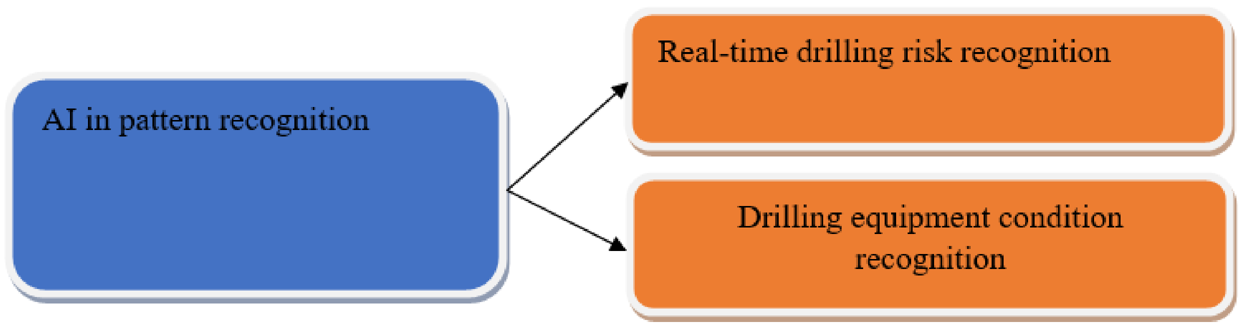


Figure 13. AI pattern recognition pattern recognition (Bello et al., 2016).

3.3.2.1. Real-time drilling risk recognition

The implementation of a real-time drilling risk indicator is crucial in order to proactively anticipate potential drilling mishaps, effectively identify the root causes of these incidents, accurately assess the level of risk associated with them, provide recommendations for preventive or control measures, and make necessary adjustments to control settings to prevent the occurrence of such scenarios. The capacity of the AI tool system to accurately identify significant oscillations in the real-time data stream originating from the storage computer (or directly from field sensors) is crucial for timely detection. The recognition method referred to as the "signal changing tendency rate automatic extraction technology" (Lian et al., 2010). Utilizing fuzzy (or case-based) reasoning, the application of live feed comparison with database reference sets and the timely identification of deviations between actual and reference function values can facilitate the estimation of drilling risk in advance and potentially enable real-time monitoring of downhole control parameters. A comprehensive analysis utilizing a robust reasoning system equipped with an extensive database of control parameter values (such as WOB, hook load, downhole torque, and RPMs) can yield consistent average risk values, occasionally punctuated by intermittent spikes. This approach allows for a meticulous and dependable detection of drilling risks by comparing them to both the upper and lower bounds of the reference values. By conducting a basic comparison using this particular reasoning system, it is possible to generate continuous average risk values that exhibit sporadic peaks. These values can then be compared to the maximum and minimum base references in order to achieve accurate and dependable detection of drilling risks. The present reasoning system is equipped with an extensive database containing a diverse set of control parameter values that are susceptible to incidents, including hook load, weight on bit (WOB), downhole torque, and revolutions per minute (RPMs). An illustrative instance of the potential application of this system involves the early detection of downhole kick. This is achieved by promptly identifying significant fluctuations in feed from flow-rate sensors, followed by monitoring gas levels in mud through surveying sensors (Lian et al., 2010).

3.3.2.2. Drilling equipment condition recognition

The tool for recognizing the condition of drilling equipment has been developed and relies predominantly on an artificial neural network (ANN) system. This system evaluates the condition of various drilling components, such as the drill string, drill bit, surface equipment, and mud, in relation to the specific formation being drilled. Additionally, it takes into account control parameters, including weight on bit (WOB), revolutions per minute (RPMs), and mud flow rate. These parameters can be obtained in real-time or through modelling. The ultimate goal of this tool is to enhance drilling efficiency by optimizing the drilling process and determining the overall state of the drilling system. The approach utilized in this method, similar to other systems, relies on the process of comparing and intelligently identifying the input data sourced from diverse datasets. Additionally, it involves comparing the provided data with information derived from previous case histories. Figure 14 depicts the utilization of an insert bit in a demanding setting for the purpose of condition assessment. the utilization of the AI tool enables the generation of comparable predictions for various types of drilling equipment (Yamaliev et al., 2009).

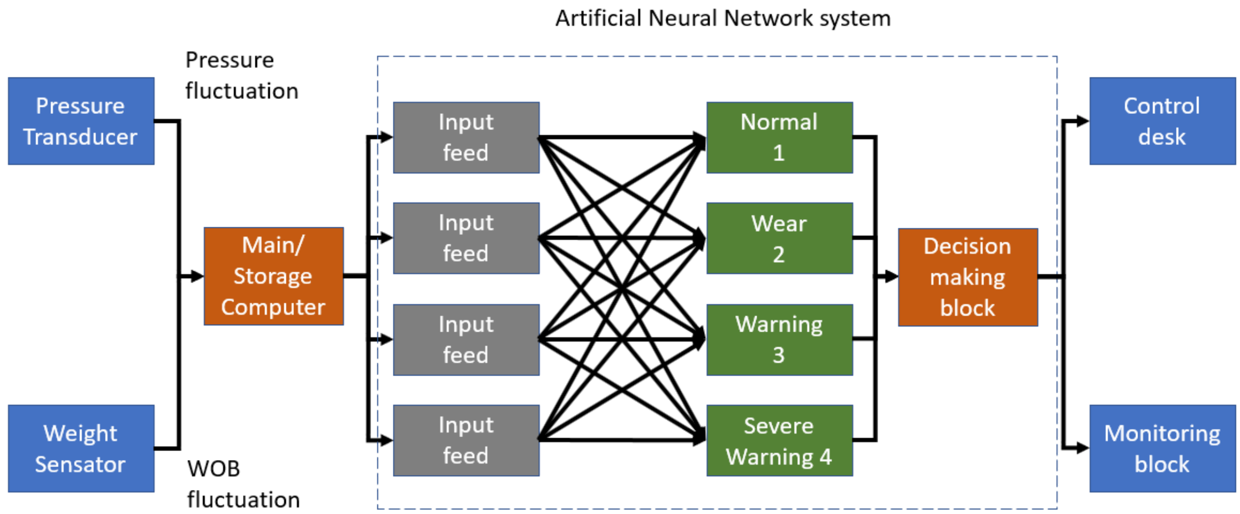


Figure 14. Detection of bit condition based on drilling environment and control parameters using intelligent AI tool (Yamaliev et al, 2009).

3.4. Production engineering

The significance of hydrocarbon production prediction is growing in relation to project development and planning, encompassing aspects such as financial and environmental regulations, as well as facility commissioning and decommissioning. The ability to make a precise forecast of a well's production performance can serve as a valuable tool for optimizing production, determining the necessity of work-over procedures, stimulating wells, designing facilities, and scheduling enhanced oil recovery procedures (Najafi et al., 2018). Machine learning is employed in various applications within the realm of production engineering in the oil and gas industries. One of the challenging endeavors involves the expeditious handling of substantial volumes of data for the purpose of making informed decisions. The recognition of production pattern data can be achieved through the utilization of machine learning methodologies. Semi-supervised learning involves the integration of data obtained from both labelled and unlabeled sources, specifically in the context of well data. Algorithms were employed for the purpose of verifying, validating, and restoring the data. These included the distinction between base production and well interventions, the assessment of physical and chemical fluid parameters for quality control, and the analysis of well logging data for rectification purposes. Significant quantities of data are generated during the process of monitoring well conditions in real time. The dataset comprises real-time measurements of pressure and flow rate, which are utilized for the purpose of graphing and analysis in order to facilitate informed decision-making. The estimation of future well output based on historical production rates necessitates a substantial investment of time and computational resources, thus necessitating the utilization of regression and simulation techniques. Drawing upon historical production statistics. Artificial intelligence (AI) methodologies can be employed to facilitate the execution of this process with greater ease and cost-effectiveness. This section focuses on the utilization of artificial intelligence (AI) techniques in production optimization procedures in the petroleum sector. Fluid level (FL) can be utilized to monitor the fluid output rate and steam composition in the multiphase flow process (Alimonti and Falcone, 2004). The estimation of fluid production rates was conducted using the DT technique, which took into consideration the interrelationships among the input parameters. The researchers conducted an assessment of the efficacy of the Decision Tree (DT) and associated techniques, and determined that both methods exhibited a high degree of accuracy and reliability. Nevertheless, subsequent analysis of statistical parameters revealed that the decision tree (DT) approach exhibited superior performance in terms of classification (Li et al., 2013).

The devised methodology demonstrated a high degree of efficacy, as it exhibited a minimal occurrence of cognitive errors and exhibited exceptional aptitude in recognizing patterns. Kamari et al. (2014) employed the Least Squares Support Vector Machine (LSSVM) methodology in combination with the Cuckoo Search Algorithm (CSA) to assess the optimal rates for fluid production and injection. Their objective was to estimate the unloading gradient pressures in gas lift-operated wells. The utilization of the adaptive neuro-fuzzy inference system (ANFIS) presents a hybrid methodology that holds the potential for cost reduction in the context of shipping multiple items to diverse destinations (Okwu and Adetunji, 2018). The Particle Swarm Optimization (PSO) algorithm has been employed in conjunction with the Adaptive Neuro-Fuzzy Inference System (ANFIS) framework for the purpose of determining the weight percentage of unstable asphaltene (Liu et al., 2018). The approach was trained and tested using data points obtained from published studies, and the accuracy was assessed using statistical metrics. Li et al. (2015) proposes the utilization of a soft computing technique to identify defects in wells produced by sucker rod pumps. This approach involves the application of the clustering index and the maximum suitable scale variable. In order to forecast gas production in a horizontal well after stimulation operations, a fusion of artificial intelligence methodologies alongside data obtained from temperature and pressure measurements, completions, and production logs may be used (Bhattacharya et al., 2019).

The study employed ANN, SVM, and RF methodologies to ascertain that the RF technique exhibited superior efficacy, characterized by the shortest computational time and convergence. Soft computing techniques can be employed to examine the production conditions of wells undergoing hydraulic fracturing (Wang and Chen, 2019). In order to predict well production data for the initial year, a range of artificial intelligence methodologies were employed. The researchers reached the determination that the RF technique, in comparison to alternative methodologies, exhibits greater accuracy due to its provision of statistical performance measure parameters that are deemed more satisfactory. The utilization of artificial neural network (ANN) methodology can be employed for the optimization of the number of separation stages, pressure, and temperature in multiphase separator equipment, based on the composition of the fluid flowing through it (Mahmoud et al., 2019). The results indicated that the methodology has the potential to predict the operational conditions of separators, thereby enhancing the quality of fluid produced by surface separators. Liu et al. (2020) emphasized the utilization of artificial neural network (ANN) and Support Vector Machine (SVM) methodologies in their study on oil production prediction. The results of their study indicated that the models successfully reproduced the target data with a high level of accuracy. A method for FL optimization was employed to ascertain the optimal artificial lift scenario for a set of wells. The application of sensitivity analysis was employed to ascertain and classify the appropriate artificial lift scenarios for the selected wells. Table 3 presents a comprehensive overview of the various applications of artificial intelligence (AI) in the optimization of production processes.

ML	Author	Input	Output	Result
ANN	Chakra et al. (2013)	Historical Production Data	Oil production	Even with few data, the model is very capable at predicting total oil output.
ANN	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	The algorithm was able to predict the total gas output through sufficient data.
BP	Osman, 2001	Temperature, heat, superficial gas velocity, and superficial liquid velocity are all factors to consider.	Liquid holdup	Prediction of liquid holdup was made possible due to the data provided.
MLP	Ghahfarokhi et al., 2018	regular flowing time; distributed temperature sensing; distributed acoustic sensing	Gas production	The approach was able to predict gas output using the algorithm.
BP	Salem et al., 2018	diagenesis; deep; GR log; neutron log; density log; sonic log; deep resistivity log	Porosity; permeability	Porosity and permeability were successfully predicted using the method.
ANN	Khan et al., 2018	calliper; porosity; gamma ray; density; neutron; three separate resistivities; gamma ray; density; neutron	Water saturation	Water saturation was predicted when the data was provided to the algorithm.
BBN	Ghoraishy et al. (2008)	Data from 59 wells	Gel treatment performance	The approach has an above 75% accuracy rate in predicting the target data.

Table 3. Applications of ML in production engineering.

4. Case study (Application of Machine Learning for Closure Pressure Determination)

Hydraulic fracturing destroys rock and generates a hydrocarbon fluid channel. Understanding rock stress helps design and execute fracturing treatments. Closure pressure equals formation breakdown pressure. Since hydraulic fracturing started, analytical methods including G-Function plot, G-dP/dG plot, square-root of time plot, and others have been used to calculate closure pressure. Due to the data analyst's bias, these methodologies must be objectively analyzed to better predict closure pressure. Machine learning teaches computers predesigned algorithms without programming. Complex mathematical models automate procedures based on critical learning aspects and predict accurately. ANNs eliminate subjectivity in closure pressure prediction in this paper. Neuronal systems include artificial neural networks. Neurons contain input, output, and hidden layers. Input, hidden, and output neurons are determined by end-result parameters. ANNs were created for closing pressure-dependent critical parameters. Data patterns predict output. Comparing this output to actual findings reduces error. Reduce mistake to align data. This article tests 20% and trains 80%. The ANN properly estimated closure pressure in this investigation.

4.1. Determination of closure pressure

After pressure testing, pressure, rate, and formation disintegration data are collected and reviewed. Closing pressure procedures differ by industry. Used are experimental/field measurement, analytical, and statistical methods. The methodology of experimental/on-field measuring techniques defines them. Hydraulic techniques such as hydraulic fracturing and sleeve fracturing, relief techniques such as surface relief and borehole relief, lifting techniques such as the flat jack and the curved jack, strain recovery techniques such as Anelastic Strain Recovery (ASR) and Differential Strain Curve Analysis (DSCA), etc. For determining closure stress, the square-root of time method, the G-function plot, and the GdP/dG plot are employed. The pressure versus square root of time graph is comprised of bottom-hole pressure on the Y-axis and square root of time on the X-axis. The study applies only fall-off or decrease data after the compressors have been shut down. On the curve, straight lines (formation disintegration and fracture extension) are depicted as tangents. The pressure data for the completely open fracture and the completely closed fracture will be linear. These tangents converge at the fracture closure pressure. The dimensionless G-function relates the shut-in time to the pumping time at a constant rate. The G-function plot identifies the closure pressure and fluid leakage coefficient. This diagram linearizes pressure during typical leak-off more effectively than the square root of time depiction. The G-dP/dG diagram is made by displaying the pressure derivative as a function of the G-function. Since the G-function is proportional to leak-off, its pressure derivative is constant. This diagram aids in the estimation of fluid leakage, fracture permeability, and fracture closure pressure.

4.2.Methodology

This research utilized five xyz field wells. Mini-frac experiments on these wells provide data. The mini-frac test bottom-hole pressure information has a high sampling rate. Therefore, pressure data can be utilized to derive geo-mechanical parameters such as closure pressure. 6 Analytical Procedure. The technique of analysis entails graphical interpretation of the square-root of time plot curve. The Y-axis represents bottom-hole pressure, while the X-axis represents the square root of time. Figure 15 illustrates an example of such a curve.

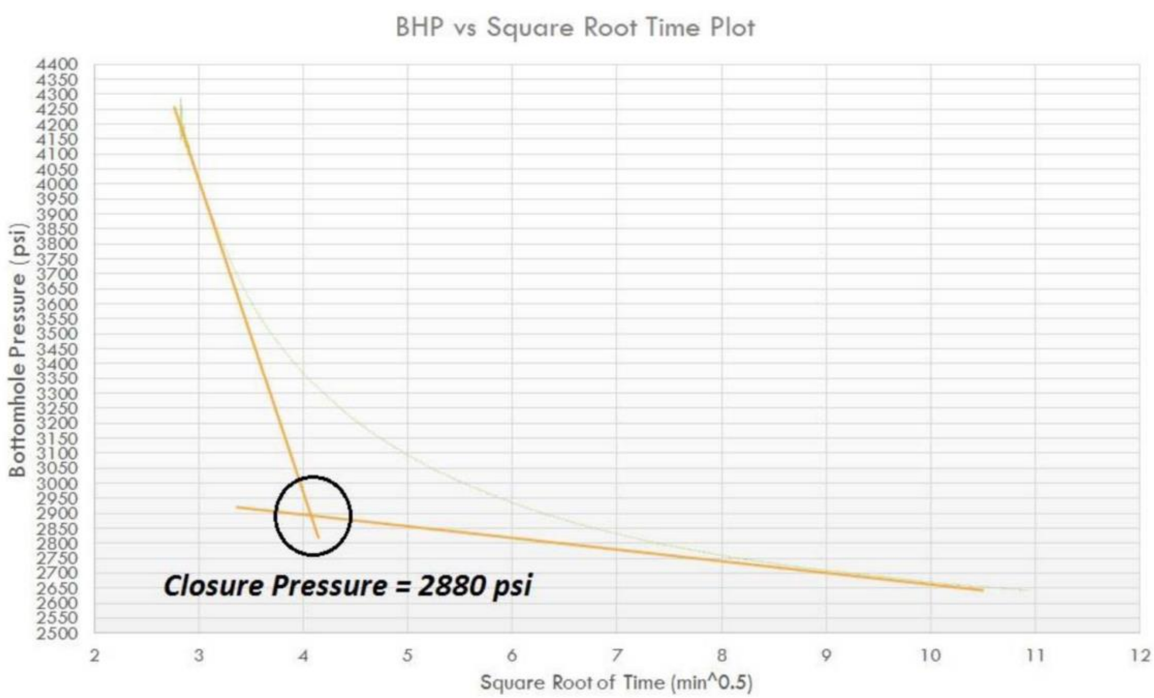


Figure 15. An example of a closure pressure curve (Nande, 2018).

The closing pressure analysis stages are:

1. Plot bottom-hole pressure vs. square root of time for each well.

2. Isolate the pressure decrease curve.

3. Plot tangents at straight line sections on the curve.

4. Determine the pressure at the tangent intersection.

5. This is good closing pressure.

Closure pressure for wells 1–5 was achieved by following these methods.

4.3. Machine learning approach

This section describes an innovative closure pressure technique. Artificial neural network, the most prevalent approach to machine learning, predicts well closure pressure. This analysis utilizes mini-frac data from five wells. Exist both training and test data. Using training data, the network forecasts the closure pressure. The trained network will evaluate the outcomes using test data. The network was trained utilizing information from three wells and validated utilizing information from two wells. This study employs a single-layer ANN architecture. Each bottomhole pressure measurement for a well is treated as a variable or feature by the input layer. Three output terminals. Each output layer node will evaluate the validity of the program by comparing the actual closure pressure to the predicted value for each well. Analytical values of closure pressure are used to program the network. The labels for input-to-hidden mapping weights are $\theta 1$. The weights concealed to output are also designated $\theta 2$. Minimize the output gap between the network and the desired output. The feed-forward method computes error $J(\theta)$. The feed forward technique employs a sigmoid function to convert the weighted sum of input variables for each layer into a logical output between $\theta 1$ and $\theta 2$.

4.4.Training the network

Construct the network and initialize the weight matrices $\theta 1$ and $\theta 2$ with random values to train it. Weights, bottom-hole pressure, and the regularization parameter λ are provided to the network. The feed-forward and backpropagation algorithms calculate the training set error $J(\theta)$ as well as the newly trained weights 1 and 2. Multiple iterations reduce the error in the training set. Using the same method, Lambda (λ) values from 0.0125 to 10.24 are calculated. For each value of lambda, the error, J (θ), and, θ1 and θ2 are calculated.

4.5.Testing the trained network

The test data set evaluates the network's performance after training. As stated, this study takes information from two wells. For each lambda value, the test set computes errors. Thetas need not be recalculated because the trained network already performs these computations. To predict precision, the lambda and theta values (θ1 and θ2) with the lowest error are chosen.

4.6.Results

This histogram compares J (θ) for different lambda values. Error for training set is blue and test set is orange. The training set and test set errors are shown for lambda values from 0.0125 to 10.24.

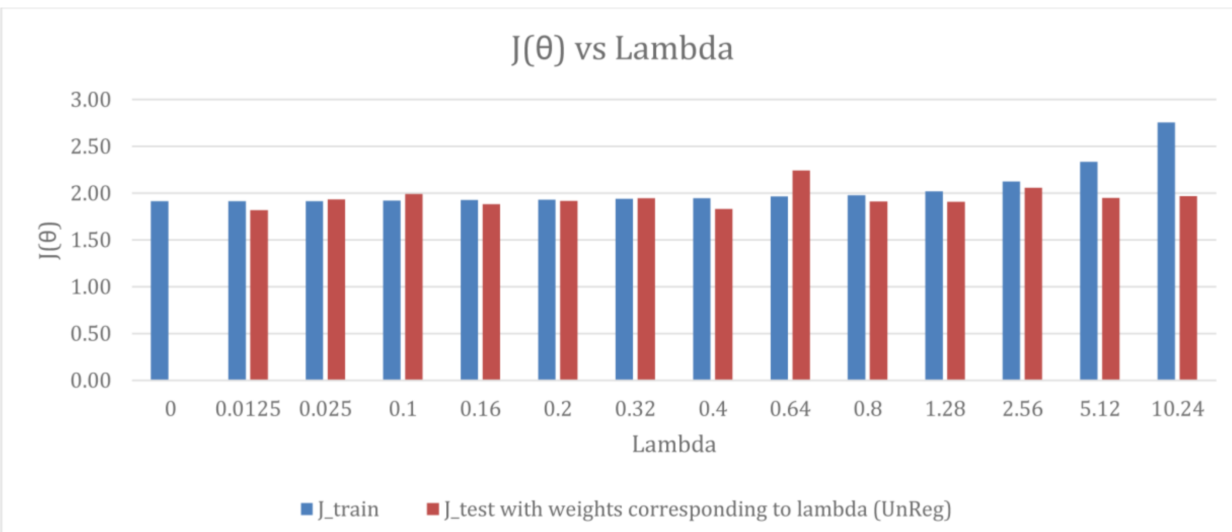


Figure 16. Histogram Chart Showing Error for Training and Validation Set (Nande, 2018).

As seen in the histogram above, lambda increases training set error (blue). Regularization increases as lambda rises. Lambda is a penalty imposed on the hypothesis (or model) in order to simplify it and reduce J (θ) cost. The model may oversimplify and underfit the data as lambda increases. Thus, lambda increases error J (θ). For the test set, thetas trained with training data were used. The accuracy of the trained network's predictions is evaluated by test data. This was repeated for the same lambdas to achieve the lowest test error. The test set error for Lambda = 0.64 is the highest in the preceding chart. Lambda = 0.4 minimizes test set error; consequently, it is utilized to forecast test data networks. The accuracy of the training set for lambda = 0.4 was 66%, indicating that the network accurately predicted the closure pressure for two out of three wells. With lambda = 0.4, the network accurately predicted the closure pressure for one of two wells. Due to insufficient training and testing data, the network's accuracy is subpar. A limited training and test set could cause the approximated error function to become confined in local minima. Since the local minima of a function are distinct from its global minima, the error may never reach the global minimum. Error cannot be minimized, so the model will never better match the data. Network performance deteriorates.

5. Current challenges of AI in oil and gas industry

Various oil and gas corporations, including Saudi Aramco, Gazprom Neft, BP, and Shell, are embarking on endeavors related to artificial intelligence (AI) through significant investments in emerging ventures and Research and Development (R&D) activities. Nevertheless, there exist various obstacles that hinder the capacity of stakeholders to efficiently and promptly integrate artificial intelligence (AI) into the exploration and production operations within the oil and gas sector. The aforementioned matter is not exclusive to the oil and gas sector, but rather a prevalent obstacle observed in the present phase of artificial intelligence advancement (Duan et al., 2019). The achievement of artificial intelligence is reliant on human intelligence. Artificial intelligence systems are not universally applicable and readily accessible for procurement. Regardless, when AI systems are created by external entities and provided free of charge, such as TensorFlow by Google, they need to be tailored to fit the unique business environment and data held by an organization (Ng, 2016). To enhance the integration of artificial intelligence (AI) in products and processes, it is recommended that organizations form internal teams comprising individuals with proficiency in information technology and AI. These groups ought to be afforded the chance to make contributions towards the progress of AI systems, encompassing algorithms and datasets, and, at the very minimum, to personalize tools that companies will subsequently utilize in their operations. In order for artificial intelligence systems to be trained effectively and function optimally, it is imperative to have a substantial amount of high-quality data. While the utilization of advanced algorithms has the potential to improve outcomes when dealing with limited datasets, it is crucial to acknowledge that no control mechanism can effectively address the issue of inaccurate or unreliable information (Ransbotham et al., 2017). Hence, the availability of comprehensive and high-caliber information plays a pivotal role in both enabling and limiting the progress of AI applications. Oil and gas fields produce a significant quantity of raw data. When considering all relevant factors, one can make the case that the Open Government Initiative (OGI) does not provide a guaranteed assurance of progress. This is primarily due to widely recognized challenges related to the dependability and precision of field data, as well as the overall limited availability of substantial amounts of verified data (Hajizadeh, 2019).

In order to optimize the informational assets held or attainable by oil and gas enterprises, it is crucial for them to reassess and adapt their organizational frameworks and activities. Oil and gas organizations are generally not acknowledged for their cohesive, efficient, and bottom-up approach to improvement. Nevertheless, their reputation is built upon their meticulous approach to regional segmentation and the implementation of cascading processes and strategies, necessitating occasional adjustments. Moreover, the incorporation of information accumulation ought to be executed in a centralized fashion, amalgamating the data into a singular or limited number of data repositories. This will enhance accessibility and utilization for both human users and artificial intelligence software. (Ng, 2016). The development of artificial intelligence (AI) is fostered in a collaborative and inclusive setting, predominantly propelled by the academic community. For a considerable duration, this has emerged as the prevailing factor in AI research, characterized by limited commercial influences. The advent of artificial intelligence has compelled organizations spanning diverse industries and geographic regions to adopt a culture of unrestricted knowledge exchange, as demonstrated by platforms such as GitHub, and open dissemination, as exemplified by platforms like arXiv. The necessity for organizations to adapt to this cultural shift has become crucial in order to achieve success in the era of artificial intelligence, thereby motivating them to actively engage in this competitive endeavor. The adoption of open innovation is progressively gaining prominence within the technology industry. Nevertheless, it is important to acknowledge that the collaborative endeavors of oil and gas companies in joint industries, particularly among competitors, are not widely acknowledged, particularly in critical areas such as artificial intelligence (Hajizadeh, 2019).

6. Future perspective of AI and ML in oil and gas industry

The presence of a conducive condition is contingent upon the extensive adoption of a framework that prioritizes the dissemination of information among various entities and across different domains. Anticipating rapid advancements in artificial intelligence (AI) capabilities across upstream, midstream, and downstream applications is a reasonable expectation due to the implementation of well-established and submitted initiatives in prominent organizations, as well as the availability of comprehensive information. The aforementioned progress will be accompanied by the advancement of artificial intelligence (AI) tools designed to facilitate dynamic operations across various levels. The authors exhibit a strong belief in the substantial potential for the progression of performability in OGI enterprises. The source of this optimism can be attributed to the significant allocation of investment funds towards expenses, as well as the capacity to minimize losses arising from suboptimal choices, which are anticipated to decrease by 50% in comparison to present levels. Moreover, it is crucial to take into account a substantial aspect of the ecological impact within this particular context.

The integration of artificial intelligence (AI) into business operations presents various possibilities for mitigating the negative consequences of technological advancements in upstream, midstream, and downstream sectors. For example, the implementation of a functional AI model can be utilized to mitigate the presence of harmful elements in well treatment procedures or to enhance the efficiency of recycling produced water, thus ensuring a suitable level of resource recuperation. The rational scenario arises when the IT platforms have been implemented, but the advancement of information sharing solutions is limited. The term "restricted" implies the existence of supplementary regulations regarding the distribution of resources, including the allocation of resources among various groups within a country. It is anticipated that specific artificial intelligence (AI) tools will gain recognition as valuable assets, leading to a shift in emphasis within the field of AI towards the development and utilization of grey box hybrid models. Within these models, the scientifically driven component that is grounded in physical principles will serve as a means to mitigate the limited availability of a significant volume of empirical data. The researchers posit that this particular scenario is the most rational, and it is expected to have a comprehensive influence on the upstream, midstream, and downstream sectors (Nishant et al., 2020). The capacity to proficiently engage with diverse subject matters and explore information empowers AI-driven startups to differentiate themselves and garner investments.

In 2019, AI-related organizations in the United States received a significant funding amount of $18.5 billion, indicating a notable rise of around $2 billion in comparison to the preceding year (O'brien, 2020). Prominent entities within the realm of artificial intelligence actively participate in the acquisition of emerging companies. Earth Science Analytics, a startup, has received investments from Saudi Aramco, a prominent energy company. The primary objective of this strategic initiative is to facilitate the advancement of artificial intelligence (AI) software in the field of oil geoscience, with the ultimate goal of laying the foundation for the future iterations of this technology.

BP has engaged in an investment endeavor by acquiring a stake in a startup named Belmont Technology. The primary objective of this investment is to augment the artificial intelligence and digital capabilities of the company, specifically within its offshore upstream business (Umar, 2019). Chevron, Saudi Aramco, and Shell have collaboratively founded a startup named "Maana" with a specific emphasis on artificial intelligence. The startup has engaged in a collaboration with Microsoft in order to utilize its distributed computing platform (Luck and Chronicle, 2019).

7. Detailed summary

From a holistic viewpoint of the industry, it is advisable to formulate a collaborative formal proposition through the collective efforts of scholars, top-level executives, and subject matter specialists. The objective of this proposal is to advocate for the establishment of a cohesive understanding and effective coordination among major oil companies, utilizing the institutional advantages inherent in our nation's socialist market economy. From a strategic standpoint, it is imperative for company leadership to priorities business orientation, problem orientation, and goal orientation. The aforementioned objectives can be accomplished by implementing integrated design, organization, and dissemination strategies. These strategies will enhance the efficiency of data flow, restructure business processes, and foster innovation, revolution, and transformation in the management approach. Finally, it is imperative to allocate equal emphasis to both software and hardware components from a disciplinary perspective. It is imperative to adhere to the principles of application-oriented approaches, which facilitate the mutual progress of both research and practical implementation. It is important to distinguish between the term "big volume of data" and the concept of "big data." The fundamental basis for the implementation of artificial intelligence (AI) applications is rooted in the utilization of standardized or normative data, as well as a repository of sample instances. The prioritization of data management is of utmost importance in the successful implementation of artificial intelligence (AI) applications. There exists a necessity to consolidate the process of data labelling, improve the interoperability of data, and strengthen data management. This is crucial in order to establish a resilient mechanism for data trust and a comprehensive framework for data management. This will enhance the process of standardizing and ensuring compliance with data sharing practices.

Currently, there is a noticeable deficiency in the realm of effective communication and mutual understanding between engineers specializing in AI algorithms and those working in the field of oil extraction. Moreover, in the process of transitioning from digitalization to intelligentization, there exists a prominent concern regarding the optimizations of production efficiency while simultaneously reducing resource consumption. This issue is observed to varying degrees. Concurrently, the development of interdisciplinary skills in the domains of petroleum exploration and development (E&D) and artificial intelligence (AI) poses challenges owing to the broad range of disciplines involved in both industries. Moreover, this procedure is characterized by a significant expenditure of time. There exists a necessity to augment the extent of collaborations between institutions of higher education and petroleum corporations, as well as between petroleum corporations and information technology enterprises, with the aim of cultivating the growth and advancement of individuals with exceptional abilities. Efforts ought to be undertaken to establish innovation consortiums that facilitate diversified fusion among oil enterprises, as well as between oil enterprises and IT enterprises, while also promoting interdisciplinary collaboration. This will enable the establishment of an efficient research and development system for AI technology in China's petroleum industry.

Within the framework of informatization construction, the oil and gas sector demonstrate the capability to proficiently manage the considerable volume of data that is both accumulated and consistently generated. Furthermore, the network and its constituent nodes possess a specific degree of computational capability. To promote the integration of intelligent technologies in the oil industry, it is crucial to undertake a research initiative centered on developing fundamental algorithms and establishing an algorithmic system with independent intellectual property rights. The subsequent table presents a selection of studies that have employed artificial intelligence (AI) in various sectors of the petroleum industry.

sector	AI Algorithm	Result	Author
Reservoir engineering	FL	Estimation of porosity and permeability of sandstone	Fang and Chen 1997
	ANN	Prediction of water saturation and distribution of fluids in a reservoir	Al-Bulushi et al., 2009
	ANN	predicted the porosity and permeability in a reservoir	Moghadam et al., 2011
Exploration	UAV	Prediction of porosity and permeability of subsurface reservoirs	Cawood et al., 2017
		Oil leakage detection	Mucsi et al., 2004
		identify hydrocarbon spills from a pipeline (threshold of 20 barrels)	Taylor, 2000
Production Engineering	ANN+SVM	The method was able to predict suitable artificial lift	Lui et al., 2020
	ANN	Optimization of the number of separation stages, pressure, and temperature	Mahmoud et al., 2019
	FL	keep track of the multiphase flow process' fluid output rate and steam composition	Alimonti and Falcone, 2004
Drilling Engineering	ANN	Bit type and performance prediction	National Oilwell Varco, 2013
	BPNN	Can predict collapse depth and probability of collapse	Salehi et al, 2007
	ANN	The technique makes predictions for slurry performance	Fletcher et al., 1994

Table 4. Applications of AI in different sectors of the petroleum industry.

8. Conclusion and recommendations

This paper presents a comprehensive examination of the recent progress made in the domain of artificial intelligence (AI) and machine learning (ML), along with their practical implementations in the oil and gas sectors. This paper presents a compilation of noteworthy instances wherein machine learning techniques have been utilized in the domains of exploration, reservoir analysis, drilling, and production. The literature review regarding the oil and gas industry is well-positioned to exploit the benefits of machine learning due to its capability to manage substantial amounts of data and execute computations swiftly. The current paper provides an overview and analysis of various supervised learning techniques. The utilization of machine learning in the oil and gas industry holds the promise of substantially altering the decision-making procedures conducted by administrators and engineers, thereby influencing a diverse array of crucial activities carried out on a daily basis.

The effective utilization of diverse data types or structures can lead to the realization of potential benefits associated with information. This transformation of data into valuable information enables informed decision-making. Various solutions, including Artificial Neural Networks (ANN), Additive Layer Manufacturing (ALM), supervised learning, fuzzy logic, linear regression, and Principal Component Analysis (PCA), can be employed to tackle the challenges faced in the oil and gas sectors and enable the formulation of lucrative strategies. It is anticipated that there will be a significant increase in the utilization of machine learning, specifically in the oil and gas industries, in the forthcoming years. The accelerated adoption of machine learning is expected to transpire swiftly, leading to substantial value generation for the respective industries.

The incorporation of both short-term and long-term strategies is imperative, as it enables the efficient application of successful experiences from specific instances to promote the extensive implementation of artificial intelligence. In order to foster collaborative innovation, it is imperative to consider a range of factors including top-level design, data management, allocation of research and development resources, talent cultivation, and value augmentation. The proposed strategy involves improving understanding and supporting educational interventions, specifically targeting individuals in diverse managerial roles. In order to create an ideal setting for the advancement of scientific and error-free artificial intelligence (AI) applications, it is crucial to give precedence to certain key domains. These include business applications, fundamental research, gradual dissemination of individual achievements, and the establishment of supportive management systems.

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