EARLY KICK DETECTION USING DATA-DRIVEN BAYESIAN NETWORK: MODEL DEVELOPMENT AND EXPERIMENTAL TESTING

by

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Abstract

Safety is one of the keys to success for offshore oil and gas development projects. Drilling operation becomes more and more complicated when moving to deeper water and harsher conditions, which requires a higher level of safety. Kick is an event that happens when the hydrostatic pressure of drilling mud is lesser than the formation pressure which let the formation fluid enter the wellbore. Detection of a kick event as soon as it happens will spare drillers more time to make decision and take necessary actions. An uncontrolled or unaware kick event may lead to a well blowout which causes major damage to infrastructure, could kill people and costs lots of money. The conventional method of kick detection entails monitoring surface parameters such as stand-pipe pressure, mud pit volume, changing in flow rate and other drilling parameters can lead to the delay in detection. Some recent studies have successfully proved the ability to employ downhole parameters to realize kick. The new methods show the robust results in detection and the improvement in detection time. Besides, data-driven Bayesian network (BN) has shown to solve the problem in historical data, which is usually available, unlike expensive, and insufficient, expert knowledge. This work presents the application of data-driven BN using downhole parameters to early kick detection. The work includes three main parts: 1) creating and testing a data-based Bayesian network based on historical experiment data and synthetic data; 2) designing drilling sample, setting up and conducting experiments with the new

large drilling simulator (LDS); 3) validating the data-based Bayesian network with the data from the LDS experiment. Upon the success of this work, the developed BN model will serve an efficient and effective way to detect kick early, which will enable appropriate corrective actions. The new setup of experiment with LDS can be used to conduct further experimentation to simulate more complicated kick scenarios during drilling operation.

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List of Abbreviations

BN	Bayesian Network
SDS	Small Drilling Simulator
LDS	Large Drilling Simulator
SCFM	Standard Cubic Feet per Minute
BOP	Blow-Out Preventer
WOB	Weight On Bit
ROP	Rate Of Penetration
usgpm	US Gallon Per Minute
MPa	Megapascal

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Chapter 1. Introduction

1.1. The Need of Early Kick Detection

Oil well drilling operation is inherently associated with high risks. One of the most common risks is well kick, which could lead to a blowout if it is not detected and controlled on time. An accident that happened in 2010 in the Gulf of Mexico killed 11 people and costed billions of dollars to resolve the consequences. This accident, accompanied with others happened in the past, emphasizes the importance of early kick detection. In conventional drilling, drilling fluid is circulating in the wellbore which provides a medium to control the well pressure. The hydrostatic pressure created by mud weight is maintained above the formation pressure. Under the circumstance that the hydrostatic pressure drops below the formation pressure, undesired formation fluid influx into the wellbore. Kick, or hydrocarbon influx, is one of the significant challenges during the drilling operation. When the presence of kick is imperceptible, the kick might subsequently develop into a blowout, which results in severe damage to infrastructure and fatalities. Detection of a kick at an early stage spares more time to take necessary actions to prevent its growth and mitigate the potential well blowout. There are varieties of methods applied for early kick detection. The conventional method entails monitoring surface parameters which leads to delay in the detection.

Some recent works show the ability to employ monitoring of downhole parameters to realize early kick detection.

Data-driven Bayesian Network (BN) has shown to solve problems in complex systems where the knowledge about the system is not adequate to apply a model-based method. Data-driven BN creates a model based on historical data, which is usually available, unlike expensive, and often insufficient, expert knowledge. The advantages of data-driven BN and the efficiency of applying downhole parameters in early kick detection demonstrated in recent research strongly motivate this work.

1.2. Objectives of the Research

The key objectives of this research are listed below:

- To develop a data-driven Bayesian network model using historical data
- To develop a new kick analysis experiment setup with the large-scale drilling setup (LDS)
- To evaluate the performance of data-driven Bayesian network model using the data from the experiment

1.3. Contribution of the Research

The main contributions of this research are listed below:

- A developed data-driven Bayesian network model

- A fully integrated downhole sensor assembly for kick experiment into new LDS system
- Complete documentation of drilling sample preparation for experiment
- Complete documentation of kick simulation data which consists of: i) Circulating-kick simulation data with small drilling setup (SDS), ii) Drilling-kick simulation data with SDS, iii) Circulating-kick simulation data with LDS, iv) Drilling-kick simulation data with LDS

1.4. <u>Thesis Structure</u>

This thesis consists of six chapters. The outline of each chapter is listed as below:

Chapter 1: This chapter introduces the research topics, the objectives and contributions of the research.

Chapter 2: This chapter presents an overview about kick and blowout, causes and indications of kick, and well control system. The kick detection techniques and Bayesian networks are also presented in this chapter.

Chapter 3: This chapter explains the steps to model a Bayesian network from two primary methods: model-based and data-based. The performances of these two models are compared to prove the usability of the data-driven Bayesian network in early kick detection. This chapter also explains creating synthetic data from a data set of experiments which is used to test the performance of the model.

Chapter 4: This chapter presents the new experiment setup with LDS, including design and casting drilling samples; manufacturing, pressure testing and integrating the new pressure cells into the LDS; re-configuring and integrating the downhole sensors assembly and kick injection system into LDS and conducting experiments.

Chapter 5: This chapter presents the results and discussions when testing the data-driven Bayesian network using the data collected from LDS experiment.

Chapter 6: This chapter summarizes the outcome and discussion of the work and provides potential future study recommendations.

Chapter 2. Literature Review

2.1. Overview of Kick and Blowout

The increase in demand for energy requires oil and gas exploration drilling into remoter areas and more sophisticated drilling conditions. The deeper the water that drilling operation moves in, the narrower the safe mud pressure window becomes. This condition raises the risk of kick and blowout occurrence. Kick is known as the first stage of the blowout event when the hydrostatic pressure of drilling mud is inadequate to hold the formation fluid. As a result, formation fluid starts to flow inside the drilling annulus and intensively migrate to the surface. Timely detection of kick occurrence will allow driller the necessary time to take action to regain control of the well and eliminate the kick. Otherwise, an undetected kick event can propagate into a blowout accident, which is recognized as the most dangerous catastrophic event in drilling operation. Blowout can cause loss of human life, significant damage to equipment and environment, and cost billions of dollars to resolve the consequences. These devastating consequences of blowout can be prevented if the kick occurrence can be detected as soon as it happens.

2.1.1 Causes of Kick

As discussed in [1] [2], the causes of kick are listed below:

- Mud weight less than formation pore pressure: in conventional drilling, or known as *overbalanced* drilling, the weight of mud pumping into borehole is maintained above the formation pore pressure to prevent the formation fluid entering the wellbore. However, the knowledge of pore pressure may be inaccurate. In some cases, operators may require drilling with the underbalance drilling to maximize the penetration rate, or when drilling through the formation where it is historically low productivity. When the mud weight is less than formation pressure, kick will occur [1].

- Improper hole fill-up during tripping: during trip out operation, the metal displacement will lead to the decrease of mud level in hole. Failure to fill the borehole with drilling mud while tripping may also cause kicks [1].
- Swabbing while tripping: during tripping out operation, the effect of metal displacement and pulling effect will lead to the drop of downhole pressure. In this case, drilling mud need to be filled to maintain the hydrostatic pressure above the formation pressure. However, if the filling rate is slower than the tripping out rate, bottom hole pressure will reduce below the formation pressure due to swabbing effect, which can lead to a kick [1].
- Lost circulation: for lost circulation to occur, the formation must have flow channel that allow passage of drilling fluid from the wellbore and there must be a positive pressure differential between the wellbore and the formation [2]. In overbalanced drilling, the hydrostatic is maintained higher the formation pressure. However, excessive high overbalance may fracture the open formation which causes the loss of

drilling fluid into the formation. As a result, the height of the fluid column decreases, and the hydrostatic will drop below the pore pressure. Tripping out of hole while losing return at the surface is extremely dangerous because an influx may be undergoing [1].

2.1.2 <u>Kick Indicators</u>

As discussed in [1] [2], Kick indicators are listed below:

- Sudden increase in drilling rate: a sudden increase in drilling rate indicates the drilling is going into a porous formation zone. This indication should alert the crew the possibility of lost circulation or kick occurrence [1].
- Increase in flow rate and mud pit level at surface: when kick occurs, the formation fluid flows into the wellbore which increases the return mud flow rate. Depending on the productivity of the formation, the increase in flow rate may be rapid or virtually imperceptible. The total volume of drilling fluid will increase due to the influx volume. As the result, the mud pit level will be increasing. Any change in mud pit level or return mud flow rate should not be ignored [1].
- Change in pump pressure: a decrease in pump pressure may cause by the drop of hydrostatic in the wellbore. When hydrostatic pressure drops, it can cause influx of formation fluid [1].
- Gas, oil or water-cut mud: when gas, oil or water-cute mud is observed, there is

possibility of kick occurrence. Without any additional material mixing with drilling fluid, the changing in properties of drilling mud is potentially coming from the formation fluid [1].

2.1.3 Well Control System

Blowout is an uncontrolled release of formation fluid on surface. Well control and blowout prevention have drawn more focus in oil and gas industry for a number of reasons: high cost of drilling, possibility of fatality, and severe damage to environment when blowout happens [2]. The key principles and components for controlling kicks and preventing blowout are discussed in [2]. A well control system consists of these main components:

Drilling fluid: As the primary barrier against kick, drilling fluid is circulating from the mud tank through drilling pipe into the annular section and return to the surface. The hydrostatic pressure generated by drilling fluid should be maintained above the pore pressure to prevent the influx of the formation fluid into the annular.

Diverter: It is used to divert a gas kick at shallow depth when only a conductor casing is in place. During this phase, the formation is too weak to contain a shut-in kick. It is safer to divert the kick flow into another direction. As shown in Figure 2.1, an annular preventer is installed on top of the conductor to seal the wellbore, the kick flow will be transfer through the diverter line install below the annular preventer [2].

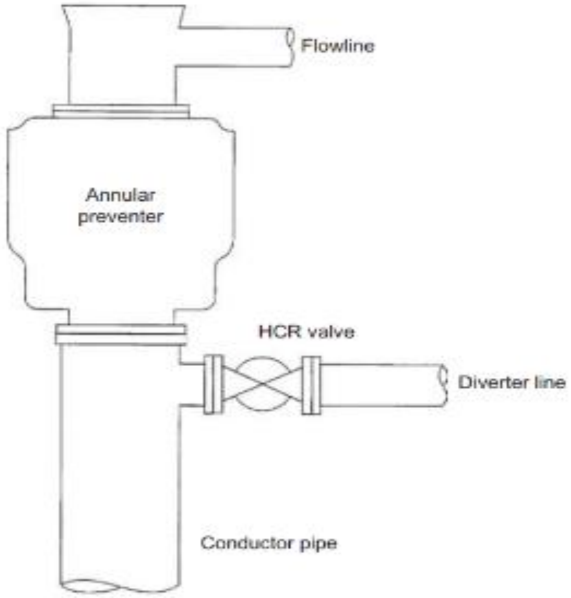


Figure 2.1 – Diverter [2]

Preventer stack: The BOP is used to seal the wellbore so that it contains the kick inside the wellbore. There are two main types of preventer in the industry: the annular preventer and ram-type preventer. As shown in Figure 2.2, a preventer stack normally consists of an annular preventer on top, followed one or more ram-type preventers. The drilling spool attached into the preventer stack to enable the connection of the kill line and choke line [2].

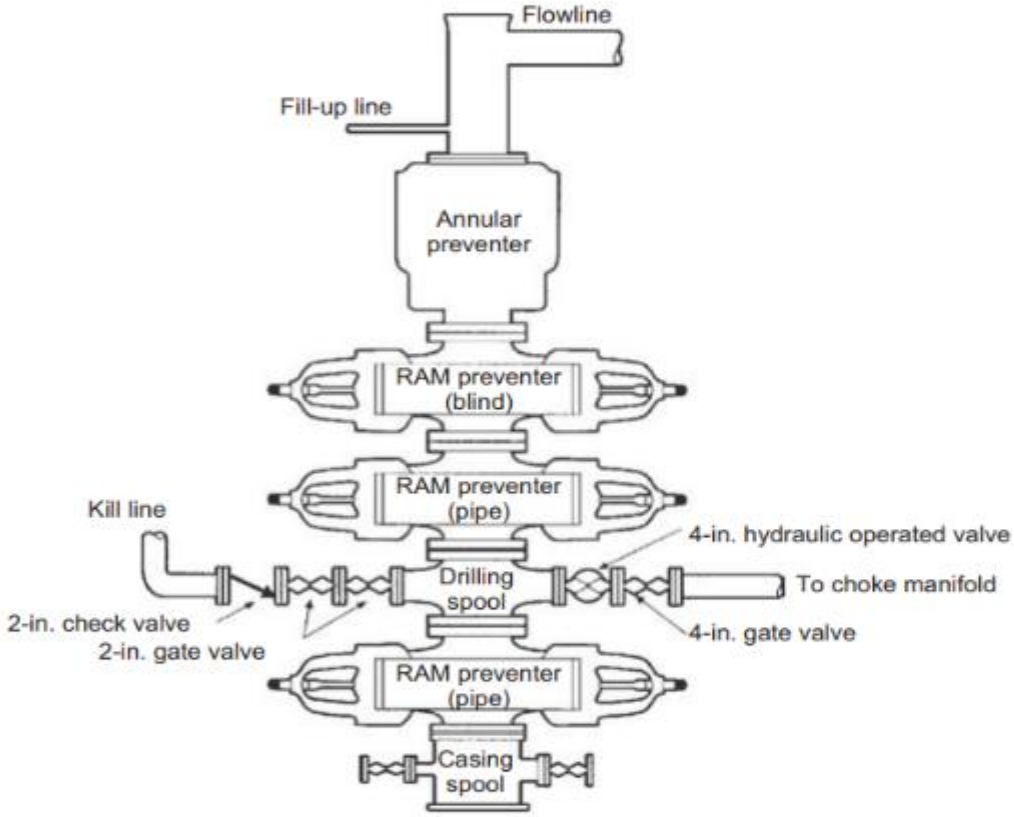


Figure 2.2– Preventer stack arrangement [2]

Annular preventer: The annular preventer is used to seal around the tubular. Due to its variable diameters, it allows tool joints to pass through when lowering pipe into the hole with presence of surface pressure. To operate, the hydraulic pressure is applied to the low side of the circular wedge which forces the sealing element toward the inside [2].

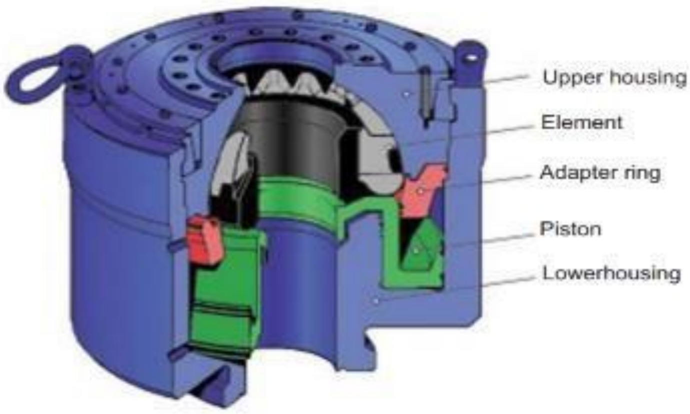


Figure 2.3 – Annular preventer [2]

Ram-type preventer: Ram-type preventers are operated by applying hydraulic pressure which closes/opens a set of rams together from both sides. They can be operated manually as a back-up measure. They can be found on almost all BOP stacks. The ram-type preventers are designed to seal against a specific diameter drill pipe. Therefore, it is necessary to change the rams when switching to a different diameter drill pipe. Ram-type preventer consists of three different types:

- Pipe/casing ram: It is used to seal against the pipe or the casing.
- Blind ram: It is used to seal the wellbore when there is no pipe presence in the hole.
- Shear ram: It has cutting edges so that it is able to shear through the drill pipe and seal over it.

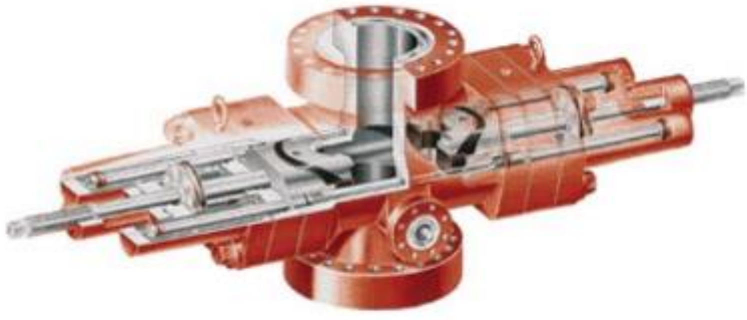


Figure 2.4 – Ram-type preventer [2]

Choke line: Choke line connects with the preventer rack at the drilling spool to direct the flow out of the wellbore to the choke manifolds. There is a manually master valve at the drilling spool and a hydraulic valve which is operated during the operation. The wall thickness of the choke line needs to be designed to handle high flow rate of drilling fluid which mix with drilling cutting.

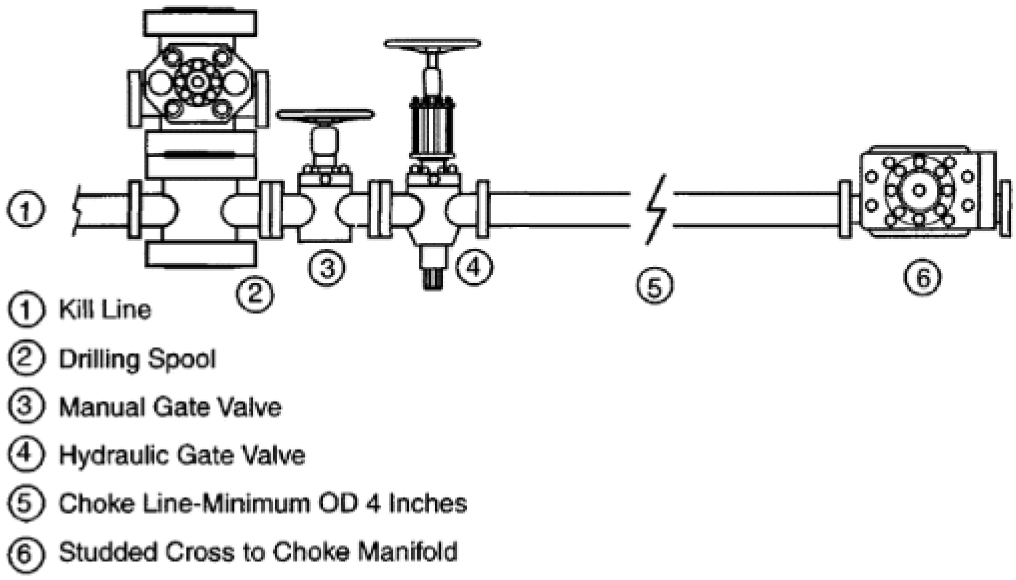


Figure 2.5 – Choke line [1]

Choke manifold: This is one of the crucial parts of well-control system. The choke manifold allows control the back pressure on the well while circulating out the kick.

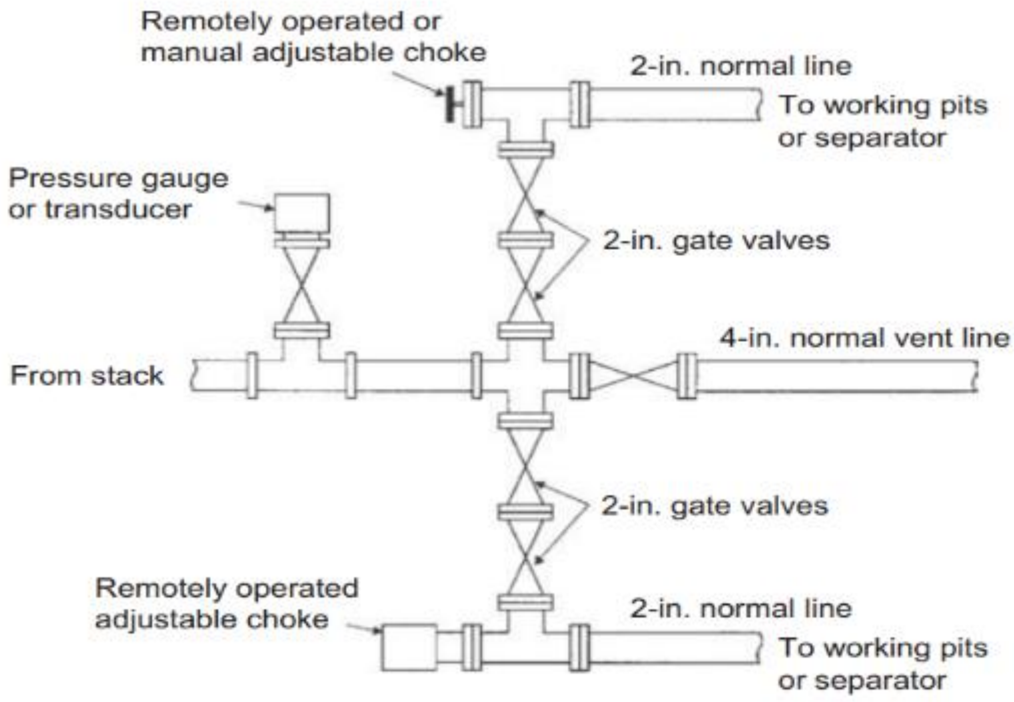


Figure 2.6 – Choke manifold [2]

2.1.3 Kick Detection Techniques:

A robust kick detection method is one of the primary requirements of the oil and gas drilling operation [1]. In conventional kick detection system, kick indicators are classified into two main groups: primary indicators and secondary indicators. Primary indicators include monitoring mud flow rate and mud volume via main mud pit tanks and trip tanks. Secondary indicators include change in mud properties and cutting size [2]. Monitoring the increase in volume of mud pit tanks or even trip tanks is not always reliable due to the fluctuation of mud level and poor reading from level sensors [3]. Schubert and Wright proposed a new method in 1998, in which, instead of monitoring the mud level through pit tanks and trip tanks, an acoustic device was installed inside the wellbore to continuously monitor the liquid level inside the annular section. Increase in liquid level inside the annular section gives the first indication of kick occurrence. This method improves the detection time by reducing the mitigation time of kick from the downhole to the surface monitoring system [4]. In the early stages of kick detection technology development, a single measurement of output flow rate was used to detect formation fluid influx or loss of drilling mud. However, the high level of measurement noise due to fluctuating output obtained from flow meters increases the false alarm rate [5]. To overcome these problems, delta-flow method was introduced in 1987, which measures the relative flow rate between input flow rate and output flow rate [6]. The delta-flow method improves the false alarm rate by removing noise inherently residing in measurement of flow meter. However, this measurement is still affected by drilling-related activities such as connecting and disconnecting of the pipe, pipe tripping and movement, which trigger false alarm [5].

A significant number of studies have focused on improving kick detection performance by investigating mud flow rate parameters. In 1987, Orban developed a kick detection system based on delta-flow theory. Different flow meters were installed on the mud return line and at the output of the discharge pump to measure output and input flow rates, respectively [3]. In 1992, a study was carried out to investigate different types of flow meters that were used to measure inlet mud flow rate and outlet mud flow rate; and evaluate their performance in kick detection [7]. Among those being tested (conventional pump stroke counters, rotary pump speed counters, magnetic flow meters, standard paddle meter, acoustic level meter) the study shows that magnetic flow meters are the best choice for measure flow rate. However, magnetic flow meters have some limitations such as high cost, pressure limitation and only use with water-based mud [7].

Besides mud volume and mud flow rate parameters, some studies consider other parameters such as pressure, density, and conductivity. These studies not only focus on single parameters but also on the combinations of several parameters to improve the performance of kick detection technologies [8]. In 1998, a new approach was proposed using the flow-rate wave into early gas kick detection. This approach investigated an utterly different parameter, which is flow-rate wave. This method was developed based on the theory that the flow-rate wave follows the same propagation principle as the acoustic wave. However, the flow-rate wave has higher anti-interference, which makes it a better choice in early gas kick detection. This method was successfully tested with field data of two oil wells [8].

As discussed in [9], conventional kick detection methods are mainly based on tracking the fluid volume to detect and quantify kicks and losses. As a result, conventional kick detection exposes significant drawbacks such as noise and error in detection. It also shows that the recovery time of four to eight days after kick and kick volume of fifty to a hundred barrels of conventional methods are far less efficient compared to advanced kick detection technologies reported recently [9]. In 2001, an approach using probabilistic focusing on mud flow rate (in-flow as well as out-flow) was proposed [5]. Several model-based approaches were reported to model regular drilling operation and kick event in different drilling-related events like pipe connection, movement of the pipe and pump activity [5]. The model-based method obtains high sensitivity in kick detection with low false alarm rate and requires less calibration. Moreover, unlike a binary output that is derived from the conventional system, the output from this system is a probability value which indicates the drilling status; this gives a high confidence to driller in deciding on the appropriate action [5].

From 2010, the need for improving safety performance through automation revolution in upstream business of oil and gas industry has been raising [10]. With an objective to understand the key factors which help to improve the efficiency of kick detection system, a sensitivity analysis-based fault tree was derived. The results indicate the importance of improvement in accuracy and reliability of sensor data and improvement of detection software [10]. In 2015, another study utilized the change in mud density to detect kick. This study applied two approaches: detect the changing of density from the mud return line through a fix-installed sensor and from bit position through measure-while-drilling (MWD) tool [11]. In the first case, a sensor package was installed just above the blowout preventer (BOP) to detect the change in density. Theoretically, mud density is one factor that responds to kick because oil and gas have lower density compared to mud. The tested sensor is similar with the ultrasonic sensor which is sensitive to density changes. In the second case, density was measured from the MWD tool which can trigger an alarm in seconds. However, as indicated in [11], the lack of field data is the main problem for other researchers to further develop this model because data mostly come from service companies, and acquiring data is a challenging task. The Influx Detection at Pump Stop (IDAPS) software was also proposed in 2015 to detect kick during drill pipe connections [12]. This work investigates five input parameters: flow-in, flow-out, pit volume, pit depth and hole depth. The IDAPS software demonstrates a low false alarm rate of one false alarm per 195 connection with 100% influx detection rate [12]. In 2016, a model-based method was developed with two input parameters, mud pressure and mud flow rate, to detect the kick [13]. A field data set was pre-filtered by multi-input and multi-output filter (MIMO) and Kalman filter. Processed data with no kick was used to localize healthy zones, collectively known as the non-kick zone. The coefficient of normal drilling condition of the model was built and stored. By keeping track of the coefficient variation of the model, anomalous drilling condition can be detected. In other words, the coefficient which falls outside this region is considered as belonging to the non-healthy state; either kick or loss of drilling fluid occurs [13].

Even though surface monitoring achieves a certain level of success in early kick detection, delay in detection time and high false alarm rate becomes the main drawbacks of these techniques. In [14] [15] [16], downhole parameters monitoring is proposed to improve the detection time of early kick detection techniques. A laboratory-scale drilling system with downhole sensors including pressure, density, conductivity, and mass flow rate, and a kick simulation system with air injection was developed by Nayeem [14] in 2016. Several experiments were carried out to investigate the changing of downhole conditions when a kick happened, which was then utilized to develop a kick detection method. This work demonstrated the usefulness of employing downhole parameters for early kick detection. According to Nayeem [14], the influx of formation fluid into the annular affects all downhole readings. Pressure and mud flow rate respond quickly with occurrence of kick while density and conductivity readings experience a few seconds of delay in detection. However, compared to surface monitoring methods, there is a significant improvement in detection time. In 2017, Islam [15] also applied downhole monitoring, associated with a dynamic risk assessment and management model based on computational fluid dynamics, to detect a kick at an early stage.

Sule [16] investigated the effect of gas kick on dynamic drilling parameters including downhole pressure, mud density, mass flow rate, volume flow rate, dynamic weight on bit, rate of penetration, torque on bit, and rotary speed. In this work, a synthetic rock was used as a drilling sample, and drilling activity was carried out during the experiment. Regarding downhole measurement such as downhole pressure, mud flow rate, and mud density, Sule obtained similar results as with the previous work of Nayeem [14]. Sule [16] observed the increase in downhole pressure and flow rate and decreasing in mud density. Those studies obtained a certain level of success to prove the effectiveness of downhole monitoring methodology in early kick detection.

In the recent years, the number of studies applied machine learning into kick detection technology has been steadily increasing. A method using long short-term memory recurrent neural network (LSTM-RNN) was proposed in 2019. This method investigates different parameters: flow rate in and out, standpipe pressure, and others. This method is also able to quantify the size of the kick [17]. In 2019, a method using artificial neural network and principal components analysis was employed to detect gas kick real-time [18]. Logging data was first collected for gas cases with twelves different input parameters. The principal components analysis was applied to reduce the dimension of parameters from twelve to seven parameters. After that, an artificial neural network with one hidden layer and five neurons was applied with seven input parameters to determine if a kick is happening. Eventually, the three gas kick accidents were studied to validate the model. All three cases showed the detection by the neural network were earlier than the detection in the field [18]. A drilling event chart was proposed by Das Purkayastha et al in 2019 [19]. The chart is an visualization of the most important drilling parameters which are used in kick detection such as: rate of penetration, stand pipe pressure, the effect of different types of mud on gas levels, the influence of lithology and rock permeability on the magnitude of gas peak, etc. The use of this chart in early kick detection was applied successfully in various basins, especially in the absence of logging-while-drilling data [19]. Another method using statistical approach on real-time data to detect kicks was proposed by Mao in 2019 [20]. There were two trend analysis methods: the divergence of moving average (DMA) and the divergence of moving slope average (DSMA). These two methods were applied to quantify the trend evolutions of three indicators: normalized rate of penetration, flow rate and mud pit volume. The proposed system was tested with data collected from fifteen wells with twenty-three kick events. The results showed that the detection time of the proposed system was at an average of 8.5 min before the record time of kick event [20]. In 2001, the probabilistic Bayesian network was applied in kick detection yields significant improvement in sensitivity and a low false alarm rate [5]. In that work, a probabilistic method was applied in field to detect kick in deep-water drilling. Model-based Bayesian network was adopted to build a detector. The detector contains a comprehensive set of flow-in and flow-out parameters in various drilling activities such as pipe movements, pump on-off, kick events. To build the models, a large data set was collected from different wells, different types of rigs and drilling activities. The detector was successfully tested with field data. The results show that this method can detect the kick event around 3 bbl in high noise data collected from a semi-submersible and 0.25 bbl in slim hole drilling condition. When testing with low noise data collected from a fixed rig, the detector can detect a kick event with less than 0.2 bbl which is at least 7.5 min prior to detection on the rig floor. The results showed improvement in detection time which gives significant advantages for the well control process when kicks happen. By applying probabilistic Bayesian method, this work reports significant sensitivity improvements because the system automatically adjusts sensitivity of noise signal. Model-based Bayesian approach also allows integration of engineering knowledge of the drilling process into the model set. With the data set collected from various sources, it enables the detector to work well in all condition regardless type of rigs and wells. Giving the probability output with level of confidence of kick occurrence is another advantage of this method, which aids the driller in making decision.

However, a model-based approach requires expert knowledge which is a challenging requirement. With complex systems, it is more difficult to acquire a complete knowledge about the system. On the other hand, the data-driven approach does not heavily rely on the underlying mechanism, when compared with the model-based approach [21] [22]. Besides, historical data of the process is often available and easy to acquire, which supports choosing the data-driven approach. In 2018, an overview of data-driven monitoring and safety control of industrial cyber-physical systems was discussed in [23]. In 2019, a data-driven monitoring approach for pipeline integrity assessment was proposed [24]. A data set of vibroacoustic signal was collected at the flow station of an oil trunk line in Nigeria for over a year. A portion of the data set with normal operation was used for training and tuning the model. With new incoming data, anomalies are automatically detected by the training model [24]. Another study investigating the performance of different data-driven approach in production prediction was carried out in 2019 [25]. Three different machine learning methods, Gradient Boosted Tree (GBT), Adaboost and Support Vector Regression (SVM), were applied with six input parameters -- on stream hours, average choke size, bore oil volume, bore gas volume, bore water volume, and average well head pressure -- to predict the production rate of five production wells in the North Sea. The performances of these three approaches were compared by measuring the mean absolute error [25]. As advantages of data-driven approach discussed in [23], the possibility of modelling Bayesian network from historical data will significantly reduce time and cost required to construct the model

2.2. Bayesian network

Bayesian networks are probabilistic graphical models which are used to present the joint probability distribution over a set of random variables. A Bayesian network is a directed acyclic graph (DAG) with nodes and edges. A node represents a random variable associated with its conditional probability table (CPT). An edge represents the conditional dependence between nodes.

The network comprises n variables X. The probability distribution P (X_1, …, X_n) is given as:

$$P(X_1, \dots, X_n) = \prod_{i=1}^{n} P(X_i \mid X_1, \dots, X_{i-1}) \prod_{i=1}^{n} P(X_i \mid Parents(X_i)). \qquad (1)$$

A typical Bayesian network contains two main parts: the network structure represented by nodes and edges, and the network parameters represented by the conditional probability table (CPT) of each node. Bayesian networks are classified into two main types: model-based Bayesian network and data-based Bayesian network. A model-based Bayesian network is constructed solely from the knowledge domain. The directed arcs, or edges, are formed based on the understanding of the system and our prior knowledge on the dependency between variables. CPT is also drawn from expert experience. This method is widely adopted, and has achieved a certain level of success, in different fields. In 2009, Si employed a model-based BN in failure importance analysis and optimized the structure of the network using immune algorithm [26]. In 2012, a model-based BN was applied to predict cyber-attacks in the network [27]. Development of model-based Bayesian network requires a thorough understanding of the system. Knowledge acquisition is usually an expensive process, which is often not feasible, especially for complex systems.

On the other hand, the amount of information, or data, is proliferating in recent decades, which supports the learning process. Data-based Bayesian network is constructed by learning from historical data. There are four common types in the learning process: known structure and complete data; unknown structure and complete data; known structure and incomplete data and unknown structure and incomplete data [28]. Hui investigated two cases in his work [28]. The first case is known as structure and complete data. This is the most straightforward, where the structure of the network is given. The task to be completed is to estimate parameters of the network, or CPT, from a complete data set. The second case is unknown structure and complete data. In this case, the edges will be created through learning process first, following by parameter estimation [28]. In 2003, a collective learning strategy in structure learning from distributed data was proposed, which reduces the number of samples in the training sample and improves the efficiency of the learning process [29].

Parameter learning, or parameter estimation, is a process to calculate the CPT of each node in the network from a given data set. There are two standard estimation techniques: maximum likelihood estimation (MLE) and Bayesian estimation. On the other hand, structure learning is a process to find the connections between nodes. There are two primary techniques adopted in structure learning: constraint-based and score-based. These learning techniques are explained in [28] [29]. As discussed in [28], in constraint-based method, the test of conditional independence is performed on the data set, the result will be the network structure that is consistent with the observed dependencies and independencies. In score-based method, the scoring function will be defined for each different structures of the networks. The scoring function will represent how well the structure fit with the data set. The result of this method is the structure that has the highest score. There are three commonly used scoring functions in Bayesian structure learning methodology: the log-likelihood, the minimal description length and the Bayesian score. In [29], a collective learning technique was proposed to construct the structure of the network from large and physically distributed data set. This technique can obtain the local structure of the network at each site and the local structure will be obtained by cross learning and combining.

Chapter 3. Bayesian Network Model for Early Kick Detection

3.1. The Methodology

As explained in Section 2.2, Bayesian network (BN) is a directed acyclic graph which is widely used to present the probability distribution over a set of random variables. One of the most significant advantages of BN is the ability to update the *a priori* probability based on observed data and deliver the output with a probability value. To construct a complete BN, there are two primary approaches: model-based BN and data-driven BN. Model-based BN required a full understanding of the system to construct the model, for which adequate information is usually not available. Meanwhile, data-driven BN can be easily constructed from historical data. The purpose of this study is to test the usability of the data-driven BN for early kick detection.

In the present study, the presence of kick is estimated as the probability of occurrence based on directly measured four downhole parameters: downhole pressure, drilling mud density, drilling mud conductivity, and flow rate. A BN model containing five nodes with four downhole parameters listed above and one state node, which indicate the status of drilling operation: normal or kick mode. Bayes Server software [30] is utilized in this work. The software provides a wide range of parameter learning and structure learning algorithms. Tutorials for the software are provided in [30]. Islam [31] carried out experiments to collect data, which was used to validate the BN-based approach proposed in this paper.

A summary of the setup of the experiment and procedure is presented in Section 3. The data set contains six episodes, comprising 8000 samples in total; each episode includes one kick event. It is divided into two parts: the training part contains three episodes with 4000 samples for creating the structure and parameters of the network; the testing part contains the other three episodes with 4000 samples for testing the model. With the proposed procedure consists of three steps as shown in Figure 3.1.

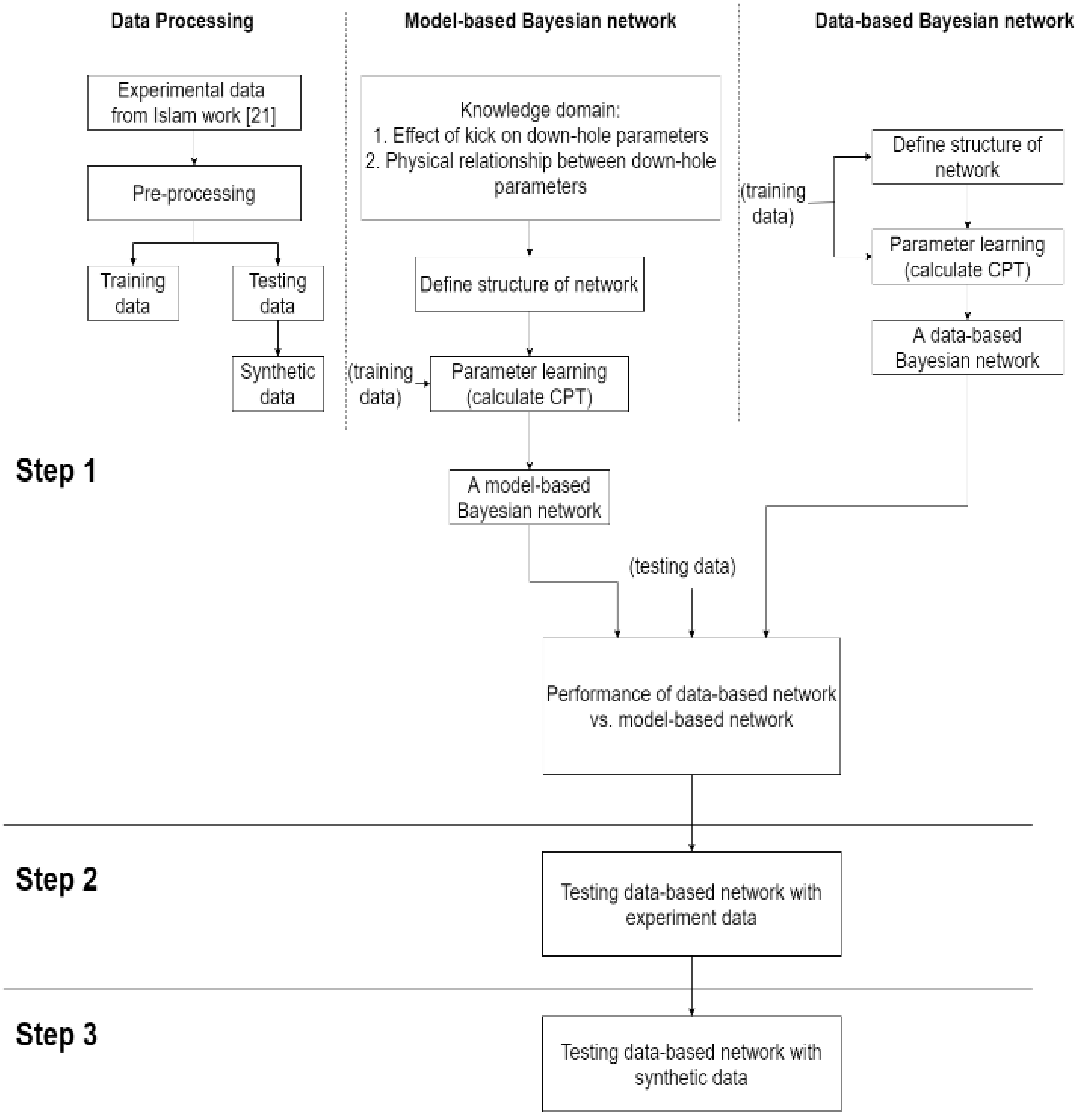


Figure 3.1– Flow chart of the procedure employed

Step 1: Data-based model creation: This step contains four main parts:

i. Processing the data: The raw data set contains 8000 samples, collected with a sampling rate of 10 Hz or 10 samples per second. A low-pass filter and median filter were applied to remove the noise and spikes from raw data. The data set was then divided into two main sets: training set and testing set. The training set is used for structure learning in the data-based BN and parameters learning for both model-based BN and data-based BN. The testing set is used for testing purposes and used for creating a new synthetic data set of 8 million samples using the bootstrap method.

ii. Constructing a model-based BN: The network contains five nodes with four downhole parameters and one state node as mentioned above. Based on the information in [4], [11], [14] and [16], we define the network configuration, i.e. whether there is an edge between any two nodes. The Conditional Probability Table (CPT) corresponding to each node is then generated by using the training set for the parameters learning process.

iii. Constructing a data-based BN: The network contains five nodes with four downhole parameters and one state node as mentioned above. To define the connection between nodes, the training set is used for parameter learning process. This part is conducted by using Bayes Server software which adopts the *search and score* algorithm for structure learning. The CPT for each node is then generated by using the training set for the parameters learning process.

iv. Testing of data: After the two models are entirely created, the testing set is fed into models. The missed detection and false detection rates of data-based BN are compared with those from model-based BN to verify the usability of the data-based model before moving to the next step.

Step 2: Testing the model using the data from experiment: The second part of the data set, which contains the other three episodes with 4000 samples, is used to evaluate the performance of the data-based model. The predicted state is plotted against the known state to calculate the accuracy of the model (missed alarm rate, false alarm rate) as well as the delay time in detection.

Step 3: Testing the model using synthetic data: A synthetic data set was created based on testing set using the bootstrapping method. 30 kick events are introduced into this data set. The predicted state is plotted against the known state to show the accuracy of the model (which is described by missed alarm rate and false alarm rate) as well as the delay time in detection.

3.1.1 Model-based Bayesian network

The structure of model-based network is created based on the following physical relationships between input parameters and their effect on output node as presented in [4] [11] [14] [16], and the parameter of the network is generated using the training data set:

- When a kick happens, it affects the flow rate (flow rate increases when formation fluid flows into the annulus), density (the presence of formation fluid changes the properties of drilling mud), and downhole pressure.
- As changes in density, the conductivity of the drilling mud changes.

Figure 3.2 shows the structure of the model-based Bayesian network which is derived from the relationships between nodes listed above.

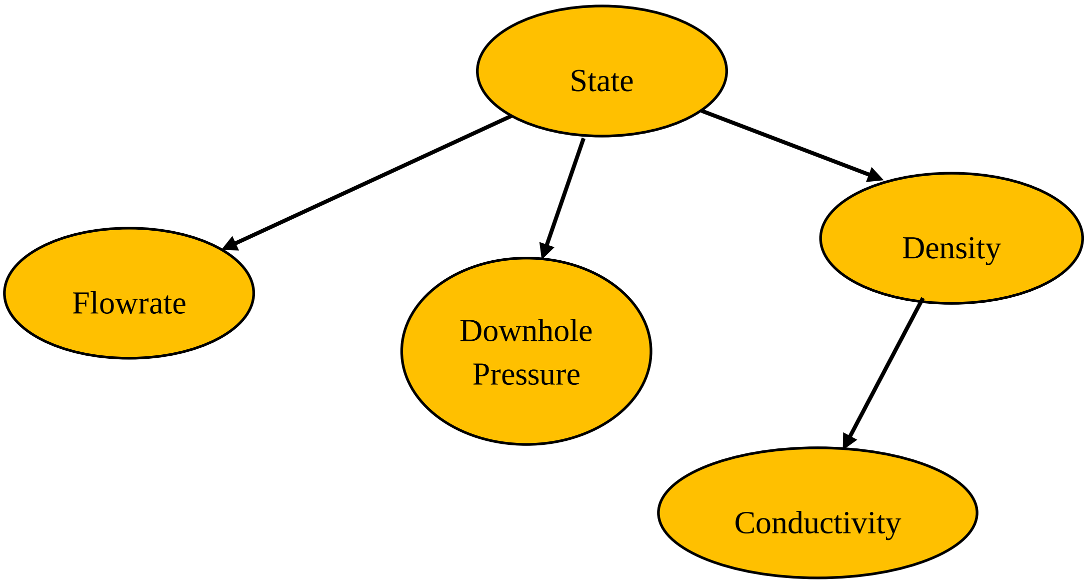


Figure 3.2 – Network structure of model-based Bayesian network

3.1.2 <u>Data-driven Bayesian network</u>

This work employs Bayes Server software, which implements the MLE technique, to calculate network parameters and Search and Score technique, to form the network structure. The mathematical background of these techniques was discussed in [28]. Figure 3.3 shows the structure of the network obtained as the result of the training process.

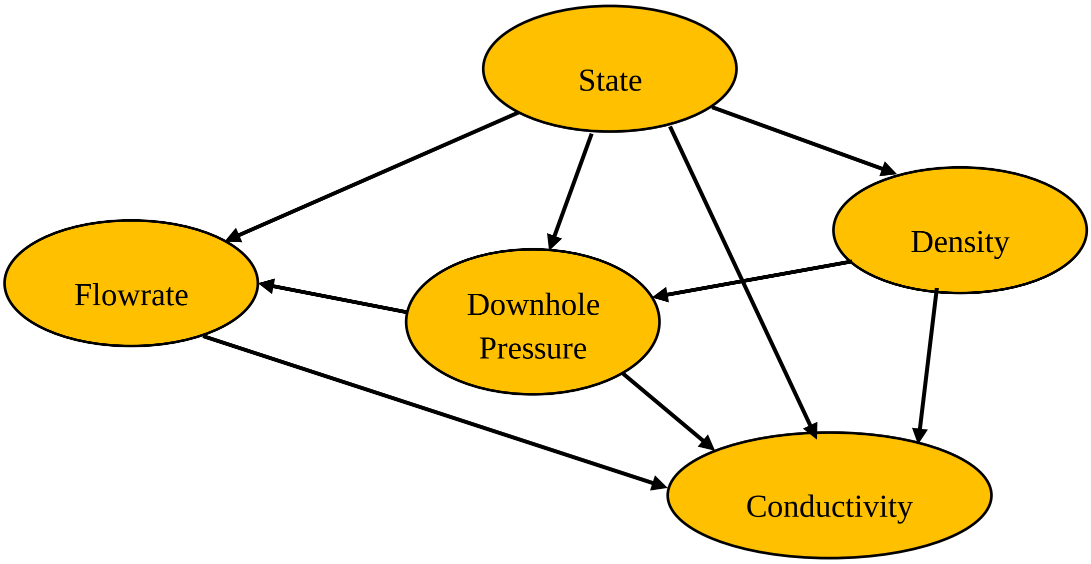


Figure 3.3 – Network structure of data-based Bayesian network

Table 3.1 shows the performance of a model-based network compared to data-based network with missed alarm rates of 1.7% and 2.3%, and false-alarm rates of 8.6% and 8.9%, respectively.

Table 3.1 – Performance of model-based network vs. data-based network

Actual	Predicted	Model-based	Data-based
kick	kick	91.1%	91.4%
kick	normal	2.3%	1.7%
normal	kick	8.9%	8.6%
normal	normal	97.7%	98.3%

3.1.3 <u>Synthetic data creation</u>

The second part of the data from experiment is used to create a synthetic data set, consisting of around 8 million samples with 30 kick events. The data from experiment contains three episodes with different flow rates and air injection pressures, which presents different kick scenarios. Figure 2.4 shows the complete data set from the experiment with six different episodes. Mud flow rate is plotted with y-axis on the right. All other parameters are plotted with y-axis on the left.

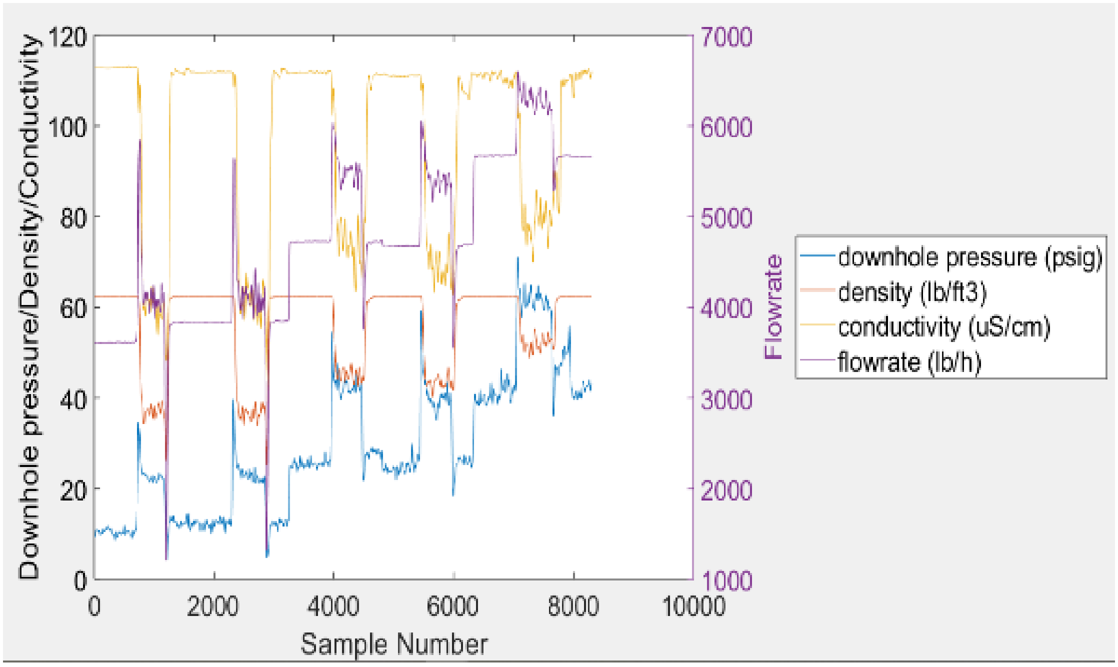


Figure 3.4 – Data from experiment

Each episode contains two periods: normal and kick. The bootstrapping technique is employed to generate data for each of these periods as per the following steps:

- The normal and kick data from each episode are separated as shown in Figure 3.5. For example, normal 1 and kick 1 are indicated normal data and kick data, respectively, from episode number 1. Therefore, three episodes correspond to six different periods: three normal periods and three kick periods.

- To generate more data point, each period is bootstrapped separately. To maintain the independence between parameters, each parameter of the period is also bootstrapped separately.
- Each period after bootstrap is split into thirty smaller chunks of data, which are re-joined to create thirty different kick events. These kick events are randomized to create the final synthetic data set. Figure 3.5 shows the steps of forming synthetic data.

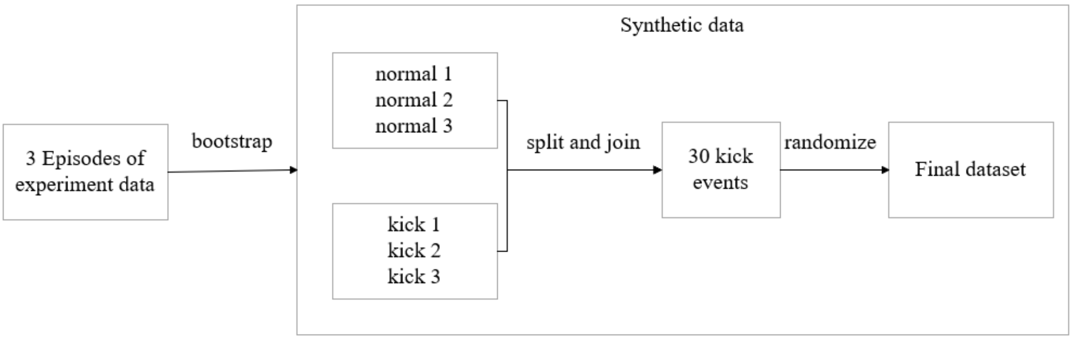


Figure 3.5 –Creating synthetic data from data set from experiment

3.2. <u>Collection of data from the experiment</u>

In this work, data collected from Islam's research [31] was utilized. This section gives an overview of the laboratory scale drilling system and describes the experimental procedure used to obtain the data.

3.2.1 Laboratory scale drilling system

The setup of the experiment includes two main parts: the drilling system and the kick simulation system. Figure 3.6 shows a diagram of the setup of the experiment [15]. A pressure cell (a steel cylinder with 14” height and 4” diameter) is the central part of the drilling system, which represents the drilling annular. A hole from the top with seal houses a pipe that represents drilling pipe. On one side, there are two ports: one attached with the mud return line and the other attached with the air injection system where the kick is introduced.

Water from a tank is circulated through the system as drilling fluid. There are a set of sensors placed on the return line that measure downhole parameters from drilling side: pressure sensor, conductivity sensor, and a Coriolis flow meter which measures both mass flow rate and density of the drilling fluid. All sensors are connected to a data acquisition system.

Kick simulation system includes a compressor to inject air from the bottom inlet of the pressure cell through a pressure regulator. On the inject line, there are two sensors to measure air inject pressure and airflow rate. These two sensors are used to set up different kick scenarios. During the experiment, these two readings are also recorded through the acquisition system.

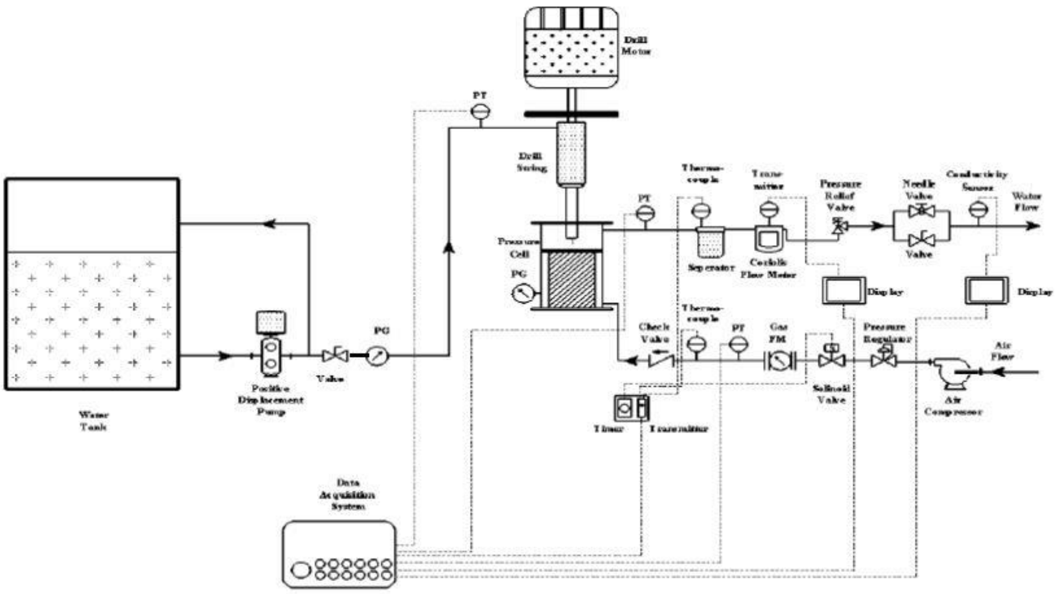


Figure 3.6 – Setup of the experiment [15]

3.2.2 Experiment procedure

The experiment conducted by Islam [15] did not involve drilling activity and so there was no multi-phase flow in the system. Water was circulated through the system with three different flow rates of 3580 lb/hr, 4652 lb/hr, and 5597 lb/hr. Each run was repeated. In total, there were six runs. In the first three runs, water was continuously circulated through the system to simulate normal drilling operation. In the next three runs, compressed air was injected from the compressor into the pressure cell from the bottom inlet to simulate kick scenarios with airflow rate of 7 SCFM, 4 SCFM, and 2.7 SCFM, respectively. The combination of data from run 1 and 4, 2 and 5, and, 3 and 6 form three episodes of data set, which include three different kick events. Each of these three scenarios was repeated. Therefore, there are six episodes, which totally include around 8000 samples with sampling rate of ten samples per second in the data set.

3.3. Results & Discussion

The first three episodes of data set with 4000 samples are used in structure learning process to form the structure of the network. The same data set is used to train network parameters. The second three episodes with 4000 samples are used to evaluate the performance of the network. Afterward, a synthetic data set with around eight million samples was used to test the network performance.

3.3.1 Testing with data from experiment

Table 3.2 shows the performance of the network testing with data from the experiment. The first column presents the actual state. The second column presents the predicted state. The third column presents the accuracy of the predicted state, which obtained by divide the number of counts of the predicted state by the total number of data point of that state. The accuracy of detection for normal condition and kick condition is 91.4% and 98.3%, respectively. The missed alarm rate and false-alarm rates are 1.7% and 8.6%, respectively. Figure 3.7 shows that with event detection, there is no missed detection or false detection. Level 0 denotes normal condition, level 1 denotes kick condition. Here, every occurrence of false detection is due to the delay in detecting the transition. In other words, there is no missed detection or false detection, despite a seemingly imperfect accuracy of detection.

Table 3.2 – Results of testing with data from the experiment

Actual	Predicted	Accuracy of predicted state
kick	kick	91.4%
kick	normal	1.7%
normal	kick	8.6%
normal	normal	98.3%

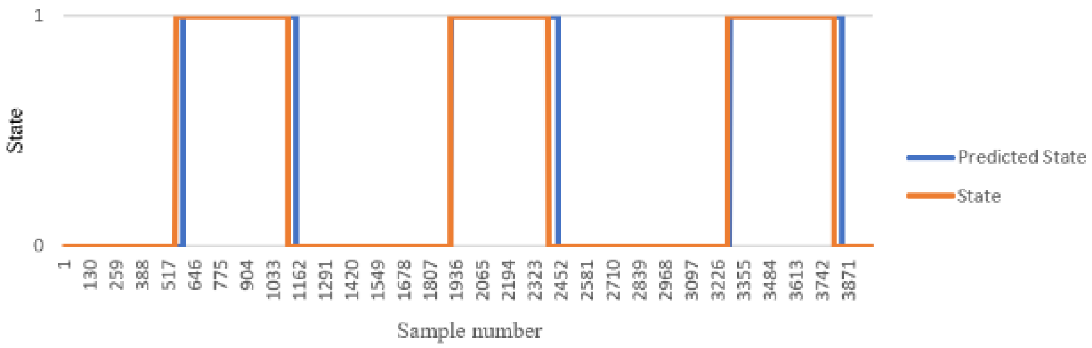
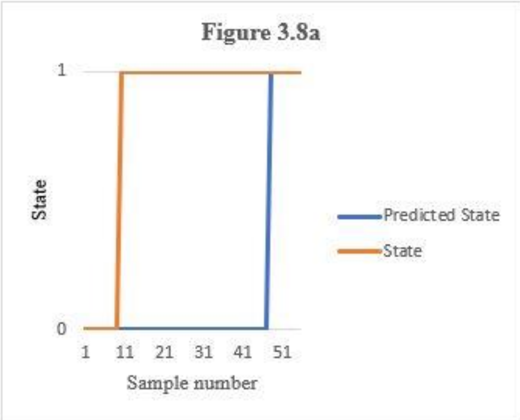


Figure 3.7 – Testing with data from the experiment

Figure 3.8 shows the zoomed view around the first two transitions in Figure 3.7 at sample 540 and 1095. This figure clearly illustrates the delay in detection time, which explains why the test results in Table 3.2 do not indicate 100% correct detection for all samples. With the sampling rate of 10 Hz, the detection time is around 3-4 s for kick detection and 4-5 s when the system resets back to normal condition. This performance of data-driven BN is slightly better compared to the performance of model-based BN. Figure 3.10 shows the performance of model-based BN with both detection time and reset time around 4-5 s.



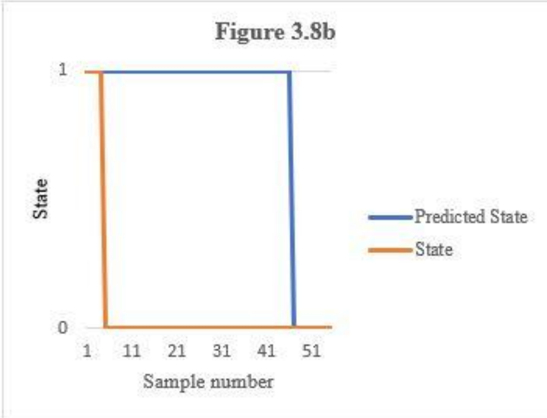
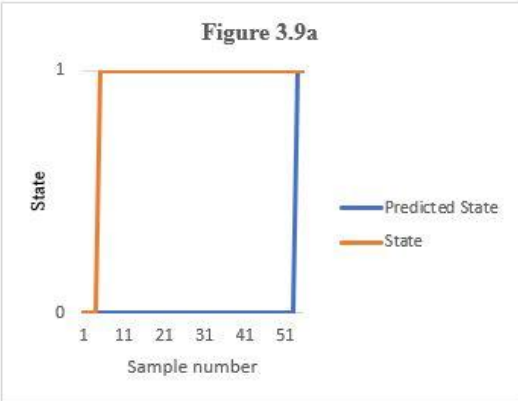


Figure 3.8 – Time delay in detection of data-based network with data from the experiment. Figure 3.8a shows the transition from normal to kick. Figure 3.8b shows the transition from kick to normal



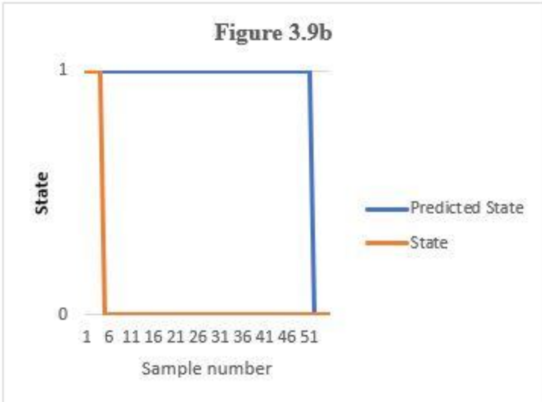


Figure 3.9 – Time delay in detection of model-based network with data from the experiment. Figure 3.9a shows the transition from normal to kick. Figure 3.9b shows the transition from kick to normal

3.3.2 <u>Testing with Synthetic Data</u>

As explained in Section 3.1.3, a synthetic data set consisting of around 8 million samples was created from data from the experiment. Thirty kick events are introduced into the data set. This data set was used to test the performance of the data-based model.

Table 3.3 shows the results of testing with synthetic data. The accurate detection for normal condition and kick condition are 99.9%. The missed alarm rate and false-alarm rate are both 0.1%. Similar with the case of testing with data from the experiment, incorrect detection happened only during transition state. As shown in Figure 3.10, the predicted state is overlapped by the state which indicates that all thirty kick events were detected without failure and there were no false alarms.

Table 3.3 – Results of testing with synthetic data

Actual	Predicted	Accuracy of predicted state
kick	kick	99.9%
kick	normal	0.1%
normal	kick	0.1%
normal	normal	99.9%

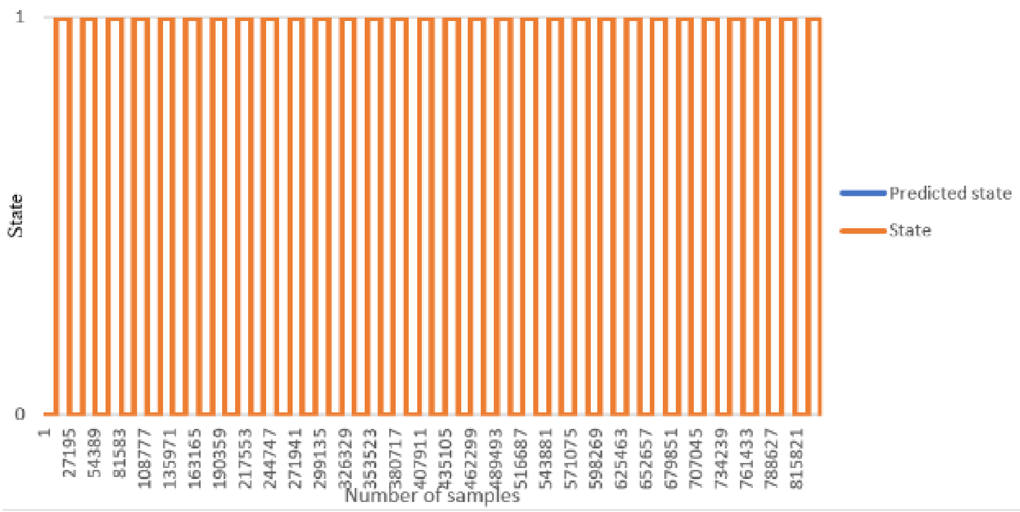
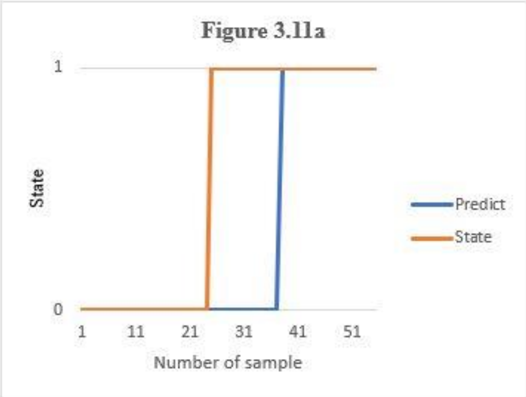


Figure 3.10 – Testing with synthetic data

In Figure 3.11, the detection time is around 1-2 s for kick detection and 3-4 s when the system resets back to normal condition.



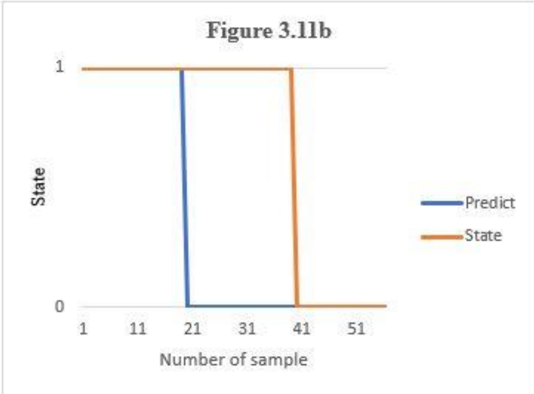


Figure 3.11 – Time delay in detection with synthetic data. Figure 3.11a shows the transition from normal to kick. Figure 3.11b shows the transition from kick to normal

When tested with data from the experiment as well as synthetic data, data-driven BN shows no missed detection and false detection to identify the kick event. It indicates that data-driven BN enables us to detect kick event without failure, and with no false alarm. This method can be applied widely because it only requires historical data which may be readily available, or less expensive to acquire, compared to expert knowledge that is needed in the case of model-based BN. Moreover, the missed alarm rate for data-driven BN is smaller compared to model-based BN, which indicates that the data-driven BN enables early kick detection. With the ability to detect kick event in 1-4 s with both data from the experiment and synthetic data, it is a significant improvement in detection time compared to surface monitoring technology. For example, kick detection by monitoring the increase in mud pit volume may vary from a few minutes up to 20 minutes depends on different in pressure between formation pressure and hydrostatic mud pressure, size of drilling hole and drilling pipe, and mud volume gain [32] [33].

Chapter 4. Experiment Setup with Large Drilling Simulator

4.1. Introduction

In this chapter, the new experiment setup with LDS will be presented. LDS is a new drilling system with larger-scale operating compared to the previous SDS. LDS was designed and constructed by researchers in Memorial University of Newfoundland, as reported by Arvani et al. in [34].

This chapter consists of three main parts:

- The structure of large drilling simulator: this part presents the structures and components of the LDS and the kick simulation system.
- Preparation of drilling sample: this part presents the design and casting of drilling sample that used in the experiment.
- Experiment procedure: this part presents the design of experiment which capture the three different phases during the experiment: normal drilling – kick occurrence – normal drilling resume after kick

This work has these contributions:

i. Completing the pressure cell: fabrication, pressure test, assembly, and integration into the LDS

ii. Manufacturing a high-pressure swivel and drilling shaft as designed in [34] for kick detection experiment

iii. Re-configuring and fully integrating the downhole assembly, kick inject system and fluid return line into the LDS

iv. Designing and preparing drilling samples

v. Conducting the experiment and generate two data sets:

- The first data set consists of 18 episodes, generated by circulating water as drilling fluid. Air is injected to simulate kick event.
- The second data set consists of 1 episode of actual drilling activity. Air is injected to simulate kick event.

vi. Validating data-driven Bayesian network with the new experiment data

The experimental setup with LDS including completing the pressure cell; manufacturing the high-pressure swivel and drilling shaft, re-configuring and integrating the downhole assembly, kick inject system and fluid return line into the LDS, designing and preparing drilling samples and conducting experiments, are the result of combined efforts with another graduate student, Somadina Innocent Muojeke.

4.2. The Structure of Large Drilling Simulator

The LDS is a fully automated drilling set up that is used to simulate field scale drilling and capable of atmospheric and pressurized drilling. The LDS consists of these principal sub-systems and components: drilling system, pressure cell, downhole sensor assembly and kick simulation system.

4.2.1 <u>Drilling system</u>

Hydraulic system: Pressurized hydraulic fluid is supplied to the LDS for introducing vibration to the system. Pressurized hydraulic fluid starts from the hydraulic pumping unit through the regulator and three solenoid manifolds on the top of the LDS, into the cylinder and circulate back to the pumping unit [34].

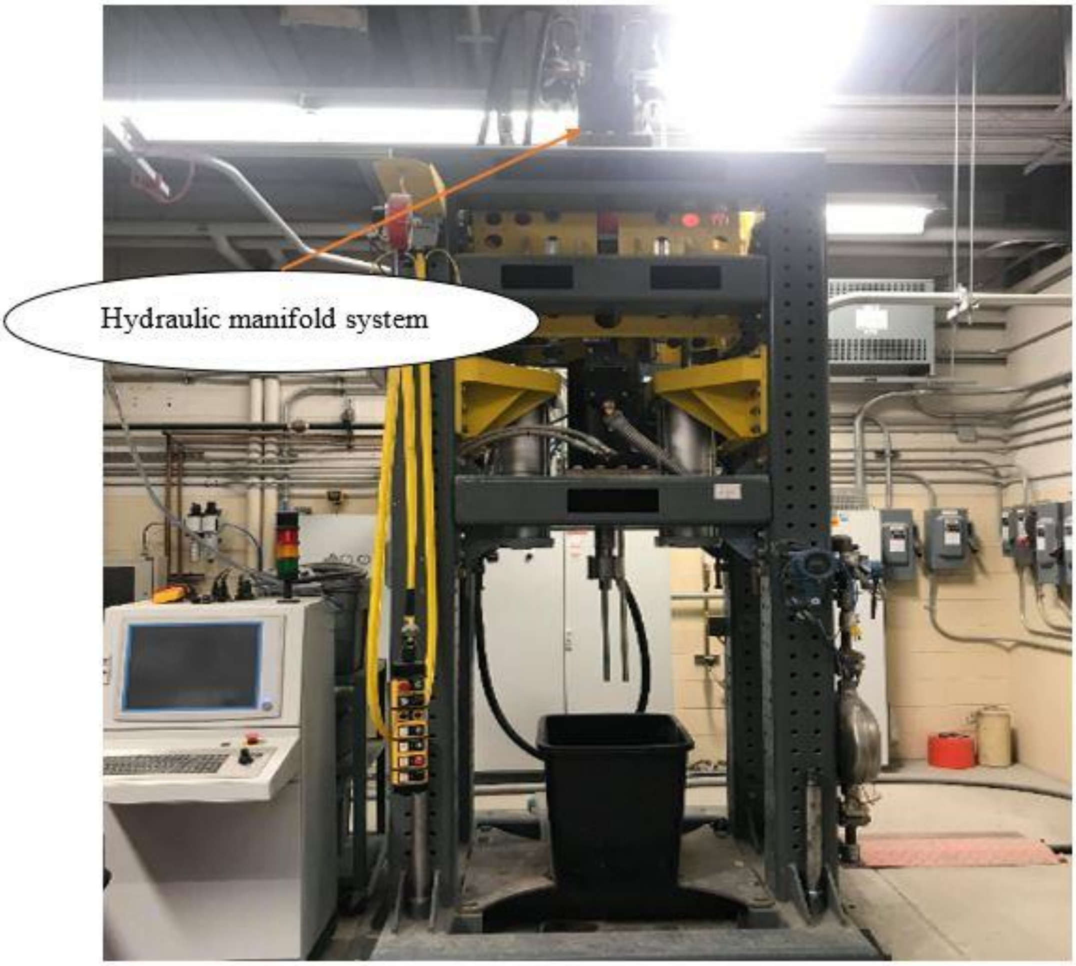


Figure 4.1 – Hydraulic manifold

Pneumatic system: The pneumatic system is used to move the drill string and apply the WOB. The system consists of air compressor breaker and pneumatic regulator. The air compressor breaker is used to start and stop the operation of the air compressor. The regulator is used to throttle the pressure supplied from the air compressor to the desired pressure. The pneumatic system also supplies air for the kick simulation system [34]

Figure 4.2 – Air compressor and pneumatic Regulator

High pressure pump: During drilling operation, water is used as drilling fluid. A high-pressure pump is used to circulate drilling fluid from the mud tank through the drilling string, into the pressure cell and discharge through the mud return line. The pump can maintain a constant flow rate between 5 and 40 usgpm with maximum pressure of 1000 psi. A pressure relief valve is installed on the mud return line to protect the downstream equipment when the pressure exceeds the designed pressure [34].

Figure 4.3 – High pressure pump

Drilling string: Drilling string consists of four main sections: upper drilling string, high pressure swivel, lower drill string and drill bit. Water is used as drilling fluid to clean the cutting during drilling operation. Drilling fluid is circulated from high-pressure pump upstream, through the inlet valve attached on the swivel, into the pressure cell and discharge through the mud return line [34].

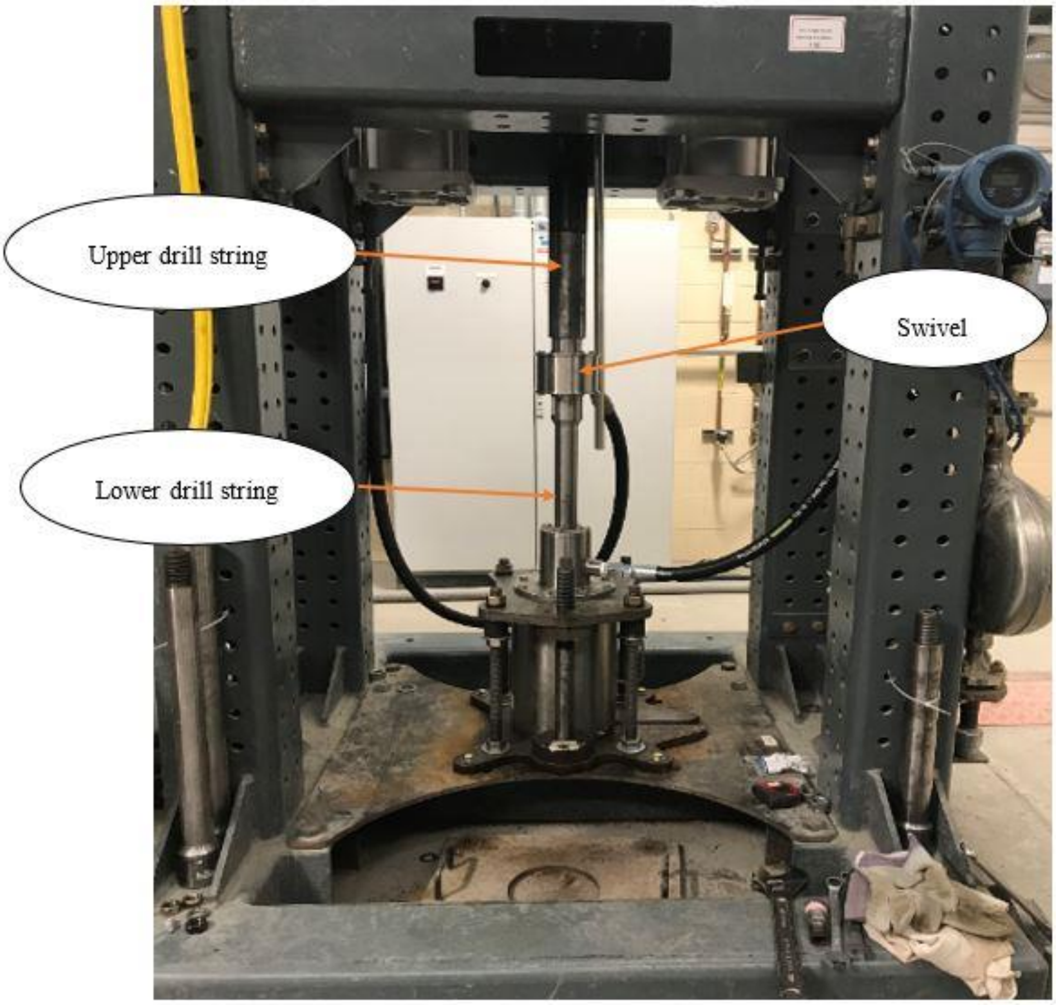


Figure 4.4 – Drilling string

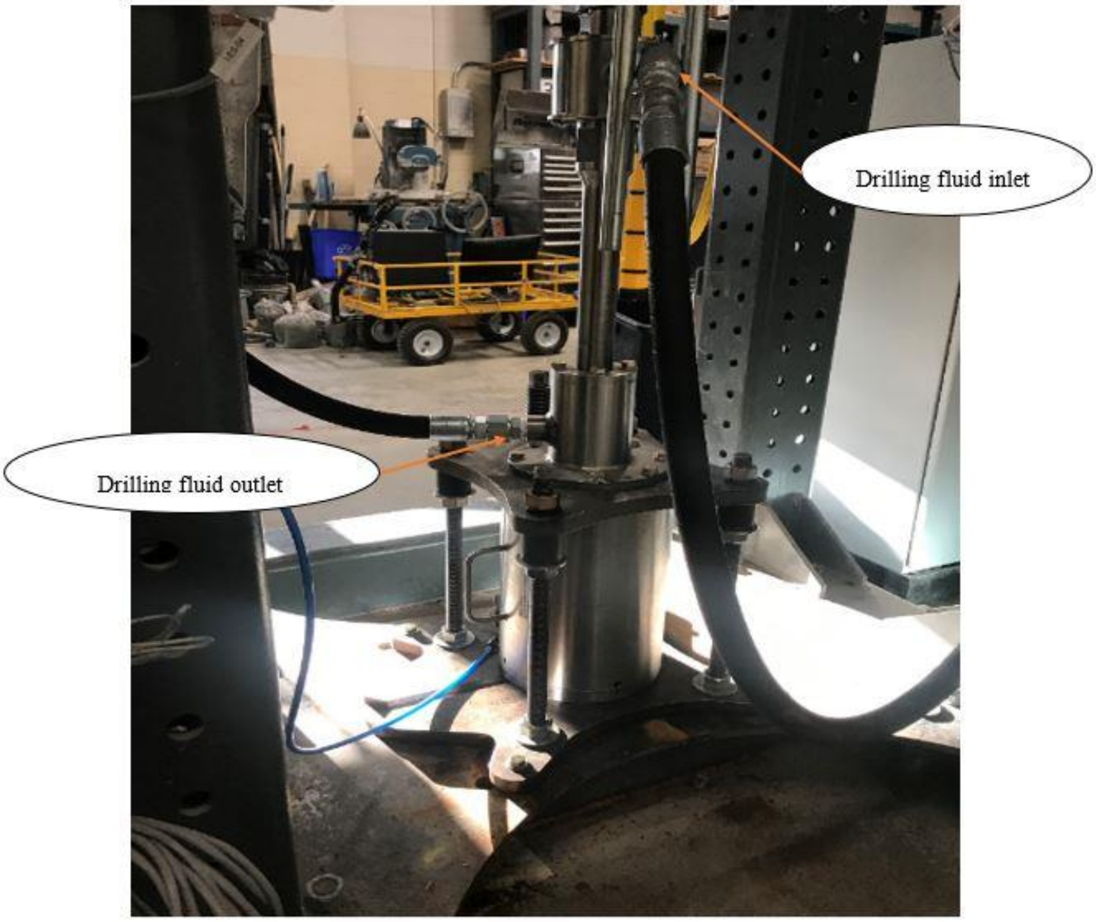


Figure 4.5 – Drilling fluid inlet and outlet

Drill bit: A 2 in Polycrystalline Diamond Compact (PDC) drill bit is used in this experiment. This is a fixed-head drill bit which consists of 4 cutters. There is one nozzle on the drill bit to let drilling fluid circulate from inside the drilling string into the wellbore.

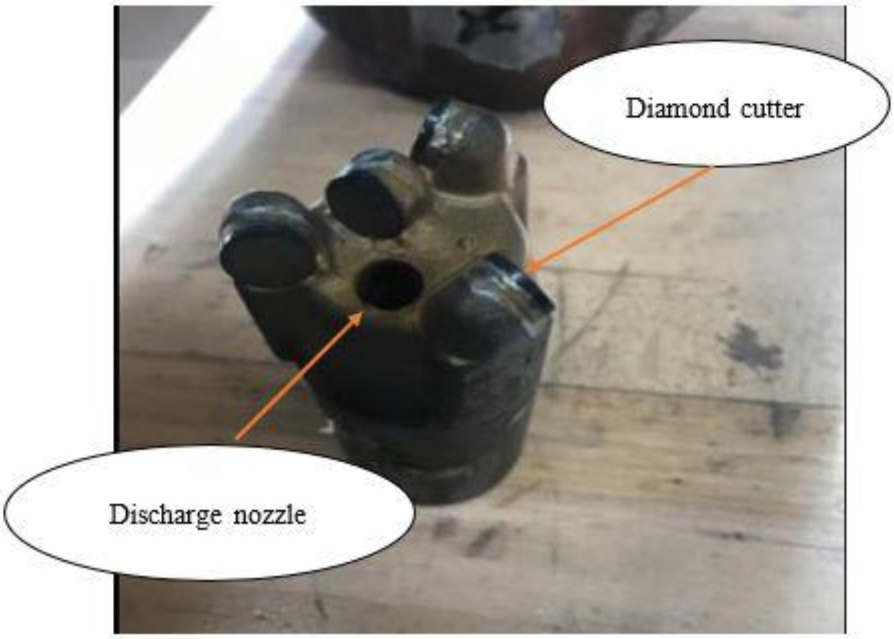


Figure 4.6 – 2 in PDC drill bit

4.2.2 <u>Pressure Cell</u>

A pressure cell of 9.5 in outer diameter and 14 in height is the central part of the kick simulation experiment. It is designed to house the drilling sample of 6 in diameter and 12 in height. The pressure cell is designed to operate up to 1000 psi. A high-pressure seal is placed on the top of the bit housing to seal against the drilling shaft. At the bottom, an air inlet is built-in to inject air from the air compressor which simulate kick events. To prevent air leaking from the bottom to the top of the pressure cell during the kick experiment, two high-pressure seals are placed at bottom cap of the pressure cell. An outlet from the side of the pressure cell connected with the mud return line to discharge the drilling fluid.

Figure 4.7 – Pressure cell

4.2.3 Downhole Sensor Assembly

An assembly consisting of downhole sensors is adopted from the SDS setup [35]. This assembly is installed in the mud return line. These sensors provide following measurements: mud flow rate, mud density, mud conductivity and downhole pressure. These sensors, as well as the mud return line, are placed as near as possible to the bottom of the pressure cell to record downhole parameters. All sensors are re-configured and integrated into the new LDS and re-calibrated.

Density and mass flow rate meter: A Coriolis mass flow rate and density meter are installed in the mud return line. This sensor can simultaneously provide three measurements: mass flow rate, density and temperature. However, only mass flow rate and density are measured during the experiments. This sensor provides good stability and sensitivity with two-phase fluid [35].

Downhole pressure sensor: A downhole pressure sensor is installed in the mud return line and placed as near to the bottom of the pressure cell as possible to measure the downhole pressure. The sensor has an operating range of 0-800 psi [35]. To calibrate the sensor, a pressure gauge is installed next to the pressure sensor using a T-junction fitting.

Conductivity sensor: A contacting-type conductivity sensor is installed in the mud return line to measure the electrolytic conductivity of the drilling fluid. Water is used as drilling fluid in this experiment which has conductivity of 50-200 μS/cm. Due to the range of conductivity of the experiment, the cell constant of 0.1 is selected which provides a range of 0-2000 μS/cm with an accuracy of 0.6% [35].

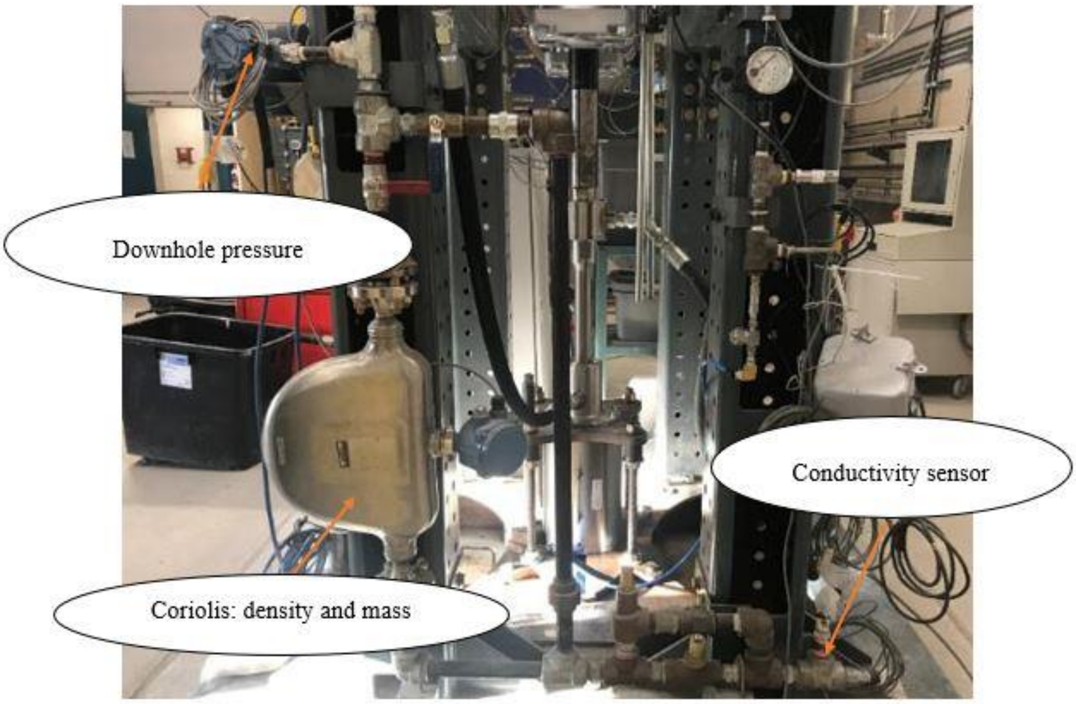


Figure 4.8 – Downhole sensor assembly

4.2.4 Kick Simulation System

To simulate kick event, a kick simulation system is designed in [35]. The system consists of these main components: air compressor, injected air pressure sensor, injected air flow rate, injected air temperature sensor, air check valve and filter, pressure regulator.

Air compressor: Atlas-Copco air compressor is used to supply air for the new LDS system and for the kick simulation system. The compressor has a maximum operating pressure of 175 psi which is adequate for the experiment operating range of 80-100psi.

Pressure regulator: An air pressure regulator is installed on the air line to adjust the air pressure up to the designed setting. The regulator has the maximum operating pressure up to 4000 psi [35]. There are two pressure gauges are installed: one to measure the input air pressure and one to measure the output air pressure. The maximum input air pressure is 175 psi which supplied from the air compressor. The output air pressure is adjusted down to 80-100 psi as per experiment requirement.

Injected air pressure sensor: To record the injected air pressure, an air pressure sensor is installed on the air line and connected with the acquisition system. The sensor has an operating range of 0-500 psi with an accuracy of 0.08% [35].

Injected air flow rate sensor: This sensor is to record the injected air flow rate. The sensor has a maximum operating pressure of up to 3000psi at 21^0 C degree with the accuracy of +/-5^0C [35]

Injected air temperature sensor: A temperature sensor is installed on the air line to measure the temperature of the compressed air. However, this measurement is not applied in this experiment.

Check valve and filter: In the final phase of the experiment, the pressure of the drilling fluid inside the pressure cell is higher than the pressure inside the air line after the air valve is closed. To prevent the drilling fluid flooding inside the pneumatic system, a check valve is installed at the end of the air line. Besides, a filter is installed next to the check valve to filter out the cutting during the drilling experiment to prevent any blockage to the check valve.

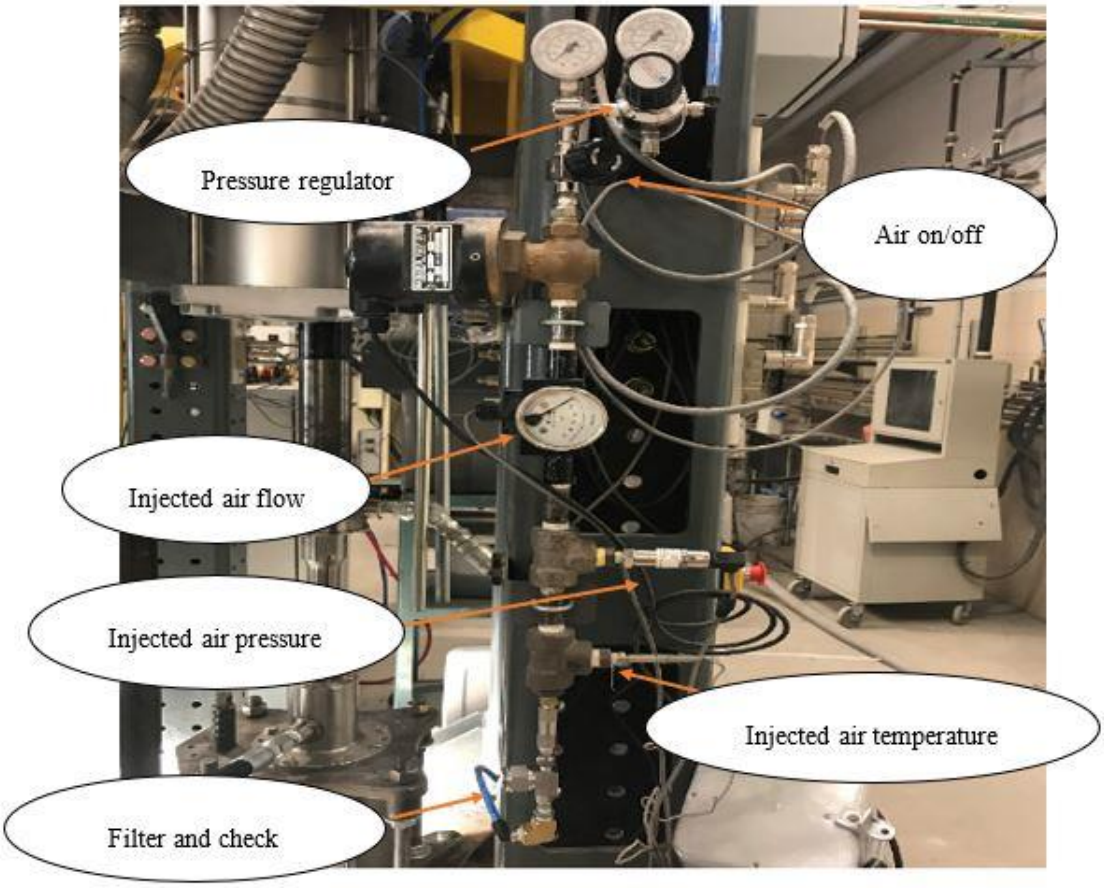


Figure 4.9 – Kick simulation system

4.3. Drilling Sample

Synthetic rocks are used in this experiment as drilling sample. To make drilling sample, concrete with 50 MPa compressive strength is casting following a specified recipe in [36]. The drilling sample has a diameter of 6 inches and a height of 12 inches, and it is secured inside the pressure cell during the drilling operation. At the top of the rock, a cavity of 3 in diameter and 4 in height is designed to house the drill bit during installation and uninstallation of drilling sample into the pressure cell. A 0.5 in drill bit is used to pre-drill the sample with 3-in length from the top and 4 inches length from the bottom. The pre-drilled hole separates the drilling samples into three separate zones: normal drilling zone (before the kick happens), isolated zone (this zone is to isolate the pressurized air of the bottom zone), and pressurized zone (this zone is pressurized with air, when the drill bit penetrates through this zone, it simulates drilling activities when kick occurs). The purpose of the pre-drilled hole at the bottom of the specimen is to create a cavity for pressurized air, while the pre-drilled hole from the top will maintain the same drilling condition (WOB, ROP, etc.) before the kick happens. The concrete slurry mixture includes aggregate, cement, water and superplasticizer. The quantity of each material was designed as Table 4.1.

Figure 4.10 – Pre-drill specimen with 0.5-in drill bit using SDS

Table 4.1 - Material usage for casting drilling sample

Material	Quantity
A : C : W	3 : 1 : 0.45
Aggregate	105 kg
Cement	35 kg
Water	15.75 kg
Water reducer	NA
Superplasticizer	Deracem 19 = 180 ml
Silica Fume	NA

Mixing and casting procedure was performed as detailed below [36]:

i. Cement and sand are put into the mixing machine to mix for 60 s. After that, water is added into the mixer and mix for 3 min, followed by 3 min rest and another 2 min of mixing (during the rest time, the mixer should be covered to prevent evaporation). After 5 min of mixing, superplasticizer is added and mixed for another 5 min.

ii. Making specimen: Concrete is filled into plastic mold into three equal layers (need to vibrate each layer before filling the next one). After filling, mold cap is used to cover the mold to prevent evaporation and the specimens will be store at 23+/-2 C degree to set.

iii. Curing: After 24 hours, the specimens is removed from the mold and kept under water until the start of the experiment.

Figure 4.11 – Completed synthetic drilling sample

4.4. Experiment Procedure

The experiment procedure was designed to capture both normal drilling and kick event conditions. The experiment includes three different stages: normal drilling – kick happens – system reset back to normal drilling. Drilling starts from the top of the drilling sample under normal drilling conditions. When the bit penetrates through the pressurized zone at the bottom of the drilling sample, the trapped air enters the borehole, which simulates the kick event. This condition is maintained for 60 s. The air valve is kept closed while the acquisition system logs data for 60 s. The experiment was conducted as following steps:

i. Install drilling sample installed and secure it inside the pressure cell.

ii. Pressurize the bottom pre-drilled zone of the drilling sample up to the designed pressure.

iii. Start drilling operation from the top of drilling sample at design mud pump-in flow rate, WOB and drilling motor speed.

iv. The kick event happens when drilling bit penetrates through the top of pressurized cavity. Maintain the air injection, drilling activities and keep logging data for 60 s

v. Close air valve while maintaining all drilling activities and logging data for another 60 s.

vi. Stop drilling activities, retrieve drilling bit and ventilate air inside the system before removing the drilling sample from the pressure cell.

Chapter 5. Validation of Data-driven Bayesian Network using Large Drilling Simulator Data

5.1. Experiment data from LDS

5.1.1 Circulating data

To generate circulating data set, water is used as drilling fluid and air is injected to simulate kick events. There are no drilling activities involved. The experiments are conducted with three different flowrates: 2000 lb/hr, 2500 lb/hr and 3000 lb/hr with the initial downhole pressure of 5 psi, 10 psi and 15 psi respectively. Three different air pressures are injected to simulate kick events: 40 psi, 50 psi and 60 psi. Table 5.1 summarize the run orders and input parameters for each run. Each run of the experiment is conducted as per the following steps:

- Injected air pressure is set to the designed setting using the regulator on the kick simulator system (the air valve remains close).
- Water is circulated from the water tank through the drilling string into the pressure cell and discharge through the return line. This phase lasts for 45 s.
- Open the air valve to introduce the kick. Keep logging the data for 60 s.
- Close the air valve to stop the kick. Keep logging the data for another 60 s. This step records the data when the system resumes to normal condition.
- Stop the water circulation.

Table 4.1 - Input parameters for circulation experiment

Run	Injected air pressure (psi)	Initial flow rate (lb/hr)
1	40	3000
2	40	3000
3	40	2500
4	40	2500
5	40	2000
6	40	2000
7	50	3000
8	50	3000
9	50	2500
10	50	2500
11	50	2000
12	50	2000
13	60	3000
14	60	3000
15	60	2500
16	60	2500
17	60	2000
18	60	2000

Figure 5.1 shows the first three episode of data set of circulating experiment.

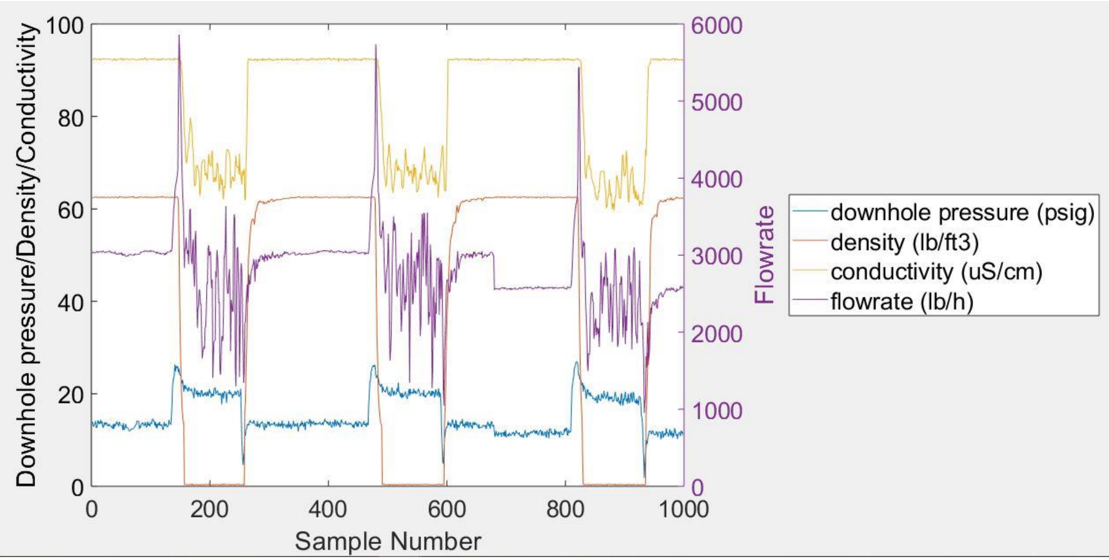


Figure 5.1 – Circulating data

5.1.2 Drilling data

To generate drilling data set, water is used as drilling fluid and air is injected to simulate kick events. The drilling sample is prepared as discussed in Section 4.3. The experiment procedure is discussed in Section 4.4. Table 5.2 shows the input parameters for the drilling experiment.

Table 5.2 - Input parameters for drilling experiment

Parameters	Description	Value	Unit
WOB	Applied weight on bit	2	kN
q	Mud pump input flow rate	5000	lb/hr
Pg	Injected air pressure	80-100	psig
N	Drilling motor speed	60	RPM
Density	Drilling fluid density	1000	kg/m3

Figure 5.2 shows the data set collected from the drilling experiment with LDS

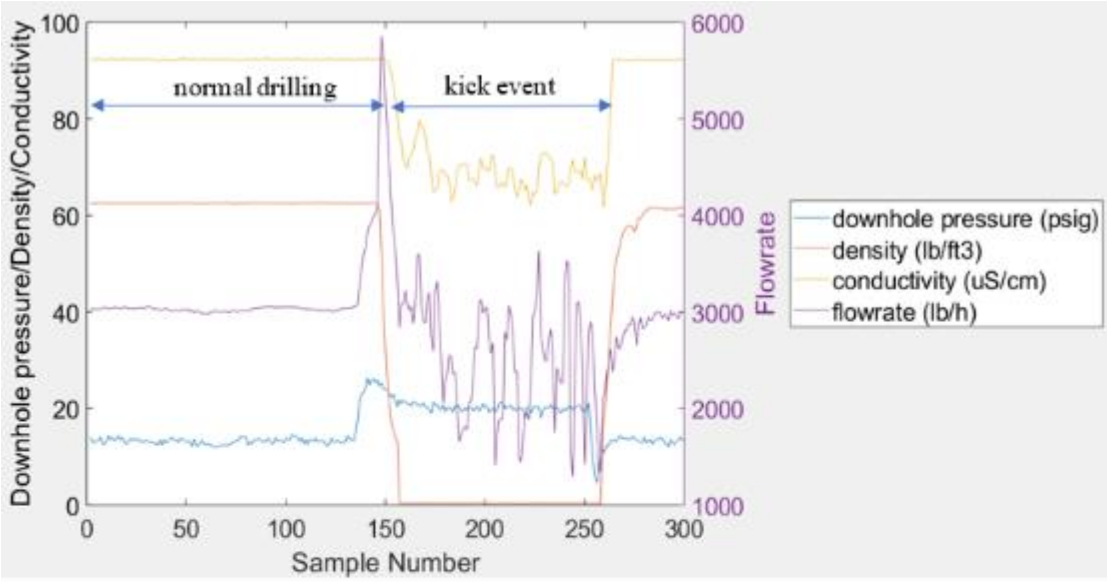


Figure 5.2 – Drilling data

5.2. Results and Discussions

5.2.1 Testing with circulating data

Table 5.3 shows the results of testing with circulating data. The detection accuracy for kick condition and normal condition are 94.6% and 91.1%, respectively. The missed alarm rate and false-alarm rate are 5.4% and 8.9%, respectively. Incorrect detection happened only during the transition state. In Figure 5.3, we can observe that the predicted state plot and the actual state plot are almost fully overlapped which indicates that all kick events were detected without failure and there were no false alarms.

Table 5.3 – Results of testing with circulating data

Actual	Predicted	Accuracy of predicted state
kick	kick	89.0%
kick	normal	4.3%
normal	kick	11.0%
normal	normal	95.7%

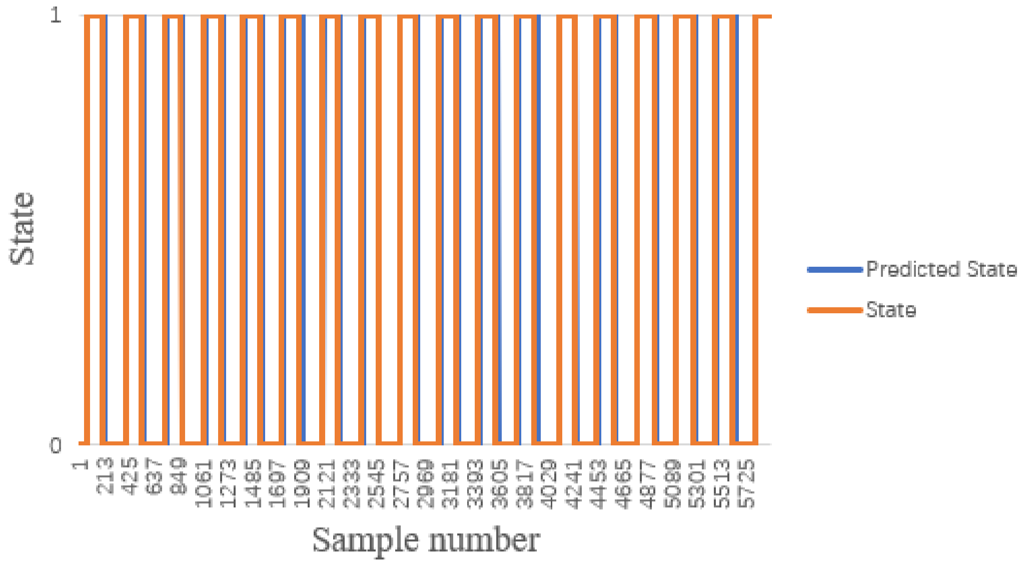
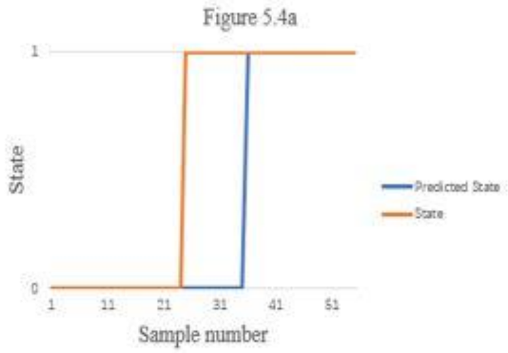


Figure 5.3 – Testing with circulating data

Figure 5.4 shows the zoomed view around the first two transitions in Figure 5.3 at sample #34 and sample #183. This figure clearly illustrates the delay in detection time. The detection time is around 1-1.5 s for kick detection and 2-3 s when the system resets.



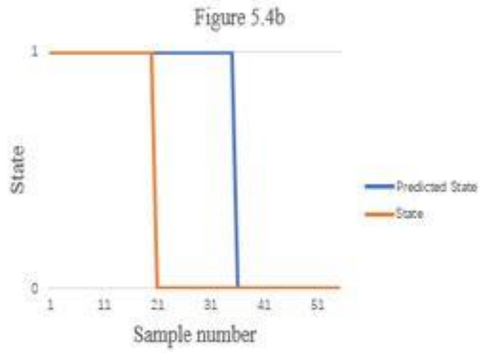


Figure 5.4 – Time delay in detection with circulating data. Figure 4a shows the transition from normal to kick. Figure 4b shows the transition from kick to normal

5.2.2 Testing with drilling data

Table 5.4 shows the results of testing with drilling. The detection accuracies for kick condition and normal condition are 91.4% and 100%, respectively. The missed alarm rate is 8.6% and the false-alarm rate is 0%. Incorrect detection happened only during the transition state.

Table 5.4 – Results of testing with drilling data

Actual	Predicted	Accuracy of predicted state
kick	kick	100.0%
kick	normal	2.4%
normal	kick	0.0%
normal	normal	97.6%

Figure 5.5 shows the results of testing with drilling data. Figure 5.6 shows the zoomed view of transition state which indicates the delay in detection of approximately 0.5 s.

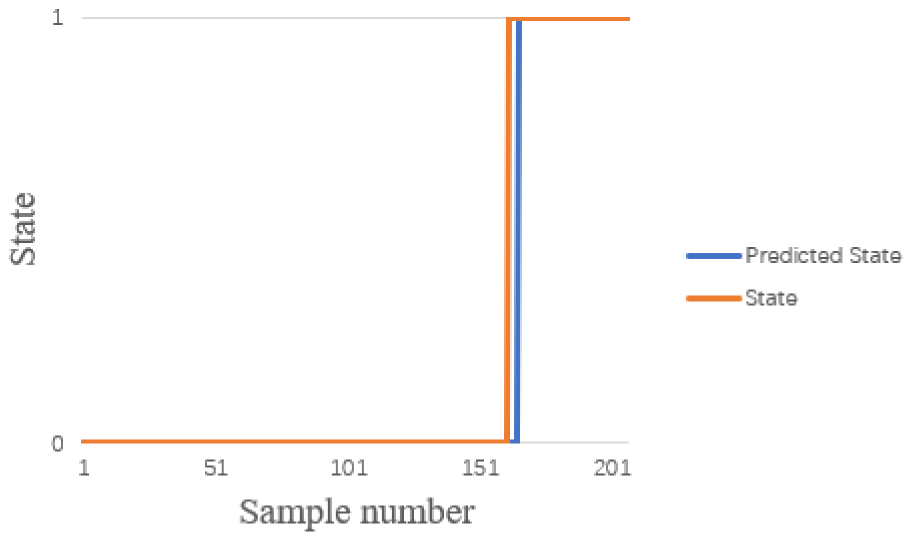


Figure 5.5 – Testing with drilling data

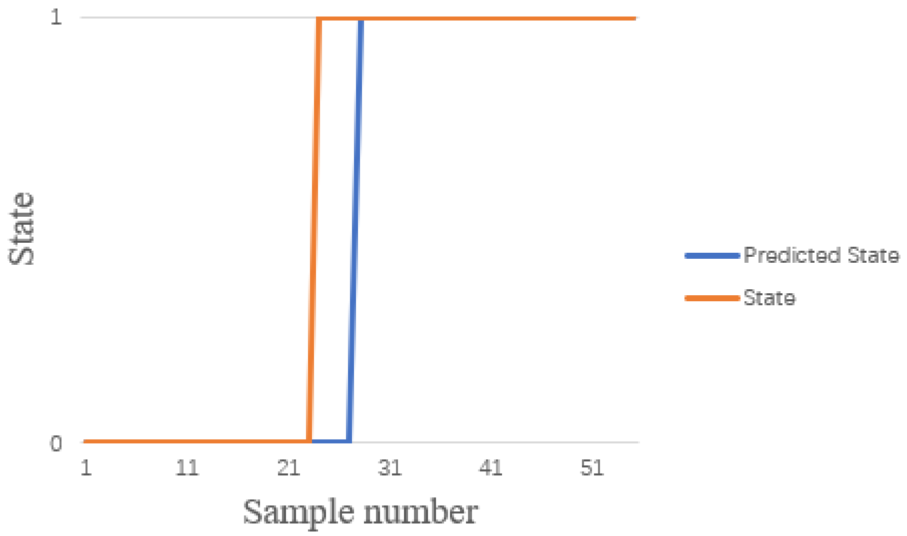


Figure 5.6 – Time delay in detection with drilling data

Chapter 6. Conclusions and Suggested Future Work

6.1. Conclusions

The results obtained in this work, as well as recent works that investigated the effect of a kick on downhole parameters, prove the effectiveness of using these parameters to realize early kick detection. As shown in Chapter 5, with the ability to detect kick in seconds, this work introduces a new method to detect kick occurrence as soon as it happens. Besides, success in developing the model from historical data without prior knowledge about the relationship between input parameters also emphasizes the advantage of a data-driven model, which can be applied to solve complex systems. With no missed detection and false detection of the kick event, this work achieved positive results when testing with circulating data obtained from SDS, as well as circulating data and drilling data obtained from LDS. The result obtained in this work is also supported by the results from Sule's work [16] when he conducted drilling experiment with SDS. He also observed the increase in downhole pressure, flowrate and decrease in density when kick occurs. The output resulting from this BN can be utilized as a part of automated well control decision-making during drilling operation. As summary, some conclusions are drawn as below:

- The results obtained in this work prove the effectiveness of applying downhole parameters in early kick detection.

- With the ability to detect kick in seconds, monitoring downhole parameters show significant advantages in early kick detection compared to conventional kick detection systems, which relied on surface monitoring techniques.
- When data acquisition process is easier and less complicated compared to expertise knowledge acquirement, success in developing the model solely from historical data emphasizes the advantage of a data-driven model, which can be applied to solve complex systems
- With no missed detection and false detection of the kick event, this work proves the usability of data-driven BN for early kick detection. The output resulting from this BN can be utilized as a part of automated well control decision-making during drilling operation.
- Success in experiment setup, integrated the kick simulation system into the LDS and the trial drilling experiment with LDS enables more kick experiment activities in the future.
- With positive testing result of the model with drilling data from LDS, it strengthens the idea of applying data-driven Bayesian network in early kick detection.
- This work assumes that downhole parameters are readily available. However, downhole measurements may experience the delay in transmission from downhole to the surface. The transmission time delay is counted as a part of delay in detection, which is not determined in this work. However, the transmission delay would be several orders of magnitude smaller than the delay due to relying solely on rig floor measurement.

6.2. Suggested Future Work

With this new setup of kick simulation system with LDS, suggested future works are listed below:

- Increasing number of experiments with drilling activities to generate more data
- Conduct experiments with different type of rocks: synthetic rocks with different properties, natural rocks, etc.
- Conduct experiments with drilling fluid with different properties, for example: increase density, viscosity by introduced some materials into water, etc.
- There are air injection flowrate and pressure sensor which can be utilized in investigation the size of the kick
- Number of kick events and different scenario of kick events can be increased by changing air inject pressure and flow rate, changing drilling fluid properties and changing drilling sample
- Current models applied four input parameters: downhole pressure, flow rate, density and conductivity of drilling fluid. The model can be expanded by increasing the number of input parameters, for example, rock properties.
- Testing and evaluating the performance of the developed model with field data

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Appendix A – Experimental data

Included in supplementary files.