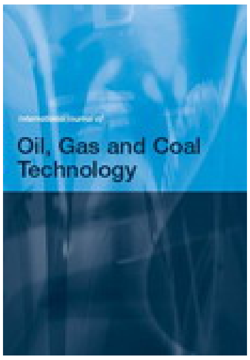

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Detection methodologies on oil and gas kick: a systematic review

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Detection methodologies on oil and gas kick: a systematic review

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Abstract: A gas kick might lead to disastrous consequences if it is not early detected and adequately mitigated. The current study provides valuable information about the latest methodologies developed as responses to a kick. A PRISMA systematic review was conducted to research the latest methods and techniques during the last decade. The review results were presented and discussed in a comprehensive and classified approach. It is worth noting that several new early kick detection approaches have been developed during the last decade. Most of the discussed developments focused on filling the gaps in the currently applied methodologies centred on traditional approaches for analysing kick's behaviour. However, due to the complex behaviour of such an event, several factors were usually oversimplified, leading to the compromised accuracy of the methodology. Recommendations were also proposed for analysing the kick's behaviour using modern and robust techniques such as computational fluid dynamics. [Received: June 28, 2022; Accepted: October 17, 2022]

Keywords: oil and gas drilling; well control; kick detection; kick prediction; PRISMA analysis.

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1 Introduction

During the oil and gas drilling operations, the unscheduled reservoir or formation fluid entry into the wellbore is called a ‘kick’. A kick occurs when the downhole wellbore pressure is less than the pore pressure of the formation, which allows the kick influx to escape to the surface. A well explosion, known as a ‘blowout’, might occur if the kick is not detected early and appropriately mitigated. The catastrophic consequences of a blowout can heavily affect and damage the environment, the financial and social status of the involved companies and even worst, it can cost human lives (Forage, 1981).

A drill rig is utilised during conventional drilling operations to develop a safe and integral conduit between the hydrocarbon-bearing formations and surface facilities. A drill string is utilised to drill down into the earth’s crust, among other essential surface equipment. The drill string consists of drill pipes and the bottom hole assembly (BHA), where all the specialised devices are installed. At the lower end of the BHA, a drill bit is attached to break the formation rocks under controlled applied weight. A fluid called drilling mud then removes the formation cuttings. The drilling mud is circulated from the surface through the drilling string, down to the drill bit, returning to the surface across the borehole’s annular space, carrying all the crushed rocks within. Additional functions of the drilling mud are to lubricate and cool the drill bit, seal off the porous formations by creating a mud cake, prevent any undesired flow from encountered strata and provide stability to the borehole by preventing it from collapsing (Abraham, 1933). Most importantly, it is used to counterbalance the formation pore pressure by delivering the required hydrostatic pressure (Hossain and Al-Majed, 2015).

The unscheduled formation fluid influx into the wellbore can occur in two fundamental ways: by reducing the hydrostatic mud column or the mud density. Both reasons can lead to a low bottom hole pressure allowing the formation hydrocarbon fluids to enter the wellbore. The loss of mud circulation into the formation or the improper hole fills up while tripping in and out of the well may reduce the height of the mud column. Since the bottom hole wellbore pressure is a product of the mud weight and the height of the mud column, the reduction of the mud column can lead to a reduction of the hydrostatic pressure allowing the formation fluids to enter the wellbore. On the other hand, the mud weight is usually programmed by estimating the formation pressures by conducting wireline or real-time logging of the well or by using available data from nearby offset wells and seismic surveys. Safety factors must be applied to the acquired data to reduce uncertainty. Nevertheless, these data can sometimes lead to incorrect estimations of the formation pressure. For instance, if an incorrect density is programmed and used for the drilling mud due to the underestimation of the pore pressure, the result will be a lower wellbore pressure that might lead to a kick of the formation fluids into the wellbore (Raabe and Jortner, 2021).

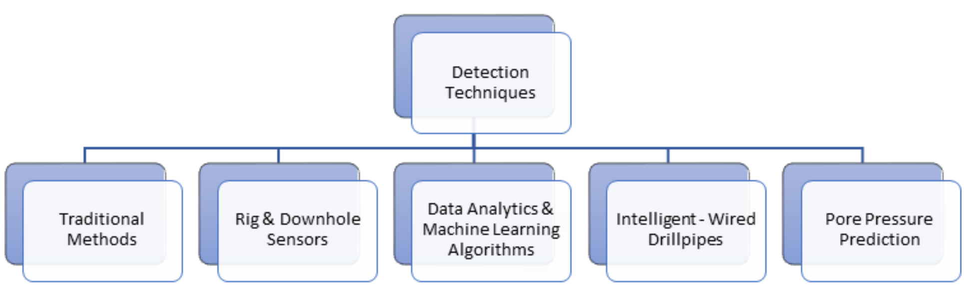
During primary control of the well, drilling mud is used as the primary barrier of the operation to restrict the hydrocarbons into the formation. By losing the primary well control, the formation fluids enter the wellbore, trying to reach the surface violently. As this kick fluid travels towards the surface into incrementally lower pressure regions, it expands and occupies more space. A blowout might occur if the kick reaches the surface and an ignition source is present. Secondary well control principles must be implemented to avoid this catastrophic event, and the kick fluid must be restricted into the wellbore. It can be done by isolating the well by closing the valves of the blowout preventer (BOP).

Heavier drilling mud, called kill mud, is then circulated in the well to displace and discharge the kick out of the well safely. If the kick is not detected early and passes through the BOP to the surface, the secondary well control is lost, and there is a high probability that the well will blow out. In this case, tertiary well control principles must be used to drill a relief well to stop the uncontrolled flow of hydrocarbons to the surface (Grace, 2017).

Several kick response methodologies and mechanisms were developed and evolved over the years to detect the kick occurrence and prevent the underlying blowout of the well. Kick detection is usually performed using the industry's well-established techniques. Such traditional methods are based on alarms and observations of the leading drill rig equipment and components (Maus et al., 1978). An increase in mud pit level or flow in the flowline while mud pumps are shut off could be strong indicators of kick occurrence (Anfinsen and Rommetveit, 1992; Maus et al., 1978). New devices, equipment and methodologies were built to detect a kick based on such or equivalent principles. Surface and downhole sensors attached to the BHA were developed utilising various engineering rules and theories (Hall et al., 2017; Pournazari et al., 2015). The oil and gas industry has also adopted machine learning algorithms and data analytics. In several cases, computer-based models were created to assist the kick detection or even predict such an event (Yang et al., 2019b). In addition, mathematical models, in combination with downhole equipment, produced robust and sophisticated systems to predict the formation pore pressure and, ultimately, detect the occurrence of a kick (Effiowan et al., 2014).

Based on the literature review, the detection techniques can mainly be categorised into traditional methods, rig and downhole sensors, models based on data analytics and machine learning algorithms, intelligent drill pipes and methods that directly predict the pore pressure (Figure 1).

Figure 1 Classification of detection techniques (see online version for colours)

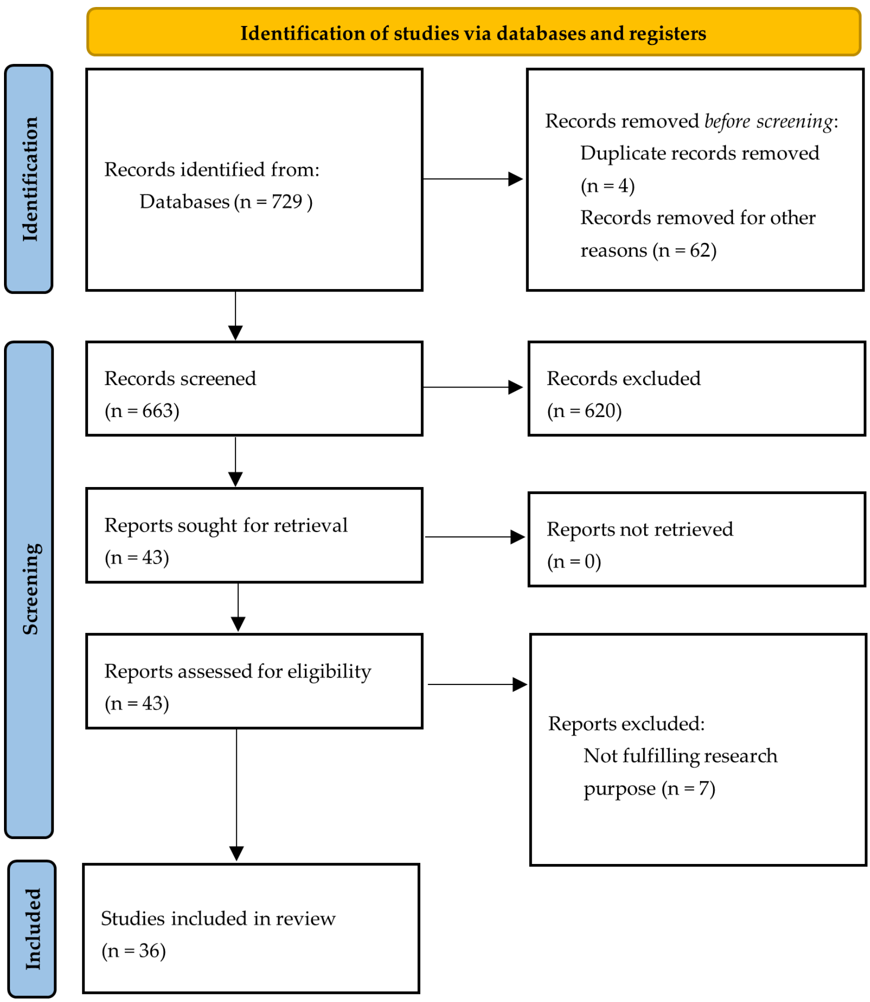


The primary objective of this study is to research and discuss the currently available methodologies used to respond to such catastrophic events. The study also aims to define the current framework that the existing methods were built on top of and propose new potential development paths to be followed by the researchers.

2 Review method

A systematic review of the currently used kick response methodologies was conducted using the preferred reporting items for systematic reviews and meta-analysis (PRISMA) system. Such an approach provides the reader with an easy and comprehensive understanding while simultaneously confirming the validity of the results and conclusions of the current research. The literature selection process is illustrated as a flowchart in Figure 2. OnePetro and ScienceDirect databases were used for the literature search. The research was conducted from April 17, 2022, to April 27, 2022, and the search results correspond to these dates. The search terms 'kick detection methodologies' and 'kick detection' were used in OnePetro and ScienceDirect databases, respectively, searching within the article title, abstract and keywords. The search results were narrowed down to relatively recent literature by applying a date filter, and only publications after 2012 were shown.

Figure 2 Literature selection process – PRISMA flow diagram (see online version for colours)



A total of 729 results were returned by the databases (655 by OnePetro and 74 by ScienceDirect), and four duplicates were initially excluded. Proceeding papers and journal articles were chosen for this literature research, so any other types of results, such as images, were excluded. Hence, 663 papers were considered for screening after removing the 62 images found in the OnePetro search results. Due to the broad usage of the search terms in the oil and gas literature, several papers had to be screened out as they were irrelevant to the current research topic and did not match the actual search criteria. Consequently, 620 papers were excluded after screening their title and abstract, 555 from OnePetro and 65 from ScienceDirect databases. Afterward, the resulting 43 papers were assessed for eligibility.

Seven papers were excluded when reading and analysing the actual content of the 43 retrieved results since they were not explicitly focused and oriented to the research topic. Consequently, they did not fulfil the current research purposes. Finally, the resulting 36 papers were included in the research and discussed next.

3 Literature results and discussion

The kick response methodologies mainly focus on early kick detection or even prediction by utilising various techniques and equipment. The conventional primary and secondary kick indicators are usually used to identify the kick occurrence. As the drilling environment differs across each geographical area and, at the same time, harsh conditions are encountered in new ultra-deepwater and high-pressure high-temperature (HPHT) wells, early kick detection becomes vital to sustaining the well control integrity.

Table 1 Common kick detection techniques

Detection mechanism	*Detection system*
Change in mud flow rate	Flow-out sensors
Increase in mud pit/trip tank volume	Level sensors
Well flows with shut-off pumps	Perform flow-check
Pore pressure monitoring	d-exponent factor

The most common kick detection mechanisms used in the past years are the change in mud flow rate, the increase of mud pit level, the annular flow when the mud pumps are shut off and the d-exponent factor (Table 1). Flow-out sensors are used to measure the change in mud flow rate, but another indicator must also be used to verify the existence of a kick. Sonar and other types of sensors are used to average the mud pit volume, aiming to detect a possible increase in the mud pit level due to the kick. Usually, even a slight increase in the mud level could be interpreted as several barrels of mud volume due to the large surface area of the mud pits. Typically, a flow check is performed after the pit volume increase to verify a kick's existence. A more accurate reading can be obtained by the level increase of the trip tank, where even a quarter of a barrel can be detected. Even though a trip tank is a reliable indicator, it can only be used while the drilling mud is not circulated. These volume indicators usually tend to be ignored, due to the establishment of several false alarms, that unfortunately lead to a trend to ignore the alarm when it becomes real (Fraser et al., 2014).

Another common way of detecting a gas kick is the 'd-exponent' factor. This factor is calculated by extrapolating several downhole parameters usually obtained in real time. D-exponent can be calculated using equation (1), where R = penetration rate (ft/hr),

d = exponent in drilling equation, N = rotary speed (rpm), W = weight on bit (Klbs) and D = bit size (inch).

$$d = \frac{\log\left(\frac{R}{60N}\right)}{\log\left(\frac{12W}{1{,}000D}\right)} \tag{1}$$

Pore pressure is then estimated and monitored. A different trend in pore pressure than the one already considered may indicate a kick (Ahmed et al., 2016). It must be noted that the given formula is only valid for constant mud weight, and in case of any fluid formation influx, the estimations will be altered. For this reason, companies prefer to use the modified or corrected d-exponent (d_c), which includes a correction for the mud density used compared to the initial mud density estimated for the respective regional profile. This method must be adjusted to the hydrostatic pressure profile of the respective field to avoid the misleading output of the d_c. The corrected model must be re-evaluated after collecting enough data to improve its accuracy and representation of the drilled basin. The corrected d-exponent can be calculated using equation (2), where MW_1 is the initial mud weight, and MW_2 is the actual mud weight (Zhou et al., 2004).

$$d_c = \frac{\log\left(\frac{R}{60N}\right)}{\log\left(\frac{12W}{1{,}000D}\right)} * \frac{MW_1}{MW_2} \tag{2}$$

Real-time mud logging can also help identify a kick by sampling the rock cuttings and the returned mud fluid. Based on this principle, Ahmed et al. (2016) proposed a methodology that utilises mud logging with downhole parameters, detecting even a small kick at near balance conditions.

Surface and downhole sensors, pressure gauges, measuring while drilling (MWD) and logging while drilling (LWD) tools are also used to detect a kick (Nayeem et al., 2016). Most commonly, these tools and methods estimate the pore pressure of the formation and a kick can be identified by monitoring these trends.

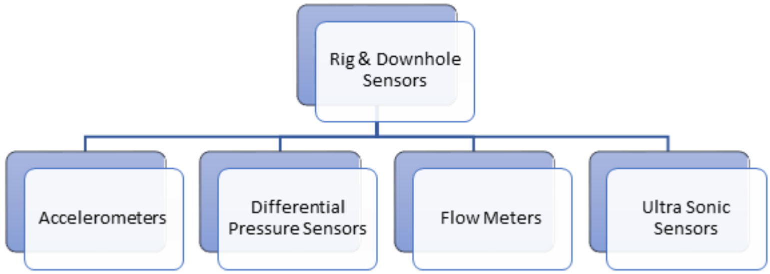
The traditional kick response methodologies, previously described, mainly rely on the judgment of the driller and the drilling crew. Consequently, the well control might be dangerous in such a case. Automated systems have been developed to minimise human error and provide more reliable kick detection approaches (Atchison and Sarpangal, 2022).

Detection methodologies can be classified into five broad categories, the traditional methods, as described above, rig and downhole sensors, methods including data analytics and machine learning algorithms, intelligent drill pipes and methods aiming to achieve direct pore pressure prediction. The most recent techniques and developments in kick response methodologies are presented below.

3.1 Rig and downhole sensors

Several rig and downhole sensor developments have been established during the last decade and are presented in Figure 3.

Figure 3 Generalised rig and downhole sensors (see online version for colours)



The articles of the respective developments are also summarised in Table 2, and the corresponding authors are also provided. Backflow is usually monitored during tripping the well and while connections are made to check for a kick. This backflow fingerprint monitoring utilises alarms whose values and thresholds are set manually. The responsible engineer usually monitors the identification of abnormalities in flow, and the whole process heavily depends on his intuition. Ali et al. (2013) developed and deployed an automated backflow monitoring system that intelligently sets the alarms. This self-adjusting alarm technology resulted in an earlier and more accurate kick or loss detection.

A simple downhole device connected above the MWD-LWD devices was proposed by Trivedi (2014) as a mud rerouting tool. This tool consists of two plates at a specified distance where voltage potential is applied across them. Any alteration to the medium due to the invaded kick fluid will change the capacitance, and the transmitted signal can immediately detect the kick. Nevertheless, several drawbacks of the system are identified, such as its effectiveness in oil-based mud's, its cost and the cutting intrusion to the system. Oil-based mud is usually utilised while drilling the well's production section, which might be one of the most prone to kick sections. Consequently, the effectiveness of this device in such environments should greatly be improved before its actual application.

A simple and cost-effective solution to kick detection is called the Differential Flow Out. A high-accuracy flow metre is installed in the flowline to measure the flow rate of the returned mud, and the measured flow rate is then compared to the theoretical computed flow rate. A decrease in the differential flow rate would sign mud losses in the formation, while an increase would indicate fluid influx into the wellbore (Dow et al., 2022). Another related solution was researched by Zhou et al. (2021), where a pair of sensors is installed along the well's riser at the section where the gas expands violently. The differential pressure is recorded, and the kick might be identified. Even though this method could detect the gas's existence, the relative time to respond from the detection time might be minimum.

A sensitivity analysis for well-control procedures and kick detection was performed by Brakel et al. (2015) in order to evaluate the response of the rig sensors and alarms. The analysis showed that the sensors' accuracy and how the driller is alerted by the alarms are equally important. An actual system equipped with improved kick detection software was built and successfully tested on an actual drill rig. The frequency of false alarms on such systems is also fundamental and should be considered. The drilling crew usually ignores or slows down their response to an alarm after getting several false alarms.

Kick detection in subsea wells might be challenging due to the high volume of mud contained in the riser. A system located at the subsea mudline level was proposed by

Toskey (2015), where ultrasonic and hydrostatic sensors measure the density of the fluids. Minimal changes in mud weight, even less than 0.01 ppg, can successfully be detected by the system, which improves the detection time up to three times compared to the traditional methods.

The viscosity of drilling mud in the annulus is reduced when a kick influx occurs, leading to the damping factor's degradation. Samuel (2018) proposed a method where accelerometer sensors are installed on the drill pipes, measuring the change in velocity and acceleration. This system also utilises an analytical model to calculate the damping ratio in fluid acceleration. Subsequently, the vibration signal combined with the calculated damping factor could be used as a kick indicator. Based on this research, it can be verified that the calculation of the damping factor can result from the utilisation of the vibration signal. A cross-validation of the obtained information could also be done by installing multiple sensors at the bit level.

A digital system with real-time monitoring of sensor data and drilling parameters was demonstrated by Mayani et al. (2019) in order to produce a system that detects anomalies early during the construction of the well and prevents costly and disastrous events such as a kick. A digital well was developed using advanced mathematical models to represent the actual well. The real-time data from the drilling operation were transmitted to the system, where diagnostics and simulations run. An actual three-dimensional representation of the well was also available, and automatic predictions were performed. A successful example of the system's efficiency was the event of a stuck pipe, diagnosed fifteen hours before the pipe was completely stuck. Such a system can produce accurate results, but its installation and monitoring complexity and cost usually prohibit its usage in smaller-scale applications.

Table 2 Rig and downhole sensors developments

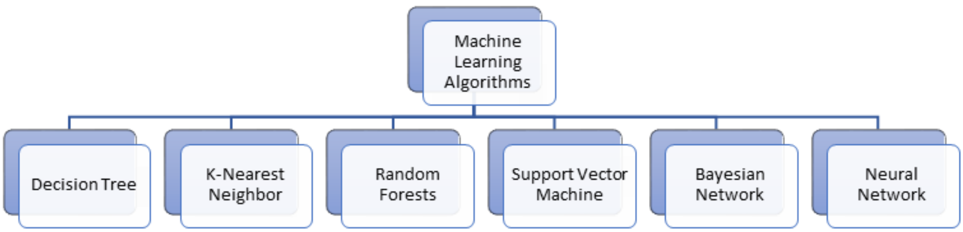
Detection method	*Developed by*	*Year*
Automated flowback monitoring system	Ali et al. (2013)	2013
Downhole device	Trivedi (2014)	2014
Ultrasonic and hydrostatic sensors	Toskey (2015)	2015
Accelerometer sensors	Samuel (2018)	2018
Real-time monitoring and simulation	Mayani et al. (2019)	2019
Formation differential pressure	Yang et al. (2019a)	2019
Formation differential pressure	Wang et al. (2020)	2020

Downhole measurement tools can measure the bottom hole's annular and formation differential pressure. Based on these data, Yang et al. (2019a) developed a pressure fluctuation model that can improve kick detection accuracy by accounting for the transient annular pressure variations based on two-point measurements. A gas kick volume of 0.5 cubic metres was confirmed in less than seven minutes of its occurrence. Wang et al. (2020) also studied dual measurement points without requiring surface or drilling data. They also developed a supervised neural network system to calculate the density and viscosity in static and circulating conditions. The model was validated by two experimental datasets raising successful and accurate results.

3.2 Data analytics and machine learning

Sophisticated surface and downhole sensors have been developed over the last years to detect and predict costly and disastrous events during drilling operations. Even so, the elevated cost of such systems usually prohibits their use in smaller rigs and field developments. Machine learning and data analytics are recently evolved and have been utilised by the oil and gas industry, aiming to improve the accuracy of conventional sensor-based detection systems. Figure 4 illustrates the general machine learning algorithms used by the researchers.

Figure 4 Graph of primary machine learning algorithms used for kick detection models (see online version for colours)



The models designed and developed during the last decade are summarised in Table 3, and the corresponding researchers are also provided.

Pournazari et al. (2015) presented a pattern recognition system with methodologies for real-time sensor calibration. The system was based on machine learning techniques and physics-based models, demonstrating how the applied real-time calibration on simple sensors enhanced the accuracy of the data obtained by sensors. Machine Learning algorithms heavily rely on the provided datasets. Even though the results are promising for a specific case, more datasets must be incorporated to test the algorithms and increase the accuracy of the results. False alarms must also be considered, aiming to reduce the frequency of their occurrence.

Alouhali et al. (2018) also used several machine learning algorithms to develop kick detection models that utilised surface data and drilling parameters. Decision tree and K-nearest neighbour models produced high accuracy results with short detection time and relatively low consumption in processing power. The physical formation, fluid and drilling parameters that can describe the drilling process were also used by Isemin et al. (2019) in combination with the power of data analytics and formation modelling to produce an accurate model for kick detection. They resulted that due to several layers of verification, higher detection accuracy can be achieved while minimising the critical time needed to estimate the kick occurrence. Additionally, such methods can become very specific and oriented to the actual formation being drilled, avoiding generalised and error-prone approaches. Such an approach might be attractive, but in case of changes in the input environment the model might fail. In addition, it is difficult to evaluate such a model in terms of its physical meaning that might also lead to incorrect predictions.

Hybrid models consisting of combined algorithms are also used for kick detection. These models use real-time data from downhole and surface sensors in combination with the drill string and casing specifications. Measurements such as flow in and out, mud and trip tank volume, pump strokes and specification are the most common inputs among other data. The novel achievement in these models is their capability to handle alterations due to various personnel operations affecting the system's inputs (Yalamarty et al., 2022). Fan et al. (2021) developed another theoretical model based on an analysis of the pressure derivative, which aids in improving the accuracy of the detection. The method resulted in the earliest possible detection based on optimising the gas influx control and experiments conducted on actual test wells.

Conventional kick detection methods usually are costly with increased response time. Shi et al. (2019) also studied artificial intelligence algorithms to develop models to detect formation influx and losses. The random forests and support vector machine algorithms were used by combining real-time and historical drilling data. After the models' processing and calibration, the resulting detection accuracy exceeded 90%, demonstrating the potential of merging machine learning and drilling data to provide new ways of kick and loss detection.

Early kick detection is usually accompanied by an increased chance of false alarms. Osarogiagbon et al. (2020) presented a methodology to reduce this chance by using recurrent neural network algorithms with d-exponent and standpipe pressure data as inputs. Satisfactory results were obtained by using the peak reduction in the standpipe pressure and the slope of the d-exponent. Another type of machine learning algorithm, the Bayesian network, was used by Nhat et al. (2020) in a similar approach by using only downhole data to minimise any delay in the kick detection. Similarly, quantitative analysis to enhance the reliability of detection system sensors based on the Bayesian Network algorithm was conducted by Jiang et al. (2020). The success of such models emphasises the advantage of machine learning data-driven models to provide solutions to complex problems such as the formation kick influx and loss circulation.

Table 3 Data analytics and machine learning detection models

Detection model	*Developed by*	*Year*
Pattern recognition	Pournazari et al. (2015)	2015
Decision tree and K-nearest neighbour	Alouhali et al. (2018)	2018
Data analytics and formation modelling	Isemin et al. (2019)	2019
Random forests and support vector machine	Shi et al. (2019)	2019
Recurrent neural network	Osarogiagbon et al. (2020)	2020
Bayesian network	Nhat et al. (2020)	2020
Bayesian network	Jiang et al. (2020)	2020
Supervised data-driven model	Muojeke et al. (2020)	2020
Time series analysis	Magana-Mora et al. (2021)	2021
Data analytics	Yalamarty et al. (2022)	2022

Similar studies focusing on machine learning approaches such as supervised data-driven models, time series analysis and data analytics were also conducted during the last two years by Muojeke et al. (2020), Magana-Mora et al. (2021) and Yalamarty et al. (2022).

The oil and gas industry is progressively adopting machine learning and data analytics in most sectors during the digitalisation era. Decision-making based on such algorithms can be vital in reservoir characterisation, drilling and well simulation. Risk mitigation and general drilling strategies already incorporate machine learning algorithms to improve accuracy and cut costs. Even so, it seems that the industry is adopting such technologies slowly, trying first to improve and harness the new capabilities of artificial intelligence, keeping operations and decisions safe.

3.3 Intelligent – wired drillpipes

Sophisticated surface and downhole sensors have been developed over the last years to detect and predict costly and disastrous events during drilling operations. In most cases, kick detection is achieved by surface sensor measurements. Downhole data are also available, but due to the limited bandwidth in the wireless transmission systems, other subsurface data are usually prioritised and obtained at the surface. Newer developed methodologies provide higher bandwidth rates by using wired drill string systems, which can transfer high volumes of data to the surface in real-time. Several pressure points can be placed along the drill string to produce the actual wellbore pressure profile. Any fluctuations in pressure at any depth can be analysed and examined. These data can be combined with surface measurements or used independently, while even a small amount of formation fluid influx can be early and accurately identified (Veeningen, 2013b).

Using the ‘intelligent’ drill pipes, when a kick occurs, the pressure along the drill string is simultaneously recorded by the sensors. By plotting the pressure derivative curves and considering the travelling time of the fluid between the measuring points, the precise depth of the kick can be identified. Intelligent wired drill pipes can drastically decrease the time required for kick detection; in some cases, this time decreases by half (Karimi et al., 2014). Due to the discrete acquisition of annular pressures, the fluid level in the annulus can be calculated even in cases where the weight and height of the mud column are unidentified. Additionally, migration of the formation gas to the annulus can be monitored in case of losses. This real-time bottom hole pressure analysis and evaluation offered a fast way of regaining the well control after the kick occurrence (Veeningen, 2013a; Karimi et al., 2014; Carpenter, 2015a). A simplified schematic of intelligent or wired drill pipes can be seen in Figure 5.

Mud density and flow rate can be calculated using the differential pressure of two points along the drill string. Differential pressure sensors are also attached to the drill string and are connected to the wired system, transmitting data to the surface in real time. The reliability of these sensors was tested in HPHT wells with a maximum error of less than 0.02% (Hall et al., 2017). Bjørkevoll et al. (2018) showed in their study how additional modelling of the obtained downhole data improves the reliability of the results. Modelling was based on physical models, while the resulting data provided information about the gas distribution in the annulus and the severity along the wellbore. This study revealed how the real-time measurements, in combination with modelling, provided a detailed and accurate view of the actual downhole conditions and well-loading, resulting in a robust kick monitoring and detection system.

Intelligent drill pipes have significantly improved during the last few years. The two-way data communication systems, which run on high transmission rates and the provided pressure and temperature profiles along the drill string, significantly contribute to better analysis and control of any formation fluid influx. The limited usage of such a system is due to two fundamental challenges: the drilling string complexity and the elevated cost of the equipment. Making and breaking connections on the rig floor needs a more complex and time-consuming approach. The wires and their connectors on the drill pipes are exposed to the walls of the well, while unexpected loads could potentially damage them. Even though the outcome of using such a system could lead to the above-mentioned benefits, the whole operation becomes more complex and prone to errors. In addition, the drilling operation costs increase as the cost of the wired drill pipes is elevated and new surface equipment is needed to translate and analyse the signals. Intelligent drill pipe technology is continuously improving and building on top of more sophisticated systems and robust materials. Ultimately, the technology will be more approachable to smaller-scale projects, providing real-time and bi-directional data transmission at a low cost and compact procedure.

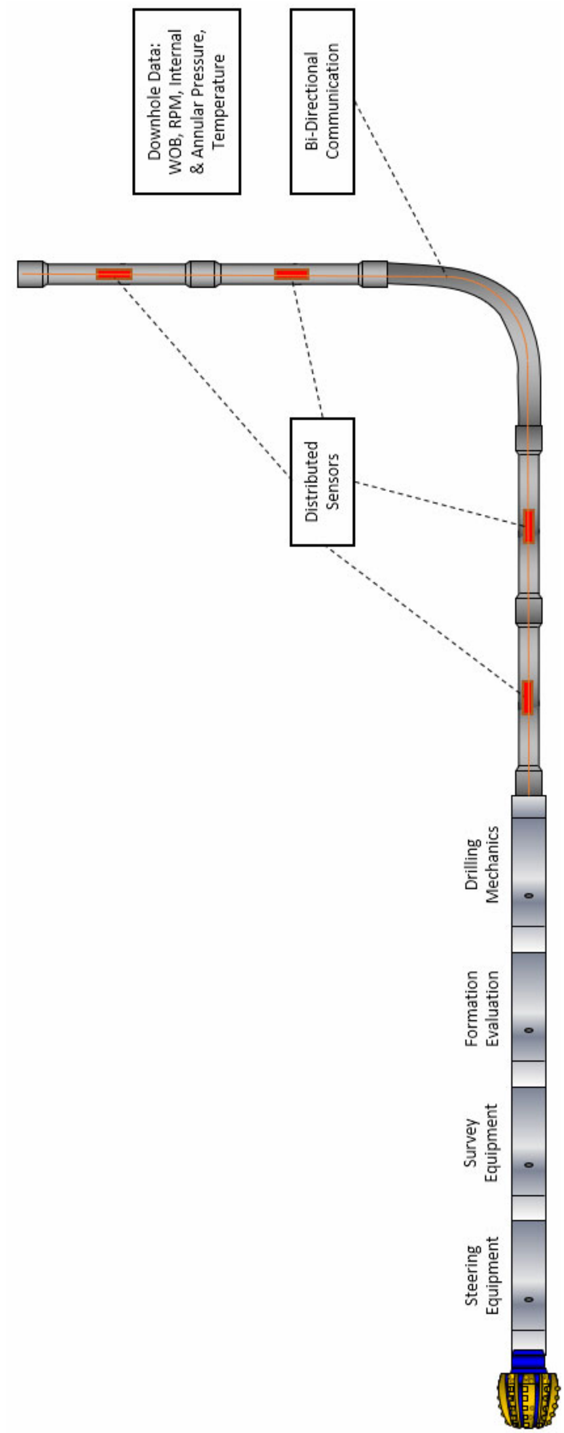
3.4 Pore pressure prediction

Several techniques have been evolved and developed to predict the formation pore pressure during the last years (Table 4). The formation pore pressure is initially estimated using mathematical correlations and data from seismic surveys. The formation pore pressure can be detected and calculated during the drilling operation in real-time or lagged time. Downhole data are gathered by MWD and LWD and other sensors installed at the BHA, and the data are transmitted and analysed at the surface (Chettykbayeva et al., 2020). Real-time pore pressure estimation is usually divided into quantitative and qualitative techniques. The former techniques usually require data such as rock resistivity, sonic and shale density; the latter utilises data such as rate of penetration (ROP), torque and drag, and the flowline temperature (Villacastin, 2012).

Rock cuttings and drilling mud also carry valuable information to estimate the pore pressure. However, the actual measurements are obtained after sampling, available only when mud and cuttings have been transferred to the surface. Wireline logging and pressure tests are usually performed after the drilling operation to confirm the pressure profile of the formation (Hossain and Al-Majed, 2015).

Manríquez (2013) proposed a passive high-resolution magnetotelluric (MRH) method to predict the formation pore pressure before drilling occurred. Same as wireline logging, the pressure prediction of this technique was indirect, and interpretation of the acquired data was required. Seismic surveys could also be used to estimate the pore pressures through the interval velocities acquired during the surveys. Several assumptions are usually made. For instance, the pore pressure was assumed to be directly related to the formation's porosity and that the rock velocities depended on the porosity and lithology, even though there might not be a relevant connection with the effective stress of the rock. Carpenter (2015b) presented a pore pressure prediction technique using seismic data based on frequency instead of interval velocity, which removed all the assumptions made between porosity and effective stress. The theory of effective stress was usually used to relate physical parameters to effective vertical stress.

Figure 5 Simplified schematic of intelligent-wired drill pipes (see online version for colours)



Consequently, the model cannot be estimated accurately and requires the normal compaction trend. Lei et al. (2019) presented a method to predict formation pore pressure using bulk modulus. In this model, the accuracy of the normal compaction trend was improved by simulating the bulk modulus and the normal compaction velocity.

Pore pressure prediction before drilling the well is getting more challenging as deeper HPHT wells are drilled. Due to the limitations of the seismic predictive methods and the associated uncertainties and errors, pore pressure prediction becomes more challenging and error-prone (Maulana et al., 2018). Many models incorporate wireline logging data and formation strengths that may again lead to errors due to the applicability of the models to clean shales and pressures generated only under-compaction. A study was conducted by Ahmed et al. (2019) using support vector machine artificial intelligence algorithms. The resulting model could calculate the formation and fracture formation pressures without needing pressure trends by only providing the real-time surface drilling parameters. The model achieved an accuracy of 99.5%. Due to the high cost of real-time logging, it is not always available during drilling operations. Bui et al. (2022) propose a predicted acoustic log in case of the absence of a measured sonic log. Physics-based models and a gradient boosting model were combined with three different data sets to train and validate the algorithm. The resulting model utilised the acoustic log to predict the formation pore pressure. As per the results, the model's accuracy was high, and the prediction could be achieved in real-time.

Pore pressure prediction or estimation can be challenging in most cases, especially when an over-pressurised zone is to be encountered. The development of the above-mentioned methodologies contributes significantly to detecting a kick, but several assumptions still have to be made. An accurate kick detection methodology should minimise or completely remove any assumptions from the models, while complexity must be encouraged and incorporated adequately by preventing simplifications of factors and conditions.

Table 4 Pore pressure prediction techniques

Detection method	*Developed by*	*Year*
Constrain normal compaction trendlines	Villacastin (2012)	2012
Passive magnetotelluric technology	Manríquez (2013)	2013
Seismic frequency and interval velocity	Carpenter (2015b)	2015
Bulk modulus	Lei et al. (2019)	2019
Geomechanical modelling	Maulana et al. (2018)	2018
Support vector machine algorithm	Ahmed et al. (2019)	2019
MWD-LWD	Chettykbayeva et al. (2020)	2020
Machine learning applications	Bui et al. (2022)	2022

4 Conclusions

The disastrous consequences of kicks forced the oil and gas industry to research and develop more sophisticated models and methods for kick detection and to produce integral well control principles. Several traditional kick response methodologies have been available in the literature during the last decades and are commonly utilised by drilling companies. Due to each well's unique conditions, more detailed approaches were proposed, capable of addressing the specificity of each environment in real time.

The most commonly used methodologies were sensor-based, either by monitoring surface or bottom hole parameters. This detection seems the most cost-effective solution but lacks accuracy, or the response time is increased in most cases. Several attempts were made to improve the reliability of such sensors and, at the same time to maintain their low cost.

More expensive and sophisticated systems, such as intelligent drill pipes, were also developed, transmitting data via a wire installed across the drill string. These systems provided high bandwidth rates and allowed several sensors to be utilised and operated from the downhole wireless transmission systems. The accuracy of the wired drill string system was very high, resulting in a very reliable kick detection mechanism. Their elevated cost and subsequent underlying complexity to the whole drilling process prohibited their regular use in most cases.

Machine learning and artificial intelligence algorithms have evolved and been utilised by the oil and gas industry during this digital transformation era. Researchers have already developed several successful models producing unexpectedly reliable and accurate results. Machine learning algorithms could handle and analyse the big data produced during the drilling operation; even using conventional and affordable sensors, kick detection, and well control could improve the kick detection and well control.

Several new approaches for early kick detection have been developed during the last decade. New and more robust detection systems have been established, utilising the power of software simulation and prediction algorithms in combination with improved surface and downhole equipment. Machine learning algorithms can handle and analyse the enormous amount of the produced data while drilling for oil and gas. Such methodologies seem to produce more accurate results based on patterns created by the algorithms. However, the reliability of the results can easily be questioned, as the physical meaning of the output is not always apparent, and the range of application is usually limited.

Additionally, due to the complexity of such an event, the behaviour of the kick fluid is not usually simulated accurately, while several factors are oversimplified or ignored. Consequently, the development of the respective response methodology is heavily influenced by the imprecise analysis of kick behaviour.

The focal point should be shifted from upgrading and modifying the existing approaches based on the traditional kick behaviour analysis techniques to producing new and accurate detection systems centred on modern and more powerful toolkits. The behaviour of a kick can be accurately analysed by computational fluid dynamics (CFD) models and specialised simulation software, which is not currently apparent in the literature. This way, realistic models can be developed that can describe the conditions, fluid flow regimes, thermodynamic fluid behaviour and geometry of the well. New equipment and methodologies could then profoundly rely on this trustworthy output.

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Author contributions

Nikolaos C. Kokkinos and Fotios N. Zachopoulos have contributed to conceptualisation, methodology, formal analysis, investigation, resources, data curation and writing – original draft preparation. Nikolaos C. Kokkinos contributed to validation, writing-review and editing, supervision and project administration. Fotios N. Zachopoulos contributed to visualisation. Both authors have read and agreed to the published version of the manuscript.

Abbreviations

Abbreviation	*Term*
BHA	Bottom hole assembly
BOP	Blow out preventer
CFD	Computational fluid dynamics
HPHT	High-pressure high-temperature
LWD	Logging while drilling
MRH	High resolution magnetotelluric
MW	Mud weight
MWD	Measure while drilling
PRISMA	Preferred reporting items for systematic reviews and meta-analysis
ROP	Rate of penetration
WOB	Weight on bit

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