Real time kick estimation and monitoring in managed pressure drilling system

by

© M.Musab Habib

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Abstract

The influx of reservoir fluid (kick) has a significant impact on drilling operations. Unmitigated kick can lead to a blowout causing financial losses and impacting human lives on the rig. Kick is an unmeasured disturbance in the system, and so detection, estimation, and mitigation are essential for the safety and efficiency of the drilling operation. Our main objective is to develop a real time warning system for a managed pressure drilling (MPD) system. In the first part of the research, an unscented Kalman filter (UKF) based estimator was implemented to simultaneously estimate the bit flow-rate, and kick. The estimated kick is further used to predict the impact of the kick. Optimal control theory is used to calculate the time to mitigate the kick in the best case scenario. An alarm system is developed based on total predicted influx and pressure rise in the system and compared with actual well operation control matrix. Thus, the proposed method can estimate, monitor, and manage kick in real time, enhancing the safety and efficiency of the MPD operation. So, a robust warning framework for the operators based on real life operational conditions is created in the second part of the research. Proposed frameworks are successfully validated by applying to several case studies.

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Chapter 1

Introduction

1.1 Motivation

We live in a technologically advanced era where strive for maintaining a standard living style increases the energy demand. The search for alternative energy has been going on, but still, hydrocarbon holds the position for the largest source of the energy supply (Ritchie & Roser, 2014). Totten (2004) provided a brief history of the petroleum industry. Explorations using bamboo poles to modern drilling equipment, the drilling technique, and procedure have changed significantly over the years. Drilling for oil and gas is a challenging and expensive operation due to adverse geological conditions. The convenient wells have already been used for extraction. These used or ongoing production sources affect the nearby wells by creating critical pressure margins (Møgster et al., 2013). The biggest challenge for the drilling companies is to access the reservoir in a cost-effective manner and ensuring the safety and maximum production during the operation. So, the necessity of continuous developments of the drilling technique is inevitable to face the challenges in the present and near future.

Detail description of the conventional drilling method can be found in Bourgoyne et al., (1986). Three columns of hollow drill pipes mounted together to assemble the drillstring.

At the bottom, different shaped and sized bits are present to crush the rock. Drilling fluid is pumped through the drillstring, jetted through nozzles in the bit, and circulated in the annulus carrying the cuttings. It is the primary safety tool to maintain well overbalanced. Pressure in the well must be higher than the pore pressure of the formation. Figure 1.1 presents the pressure margins in the well.

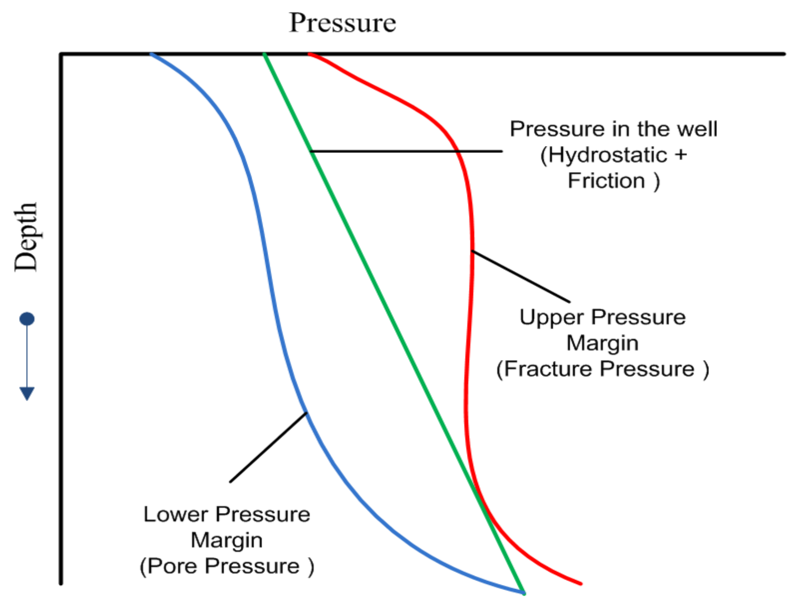

Figure 1.1 Pore pressure, fracture pressure and the pressure in the well

Mitchell & Miska (2011) provided an overview of pressure management in the drilling operation. The pressure profile is mainly dependent on bottomhole pressure (BHP), reservoir pressure, and fracture pressure. Hydrostatic pressure can be defined as the following equation-

$$P_h = \rho g h \qquad (1.1)$$

Here, ρ is the fluid density and h is the total height.

BHP depends on the hydrostatic pressure, pump pressure and frictional pressure drop. Generally, a pump circulates the drilling fluid under a pump pressure P_p at a particular flow rate q_p. The drilling fluid continues through the bit with a flow rate of q_{bit}., and pressure at the bit is denoted as P_{bh}.. When the drill string reaches the reservoir zone, the reservoir fluid exerts pressure *Pres* at the bottomhole through porous rock formation BHP can be presented by the following equation:

$$P_{bh} = P_h + P_p - P_f \qquad (1.2)$$

Here, P_f is the fractional pressure drop. Operators modify the circulation rate of the drilling fluid, pump pressure, and mud properties to maintain the desired BHP. During drilling, the length of the drill string is gradually increased by adding stands of pipe, referred to as making a pipe connection. During that time, frictional pressure will be absent because there will be no mudflow. Mud density must be chosen carefully to maintain the hydrostatic pressure above the formation pressure. As the depth increases, the pressure margins become narrower, creating complexity for the operators. The pressure manipulation is limited in conventional drilling techniques. So there is a high chance of BHP exceeding the fracture pressure causing loss of drilling fluid in the formation (Rehm et al., 2013). On the other hand, if the BHP goes below the reservoir pressure, a reservoir influx of fluid called kick will encounter in the system. Controlling pressure is critical for an event free drilling operation. BHP must be kept in between the formation pressure and fracture pressure.

Formation Pressure < BHP < Fracture Pressure.

A kick can occur in the system for multiple reasons. Hughes (1995) identified five main reasons for kick occurrence. There are:

- The majority of kicks occur when the bit is off the bottom while tripping.
- Swabbing of formation fluid into the borehole
- Insufficient mud density.
- Poor well planning.
- Loss circulation due to fracturing.

Controlling the pressure is essential to prevent uncontrolled kick and, among other issues, prevent boreholes from collapsing, minimize loss of mud when drilling into depleted sections of reservoirs, reduce danger when drilling into high pressure. Unmitigated kick can turn into blowouts, which creates financial losses and affects the environment and human lives (Hauge et al., 2013). The Macondo incident in the Gulf of Mexico is the prime example of a catastrophic accident due to kick. In conventional drilling, when a kick is encountered drilling has to be stopped, and a heavier mud is pumped to take the BHP above the reservoir pressure, and that is a significant drawback of conventional drilling as stopping of drilling contributes to nonproductive time (NPT). Further, the mitigation of kick depends on the operator's skills and expertise. Therefore, to increase the safety and productivity in the drilling operation, Managed Pressure Drilling (MPD) has emerged powerfully to control the pressure profile in the well effectively.

1.2 Managed Pressure Drilling (MPD)

MPD offers a solution to many drilling issues by dynamically adapting the drilling condition at a particular moment. MPD is a marginally overbalanced drilling technique that keeps the BHP in the safety region by manipulating the automated choke valve (Nandan & Imtiaz, 2017). It treats the mud circulation system as a closed vessel rather than an open system. MPD uses back pressure devices like choke to manage the BHP actively. So, MPD can perform in a narrow pressure window for having higher precision and flexibility than the conventional drilling procedure. The International Association of Drilling Contractors (IADC), the official definition of MPD, is "an adaptive drilling process used to more precisely control the annular pressure profile throughout the wellbore. The objectives are to ascertain the downhole pressure environment limits and to manage the annular hydraulic pressure profile accordingly. MPD intends to avoid the continuous influx of formation fluids to the surface. Any influx incidental to the operation will be safely contained using an appropriate process" (Reitsma & Couturier, 2012).

A schematic representation of MPD drilling is presented in Figure 1.2. It has mainly two control volumes: drill string and annular mud return section. Pump supplies the drilling fluid to the drillstring under pump pressure P_p with a flow rate of $q_{p.}$ The drilling fluid passes through the bit with a flow rate of $q_{bit.,}$ and pressure at the bit is denoted as $P_{bh.}$ A choke at the exit of the annulus control volume provides a back pressure P_c and mud flows through it at a volumetric flow rate q_c

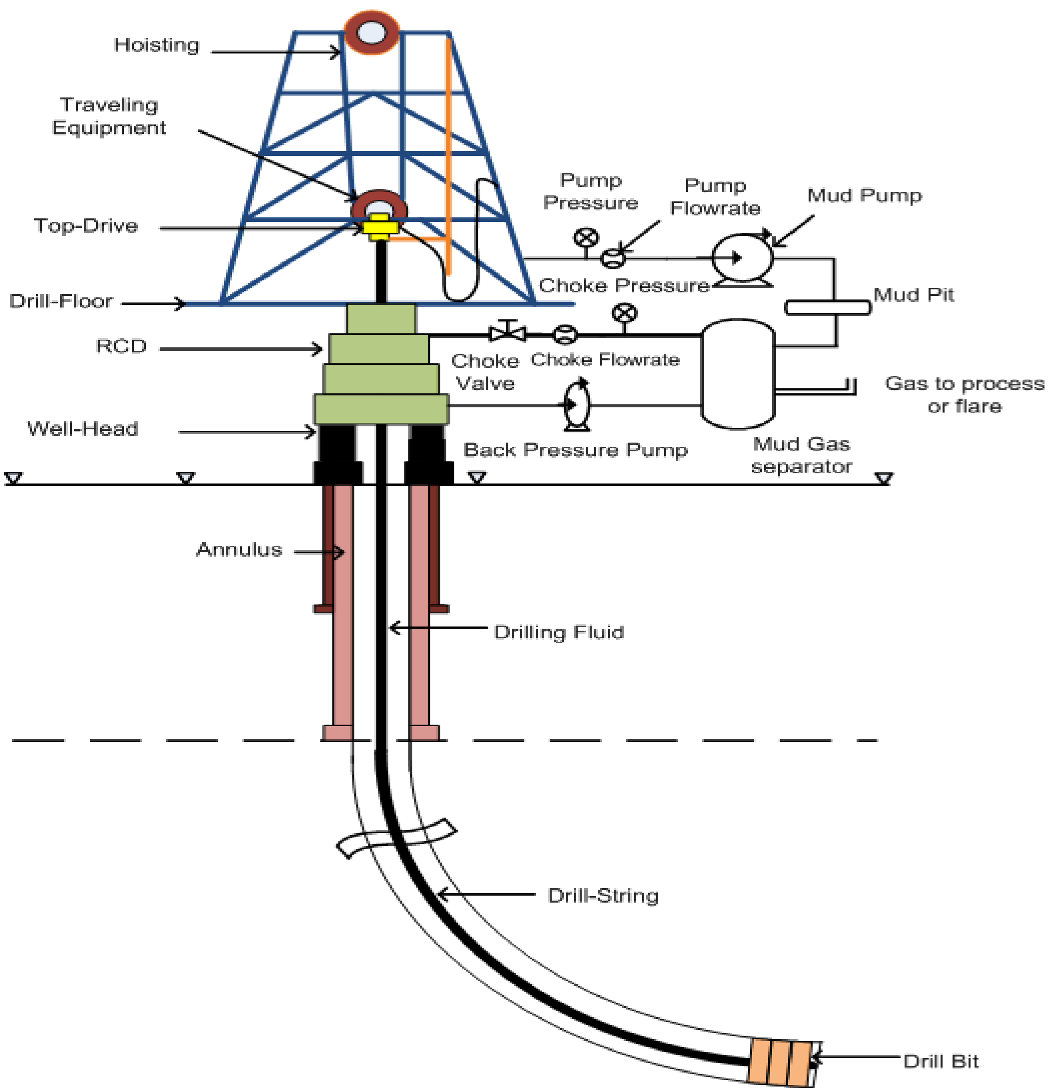

Figure 1.2: Schematic representation of MPD drilling (Zhou and Krstic, 2016)

In MPD, P_{bh} does not completely dependent on hydrostatic pressure P_h and pump pressure $P_{p.}$ Choke valve and backpressure P_b provide more flexibility for pressure control as shown in Figure 1.3. So, BHP can be presented as –

$$P_{bh} = P_h + P_{p.} + P_b - P_f \quad \text{………..……………………..……..….} \quad (1.3)$$

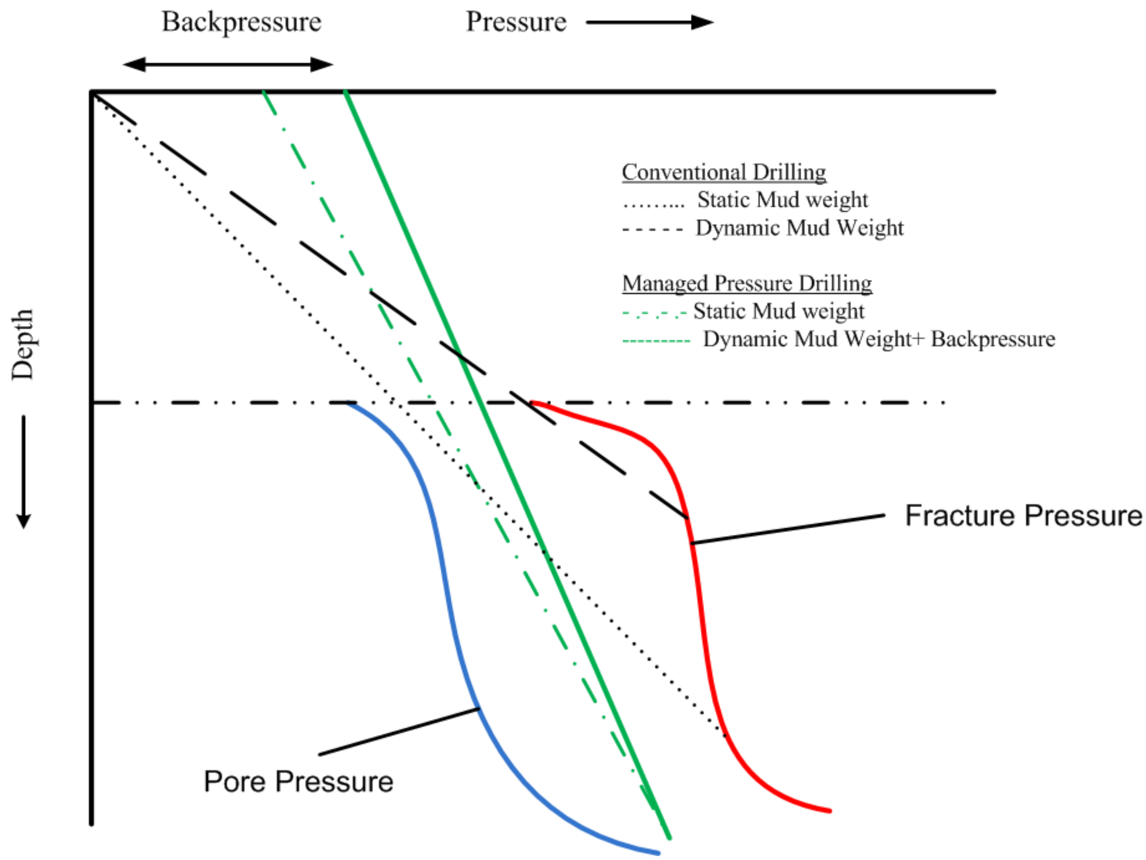

Figure 1.3: Comparison between conventional and managed pressure drilling

The main objective of MPD is reduced the production cost and NPT time (Vieira et al., 2008). MPD increases the safety with specialized techniques and surface equipment and makes many drilling operations economically viable (Rehm et al., 2013). As reported in Vieira et al., (2008), MPD reduced the time of drilling operations from 65 days to 45 days. MPD can reduce the cost of drilling by $25 to $40 per foot (Rehm et al., 2013). Apart from economic advantages, MPD provides the solution to other conventional drilling drawbacks. These are (Rehm et al., 2013)-

- Reduction of total number of casing points
- Strings and the subsequent hole size reduction.
- Limiting the NPT associated with a differentially stuck pipe.
- Limiting lost circulation.
- Drilling with total lost returns.
- Increasing the penetration rate.
- Deepwater drilling with lost circulation and water flows.

Manually controlled MPD depends on operator’s skills and expertise. Automation of MPD can provide an extra helping hand to the operators. Godhavn & Asa (2010) discussed about the necessity of automated control system for high performance MPD operation. The researchers implemented a proportional integral derivative (PID) controller to track the choke pressure and (Johannes et al., 2013) extended this work by implementing a model predictive controller (MPC). In MPD operations, controller ranges from PID controllers to model based advanced controllers such as nonlinear model predictive controller (NMPC). But there are mainly two ways to control the MPD operation and these are flow control and pressure control. The Pressure controller tracks the bottomhole pressure but allows influx of the fluid in the reservoir. On the other hand, flow controller is the best possible method to mitigate the kick but it does not track the bottomhole pressure during normal conditions. Zhou et al., (2011) proposed a novel switching controller to overcome these drawbacks. The controller acted like a pressure controller under normal condition and switched to flow controller mode during abnormal condition to mitigate the kick. The proposed controller showed superior performance over the conventional drilling process but it was checked only for one case scenario. Different scenarios can be considered to check the controller's performance properly. Siahaan et al. (2012) proposed a switching scheme of a PID controller where the tuning parameters are selected from real time measurement data and cost function. The researcher employed WeMod, which is a drilling simulator, to utilize an actual off-shore drilling operation in the North Sea. The tuning parameters of PID controllers were fixed at constant values and there is a possibility of oscillation in the states when the flow demand changes. The controller tried to compensate for the changes based on real measurement data and evaluation of cost function. The success of this operation depends on choosing the right tuning parameters to mitigate the oscillation effect. However, the computation for selecting the right setting is challenging without prior knowledge and expertise of the system.

Reitsma & Couturier (2012) provided a brief description about the progress of automated choke controller in MPD system. They implemented a modified proportional integral (PI) controller. Espen Hauge, Aamo, & Godhavn (2012) presented a model based on in/out flux detection scheme for MPD along with an adaptive observer to estimate the unknown states and parameters of hydraulic scheme. Hauge et al. (2013) extended this work by implementing the controller in an experimental setup and high fidelity OLGA simulator. The controller used the flow control theorem to mitigate the kick. Nandan, Imtiaz, & Butt (2017) implemented a gain switching controller to deal with the nonlinearity of the system.

Multiple controllers were used, and those were selected by total flow rate and choke openings. The nonlinear ODE based observers are used to estimate the reservoir pressure during kick and a new pressure set point is selected to mitigate kick in the system.

G. Nygaard & Nævdal (2006) implemented the NMPC controller, which is based on the first-principles two-phase flow model using spatial discretization of the complete well. They used the Levenberg–Marquardt optimization algorithm for the optimal choke settings. The goal of the controller is to control the choke opening based on the fluctuating flow needs in the drilling operation. The performance of the controller was evaluated by comparing the results with feedback PI controller. The PI controller's configuration varies with the changes in the tuning parameter, and that is why the proposed controller had better performances than the PI controller. The model considered for the simulations in this experiment is different from the practical operation. Nandan & Imtiaz (2017b) developed a new model of NMPC which switches to flow control mode from pressure control in case of reservoir kick by utilizing the constraint handling capacity of NMPC. The controller was designed as an output feedback control architecture and used active set method for computing control inputs. A nonlinear ODE solver was used to estimate the bit flow rate and kick volume. Whenever the kick volume went beyond a threshold value indicated by the difference between inlet and outlet flow rate, the flow control mode was activated to drive the kick out of the system. An optimal choke opening was achieved by optimizing the constraint values in predefined cost function and for that the controller was tested on a simulated ODE model.

The automated MPD system requires an accurate measurement of each state and variable. In MPD system, normally, top side measurements are available only, such as pump pressure, choke pressure, pump flow rate, and choke flow rate due to lack of proper instrumentations. Kick is the unmeasured disturbance, which makes the system more critical. An accurate estimation of the kick is inevitable to enhance the safety and efficiency of the MPD system.

1.3 Estimators

Kalman based estimators are the most popular approach for state estimation. Kalman (1960) first introduced this concept for linear filtering and state estimation purposes. The proposed concept was implemented in two case studies to confirm the method. Other common observers are Luenberger observers. Luenberger (1971) presented this idea for state estimations. These two types of concepts are the base for most of the observers. They have been modified and improved over time. Dochain (2003) discussed the extended Luenberger observers (ELO) and extender Kalman observers (EKO). The researchers identified the limitation of these observers and modified them for better performance. (Radke & Gao, 2006) discussed Luenberger observers in their review work on observers for process industries and identified the advantages of these observers. A brief overview of the observers can be found in Mohd et al. (2015). The researchers concluded that Luenberger observers are suitable for a simple linear system. The performance degrades in the presence of model mismatch and a higher noise level. They presented the Bayesian estimator as an alternative of Luenberger observers. Chen et al. (2009) developed a disturbance observer based multi-variable control (DOMC) scheme for a control system. This work was further modified by Yang et al. (2011) . They considered both internal and external disturbances. A modified observer showed better performances than the other disturbance observers. Corless & Tu (1998) proposed a framework to estimate states and inputs simultaneously using 'Lyapunov-type characterization.' The proposed estimator was suitable under very strict conditions. Researchers considered linear cost function and known state and parameter values. Xiong and Saif (2003) extended the work by proposing a state functional observer with reduced restrictive conditions.

The above-discussed observers apply to linear systems. However, real-world systems are nonlinear. Designing an observer for a nonlinear system is complicated and challenging (Imsland et al., 2007). The researchers presented an unknown input observer to handle the nonlinearity. In Alessandri (2004) adaptive high-gain observers were proposed based on linear matrix inequalities (LMI) to solve the observer designing problem. They also identified the difficulties associated with the construction of a state observer for the nonlinear system, and these were investigated by using input-to-state stability (ISS) properties. Junqi et al. (2016) proposed an adaptive $H\infty$ observer for Lipschitz nonlinear system. Measurement noise was combined with the state vector, and states and measurement noise were estimated simultaneously. This approach is restricted to the Lipschitz type system. Patwardhan et al. (2012) presented a brief review of nonlinear Bayesian state estimation. They classified the Bayesian estimators based on the nonlinearity handling approaches.

However, high measurement noise affects the observer significantly. Boizot et al. (2010) provided a solution to deal with the noise sensitivity issue by applying the extended Kalman filter (EKF). The researchers introduced a new method to adjust the gain. They also provided guidelines to tune the parameters for the EKF to achieve desired results. Ghahremani & Kamwa (2011) modified the EKF with unknown inputs (EKF-UI) and implemented it on a synchronous machine. They considered field voltage as an unknown input, and signals were obtained from Phasor Measurement Unit (PMO). States and input estimation were done simultaneously, and parameter estimation was done excellently.

EKF cannot be applied directly to the nonlinear system. The nonlinear system needs to be linearized to apply this kind of observers. Linearization can be difficult or even impossible in some cases. Julier & Uhlmann (2004) addressed these limitations and proposed the unscented Kalman filter (UKF) for a nonlinear system. UKF is the extension of the unscented transformation (UT) and can deal with the nonlinearity directly. A weighted set of deterministically chosen sampled points called sigma points are used for state distribution, and it can capture the true mean and the covariance of the Gaussian random variable and also captures the posterior mean and covariance accurately. The difference between EKF and UKF are summarized in Kandepu et al. (2008). Their performances were evaluated in four simulation studies, and UKF performed better in each scenario. UKF was used as an unknown input observer (UIO) for fault detection purposes (Zarei & Poshtan, 2010a) in a large class of nonlinear systems. The developed observer was applied to a continuous stirred tank reactor (CSTR) to show the robustness and effectiveness of the proposed scheme. In Liu & Gao (2013), UKF was applied in a neural mass model. A UKF based controller was developed, and the observer was used to estimate the unknown parameters. Both UKF and EKF are dependent on Gaussian noise distribution. Particle filter (PF) is an alternative approach that can perform in any noise distribution (György et al., 2014). But the number of particles affects the computation time of the estimation. (Rawlings & Bakshi, 2006) presented an overview of state estimators and identified the advantages and disadvantages of these methods. Their research work concluded that PF is less sensitive to the choices of initial states because it uses resampling technique.

Observers play a crucial part in the MPD system. Several research works have been done on estimators in the drilling system. Lorentzen et al. (2003) developed an ensemble EKF for tuning the first principles based 2-phase flow model. Stamnes et al. (2008) designed a Lyapunov based adaptive observer to estimate BHP in a well during a drilling operation. The estimated BHP converged to the actual BHP in the presence of unknown frictions, and density and verification were done by using real field data. Zhou et al. (2009) extended this work by adding parametric uncertainties in unmeasured states.

Zhou et al. (2010b) designed a novel observer for kick and loss detection. The researchers considered both bit flow rate and annulus flow rate as unknowns. Estimated kick was determined from the difference between the predicted and actual flow rates. Zhou et al. (2011) extended this work for kick detection and attenuation. Differences between the predicted and actual pump pressure were injected into the dynamic observer equation for the bit flow rate estimation. The kick was estimated using the difference in the actual and predicted bit flow rates and was mitigated by applying a switching based controller. Nandan & Imtiaz (2017a) adopted a similar approach for the bit flow rate and reservoir pressure prediction during nonlinear model predictive controller (NMPC) implementation. Zhou & Nygaard (2011) continued this work by applying an adaptive observer for estimating the annular pressure profile throughout the wellbore during a drilling operation. Zhou & Nygaard (2010) implemented a similar method to estimate downhole pressure. Kaasa & Stamnes (2012) experimented with a similar type of observer to estimate downhole pressure. This method is dependent on real time measurements of downhole pressure. Sui et al. (2012) implemented a moving horizon estimator (MHE) to estimate BHP during drilling and pipe connection operation. State's and parameter constraints, as well as noise filtering, was introduced to improve the traditional MHE approach. A linearized MPD was used in this work. The model based approach is also popular for estimation purposes. Hauge et al. (2012) used a model based approach in a linearized MPD model for kick detection. Kick's magnitude was identified from the difference between the actual and predicted flow rates. A model based approach was used for reservoir pressure estimation in Holta et al. (2018). They considered bit flow rate and BHP as known measurements, and reservoir pressure and productivity index as unknown parameters. Nygaard et al. (2007) applied UKF for state estimation as a part of NMPC to control the well pressure. The accuracy of the estimation decreased during the pipe connection scenario. Gravdal et al. (2010) to predict the essential parameters in a well-flow model using UKF. Friction factors were calibrated using UKF, and the parameters were updated every thirty seconds by estimating the bottomhole pressure. The proposed method was applied to three case studies to validate it. Mahdianfar et al. (2013a) designed a joint UKF to estimate states and unknown parameters in a well simultaneously. Estimation was done using only topside measurements like pump pressure and choke pressure. The frictional flow model and geometry terms were augmented with unknown parameters. These parameters were combined in a state vector and were estimated simultaneously with the states using available topside measurements. Next step after kick estimation is to develop a warning system. A robust warning system can lead to an accident free drilling operation.

1.4 Warning system

In the process industry, alarms are mostly generated when the measured variable exceeds the safety limit. Prediction of future value in the horizon can lead to a predictive and real time warning system. Primbs et. (1999) reviewed the control Lyapunov function and receding horizon control for the nonlinear optimization problem. The researchers analyzed the strengths and limitations of the approaches, and also provided new ideas for the control design. The control Lyapunov method is better suited for off-line computation, and a receding horizon performs better in on-line control. The safety system is an integral part of a control and monitoring system. A brief review of the control system with safety features are presented in Albalawi et al. (2018). They identified and discussed some key prospects to increase operational safety. They suggested closed loop state predictions to generate a warning. Varga et al. (2010) developed predictive alarm management (PAM) system using a simulator based approach. The controller output was identified using the Lyapunov secondary stability analysis. The alarm was generated when there was no feasible solution. The proposed method was validated by applying two case studies. Ahooyi et al. (2016)

presented a design based model predictive safety system to detect hazards in the system. Safety system is combined with a set of operability constraints and a robust state estimator. An extended Luenberger observer (ELO) was used as a state estimator to predict the present and future state variables. A real time receding horizon operability analysis was done to identify the predicted operational hazards, and alarm was generated when the process violated the operability constraints. In the process industry, variables are interconnected. Therefore, optimizing one extreme state using one manipulated variable may cause other variables to exceed the safety limit (Amin et al., 2018). Ahmed et al. (2011) proposed a risk based alarm design. The complexity of the warning system was reduced by assigning the alarms into the sets of variables instead of an individual variable. Researchers also identified future risks associated with the present state variables. The alarms were prioritized based on the severity. There are mainly two types of safety monitoring system failure events: failed dangerous (FD) and failed safe (FS). Kohda & Cui (2007) proposed a diagnosis framework to overcome these failures. Yu et al. (2015) developed a new method for detection and assessment of risk. The proposed method used the Self-Organizing Map (SOM) and probability analysis to capture the nonlinear behavior of the system states. SOM monitored the variation of states for early fault detection. Risks associated with the faults were classified according to the hazard potential, and root cause analysis was done.

Hashemi et al. (2014) developed a risk based warning system using loss function (LF). The advantages of LF was presented by applying it to assess operational stability and system safety. Researchers generated the alarm based on risk. Thus, the significance of the risk determined and minimized the operational and maintenance loss in the system. A simulated case study on a reactor system was demonstrated to verify their findings. Hashemi et al. (2014) created a real time risk profile to help the operators in decision making. LF, combined with the probability of undesired process states were used to estimate the risk continuously. A similar approach was followed by Abimbola and Khan (2018) to provide real time blowout risk analysis by estimating operational risks for drilling operations. Every possible loss due to risk was determined to create a robust risk assessment system. Pui et al. (2017) implemented an advance dynamic risk-based maintenance (RBM) method to create risk profile in offshore MPD system for rotating control device (RCD) and blowout preventer (BOP). The applied framework was applied to an offshore case study and displayed good performances on minimizing the operational maintenance and identifying the critical components in the MPD system.

1.4. Objectives

The goal of this research is to develop a real time kick management to the MPD system. A UKF based observer is implemented to estimate the unmeasured kick in the system. The first part of the thesis presents the methodology and performances of UKF in different case studies. The estimated kick is further predicted over a prediction horizon to identify the mitigation time and total kick volume entered in the system. In the second part, the warning system is created based on the real life operational conditions to fulfill our objectives.

The main objectives of this thesis are to:

- Early detection of the kick in an MPD system considering noise and uncertainty in the system model.
- Estimation of kick size using surface measurements, i.e., the choke pressure, pumping rate, pump pressure.
- Prediction of kick mitigation time, and total kick volume and pressure fluctuations in the presence of kick.
- Develop a robust warning framework, based on the real field operational conditions.

1.5. Thesis Structure

This thesis is a manuscript styled thesis which includes two submitted manuscripts. It is composed of four chapters. Chapter 1 briefly presents the motivation for this research. An extensive literature review on MPD, estimators, and warning systems are presented in this chapter. In chapter 2, UKF based estimator is implemented for kick detection and estimation. A real time warning system is presented in Chapter 3. Finally, the outcomes of this thesis are summarized, and some future recommendations to improve this research are presented in Chapter 4.

Co-Authorship Statement

I, M. Musab Habib, hold principal author status for all the chapters in this thesis. However, each manuscript is co-authored by my supervisors and co-researcher, who has directed me towards the completion of this work as follows.

- M. Musab Habib, Syed Imtiaz, Faisal Khan and Salim Ahmed, "**Early detection and estimation of kick in managed pressure drilling**". Submitted to SPE Drilling & Completion journal (under review).

Statement: The research was conducted by M. Musab Habib as the first author. He prepared the manuscript. Co-authors supervised and reviewed the manuscripts.

- M. Musab Habib, Syed Imtiaz, Faisal Khan and Salim Ahmed, "**Real time kick monitoring and management in the managed pressure drilling operation**" Submitted to Journal of Petroleum Science and Engineering (under review).

Statement: The research was conducted by M. Musab Habib as the first author. He prepared the manuscript. Co-authors supervised and reviewed the manuscripts.

Chapter 2

Early detection and estimation of kick in managed pressure drilling

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Abstract

Drilling in the offshore environment involves high risks mainly due to uncertainties in reservoir conditions. Unplanned events such as the influx of reservoir fluids (kick) may lead to catastrophic accidents. Therefore mitigation of kick is extremely crucial to enhance safety and efficiency. As kick is an unmeasured disturbance to the system, it needs to be estimated. In the current study, unscented Kalman filter (UKF) based estimator is used to simultaneously estimate the bitflow-rate, and kick in a managed pressure drilling (MPD) system. The proposed estimator uses sigma point transformations to determine the true mean and covariance of the Gaussian random

variable (GRV) and capture the posterior mean and covariance accurately to the 3rd order (Taylor series expansion) for any nonlinearity. In the proposed UKF formulation, hidden states and unknown inputs were concatenated to an augmented state vector. The magnitude of the kick is estimated using only available top-side measurements. The applied method was validated by estimating the gas kick magnitude in a lab scale setup and data set from a field operation. The proposed estimation method was found robust for the MPD system under different noisy scenarios.

Keywords- Unknown Input Estimator; UKF; Kick; Bit flow rate; MPD

2.1 Introduction

The challenges of ensuring energy supply for the future is driving hydrocarbon exploration in extreme and harsh offshore environments. Most of the conventional wells are already producing or, are becoming depleted which makes the exploration more challenging. In the offshore, usually, reservoirs have narrow pressure margin between the fracture pressure and the pore pressure. As a result, offshore drilling presents additional technological challenges (Møgster et al., 2013). Drilling in narrow pressure window wells creates potential influx situations in these wells. Maintaining bottomhole pressure (BHP) within the pressure window between reservoir and fracture pressure is essential. An influx of reservoir fluid, referred to as reservoir kick, is encountered if the reservoir pressure exceeds the BHP.

On the other hand, drilling fluid will be lost to formation if BHP exceeds the fracture pressure (Nandan & Imtiaz, 2016). These unplanned events can lead to catastrophic accidents that can impact human lives on the rig as well as cause significant damage to the environment (Hauge et al., 2013). The Macondo tragedy created more awareness of the challenges, uncertainties in drilling and the aftermath consequences of an accident. Under the above mentioned circumstances, Managed Pressure Drilling (MPD) has become a powerful method for precise control of wellbore pressure (Breyholtz et al., 2010). The automated MPD system requires accurate measurement of each state and variable. During a drilling operation, many of the states are unmeasurable due to lack of proper instrumentation. Presence of unknown disturbances such as kick makes the overall process more critical. The estimation of these hidden states and unknown inputs must be done from available process measurements to enhance the safety and efficiency of the MPD system. This work focuses on implementing an observer to simultaneously estimate the unmeasured states and unknown inputs from the measured variables using the available surface instruments in a MPD system.

Kalman filter based estimators are popular for hidden state estimation. They were first introduced by Kalman (1960) for linear filtering. Later on, state observers were proposed by Luenberger (1971) for state estimation. These estimators were modified and improved over time. Mohd et al. (2015) briefly discussed the application of the observers to the chemical process systems and classified them based on their features. These features presented the attributes, advantages, limitations, and guidelines for implementation. Based on their classifications, proper criteria for the observer designs were proposed for different types of applications. Chen et al. (2009) proposed a specific observer only for disturbance estimation, and it was further improved by Yang et al. (2011). Extended Luenberger observer (Dochain, 2003), sliding mode observer (Floquet et al., 2004) and adaptive state observer (Vries et al., 2010) are commonly used for their simple implementation. However, these observers are not applicable to a complex system. In Corless and Tu (1998), an estimator was designed to estimate the states and inputs; Lyapunov-type characterization was used for the construction of a combined state/input estimator. The proposed estimator was suitable under very strict conditions. Xiong and Saif (2003) extended the work by proposing a state functional observer with reduced restrictive conditions.

The above mentioned observers are restricted to linear systems. Designing an observer for a nonlinear system is complicated and challenging (Imsland et al., 2007). In Alessandri (2004), difficulties associated with the construction of a state observer for the nonlinear system were investigated by using input-to-state stability (ISS) properties. Adaptive high-gain observers were proposed based on linear matrix inequalities (LMI) to solve the observer designing problem. This work was further extended by applying ISS Lyapunov functions (Alessandri, 2013). Adaptive H_∞ observer was proposed for Lipschitz nonlinear system (Yang et al., 2016). Measurement noise was considered as an extended state vector to estimate the states and measurement noise simultaneously. This method is limited to Lipschitz type system.

A review of nonlinear Bayesian state estimation was illustrated in Patwardhan et al. (2012). This work focused on the constrained state estimation, the handling of multi-rate and delayed measurements and recent advancement in model parameter estimation. Bayesian estimators were classified based on the nonlinearity handling approaches. A solution was provided to the noise sensitivity of high-gain observers by applying the extended Kalman filter (EKF) (Boizot et al., 2010a). They implemented noise smoothing for small estimation error and introduced guidelines for the tuning of the parameters. EKF with unknown inputs was applied to a synchronous machine to estimate the states and input simultaneously (Ghahremani & Kamwa, 2011) where field voltage was considered as an unknown input, and signals were obtained from Phasor Measurement Unit (PMO). The proposed estimator showed good performances, and the parameter estimation procedure was also demonstrated effectively.

The use of the EKF has been the most common way to deal with state estimation of nonlinear systems, but there are some complications in implementing EKF. Linearization can be very difficult. These limitations were addressed in Julier and Uhlmann (2004). They proposed the unscented Kalman filter (UKF) which can deal with nonlinearity directly. Unscented Transformation (UT) was developed to propagate mean and covariance in nonlinear transformation. Sigma points were deterministically chosen from the statistics of the transformation to capture the distribution with fixed small points. A higher number of sigma points can increase the computational cost of UT. The differences between EKF and UKF were shown in Kandepu et al. (2008). Four simulation case studies were considered to evaluate the performances, and UKF delivered superior performances over EKF in terms of robustness and speed of convergence. The computational load was the same for both methods. UKF was used as an unknown input observer (UIO) for fault detection purposes (Zarei & Poshtan, 2010b) in a large class of nonlinear systems. The developed observer was applied to a continuous stirred tank reactor (CSTR) to show the robustness and effectiveness of the proposed scheme. Joint UKF was implemented in a simulated MPD system for state and parameter estimation (Mahdianfar et al. 2013b). The model parameters were considered as states and estimated simultaneously with other states.

In Liu and Gao (2013), UKF was applied in a neural mass model; the proposed model based estimator was able to estimate the unknown parameters for the model. A UKF based control was also developed to reconstruct the dynamics of the model, and showed better results than EKF based control. However, both UKF and EKF require that the process and measurement noises are gaussian distributed (György et al., 2014). For noises with non-gaussian distribution, the Particle Filter (PF) can be a good approach for estimation purposes. An overview of state estimators was presented in Rawlings and Bakshi (2006) by identifying the advantages and disadvantages of these methods. Their research work concluded that PF is less sensitive to the choices of initial states. PF was also developed by using an approximate Bayesian classifier for a nonlinear chaotic system (Mejri et al., 2013); the proposed method estimated chaotic states and unknown inputs for Gaussian and non-Gaussian noise scenarios. PF implementation issues were addressed in Imtiaz et al. (2006). This methodology was performed in a simulated non-linear CSTR and an Experimental Four Tank system. Jampana et al. (2010) applied PF to estimate the interface level of a sensor, and performance was evaluated by using industrial data. The number of particles significantly affects the performance of PF. For a high number of particles, computational time increases significantly compared to other methods (György et al., 2014).

Several researchers have worked on estimation and controller design in the MPD system. Stamnes et al. (2008) designed a Lyapunov based adaptive observer to deal with unknown frictions and density, and estimate bottomhole pressure in a well during operation. The estimated BHP converged to the actual BHP under some conditions and verification was done by using real field data. Parametric uncertainties in unmeasured states were included in Stamnes et al. (2009) to check the robustness of the Lyapunov based adaptive observer. They analyzed the stability and convergence of the error with or without the persistency of excitation. A novel observer was designed by Zhou et al. (2010) for kick and loss detection. Both bit flow rate and annulus flow rate were considered as unknown, and the kick was estimated from the difference of the predicted unknown flow rates. Reservoir pressure was also estimated to set the new reference point for BHP. Zhou et al. (2011) extended this work for kick detection and attenuation. The bit flow rate was considered as an unknown state, and it was estimated by injecting the error in pump pressure into the dynamic equation of bit flow rate. The kick was estimated using the difference in the flow rates and was mitigated by applying switching based controller. A similar approach was followed by Nandan and Imtiaz (2017) for the bit flow rate and reservoir pressure prediction during nonlinear model predictive controller (NMPC) implementation. Zhou and Nygaard (2011) continued this work for estimating the annular pressure profile throughout the wellbore during a drilling operation. An adaptive observer was implemented to estimate state and parameter in an MPD system. A similar method was applied to estimate downhole pressure in Zhou and Nygaard (2010). Kaasa and Stamnes (2012) experimented with a similar type of observer to estimate downhole pressure. They developed a simplified hydraulics model to capture the dominating hydraulics of the MPD system and used topside measurements and downhole measurements to calibrate the uncertain parameters in the annulus. This method is dependent on real time measurements of downhole pressure. Moving horizon (MHE) based observer was applied by Sui et al. (2012) to estimate bottomhole pressure during drilling and pipe connection operation. They used a linearized model of the MPD system and solved a least- squares optimization problem to estimate the states. The proposed method improved the traditional MHE approach by including the state's and parameter's constraints and noise filtering.

Hauge et al. (2012) used a model based kick detection method for the MPD system. A stable adaptive observer was designed to estimate the unknown states and unknown parameters. Kick and location of the leak were selected as unknown parameters and estimated by the difference of the flow rates. They have also considered a linearized MPD model for their work. This research was extended in Hauge et al. (2013). The applied observer monitored the change in frictional pressure drop to identify the leak position. The localization algorithm was highly sensitive to the friction parameters in the drillstring and annulus. Another model based approach for kick and loss detection in the MPD system was presented by Holta et al. (2018). Their method considered bit flow rate and bottomhole pressure as known measurements and reservoir pressure and productivity index as unknown parameters.

A swapping based filter was combined with a closed loop controller to keep the bottomhole pressure close to the predicted reservoir pressure. The time delay was neglected for the bottomhole pressure measurement. Model based estimation using a approach to predict the key parameters simplified two phase model for real time estimation of influx rate was introduced by Ambrus et al. (2016) that comprised the reduced drift flux model, and an estimation algorithm which was built upon a reservoir inflow model. An experimental dataset was used for model validation. A low-pass filtered version of the pressure dynamics equation from the reduced DFM was used for dynamic estimation of the reservoir inflow rate, pore pressure, and reservoir productivity from real-time pressure and flow data. The recursive least squares (RLS) method was used for the instantaneous estimation of kick. Nygaard et al. (2007) implemented NMPC to control the well pressure and used UKF for estimating the states, and the friction and choke coefficients. Estimation was accurate during normal operation but showed oscillation after the pipe connection. Gravdal et al. (2010) presented a new approach to predict the key parameters in a well-flow model. UKF based estimation method was applied for accurate calibration of friction factors in the drillstring and annulus using topside and bottom-hole pressure measurements and uncertain parameters. The parameters were updated every thirty seconds by monitoring the bottomhole pressure.

The method was applied to three case studies and showed satisfactory results. Robustness of the UKF was shown by many researchers, for example, Mahdianfar et al., (2013) designed a joint UKF to simultaneously estimate states and unknown parameters in a well using topside measurements. Friction factors and bulk modulus were considered as unknown parameters. These were combined as a part of a state vector, and their values were estimated simultaneously using UKF. UKF delivered good performances for state and parameter estimation under different case studies. Our main objectives are as follows-

- Early detection of the kick in an MPD system considering noise and uncertainty in the system model.
- Estimation of kick size using surface measurements i.e., the choke pressure, pumping rate, pump pressure.
- Validation of the proposed approach using different case studies.

The above literature suggests that UKF is the most suitable tool to estimate unknown states and unknown inputs in the MPD system. It is capable of handling nonlinearity and also not computationally expensive which makes the estimator relevant for online applications. The rest of the paper is organized as follows: the model development for the MPD system is described in Section 2.2, followed by the problem formulation and observer design in Section 2.3. The simulation results, experimental results, and field validation are presented in Section 2.4 with concluding remarks in Section 2.5.

2.2 System Description

The hydraulic model of an MPD system is derived from the mass and the momentum balance equations. A 1D model was originally developed by Kaasa and Stamnes (2012) assuming incompressible fluid with negligible variance in viscosity, and isothermal conditions. The model considered two control volumes: drill string and annular mud return section. As shown in Figure 2.1, Pump supplies the drilling fluid to the drillstring under pump pressure P_p with a flow rate of $q_{p.}$ The drilling fluid passes through the bit with a flow rate of $q_{bit.,}$ and pressure at the bit is denoted as $P_{bh.}$ A choke at the exit of the annulus control volume provides a back pressure P_c and mud flows through it at a volumetric flow rate $q_{c.}$ β_d and βa represent the bulk moduli of mud in the drill string and annulus and ρ_d and ρ_a are the mud densities. V_d and V_a are the volumes of the drill string and the annulus, respectively; f_d and f_a are frictional loss coefficients in the drill string and the annulus, respectively. We included the detailed derivation of the model in the Appendix as the derivation is not available in the literature. The hydraulic model of an MPD system derived from mass and momentum balances can be written as (Kaasa and Stamnes, 2012):

$$\dot{P}_p = \frac{\beta_d}{V_d}(q_p - q_{bit}) \qquad \text{……………………………………………………...… (2.1)}$$

$$\dot{P}_c = \frac{\beta_a}{V_a}(q_{bit} - q_c + q_k) \qquad \text{…………………..……………………….……..…... (2.2)}$$

$$\dot{q}_{bit} = \frac{1}{M}(P_p - P_c - f_d q_p^2 - f_a q_{bit}^2 - (\rho_a - \rho_d) g h_{TVD}) \qquad \text{…….……………..……..….…. (2.3)}$$

$$P_{bh} = P_c + Pf_a + \rho_a\, gh_{TVD} \quad \text{(2.4)}$$

$$q_c = u_c K_c sign(P_c - P_0)\sqrt{|P_c - P_0|} \quad \text{(2.5)}$$

$$q_k = K_p(P_{res} - P_{bh}) \quad \text{(2.6)}$$

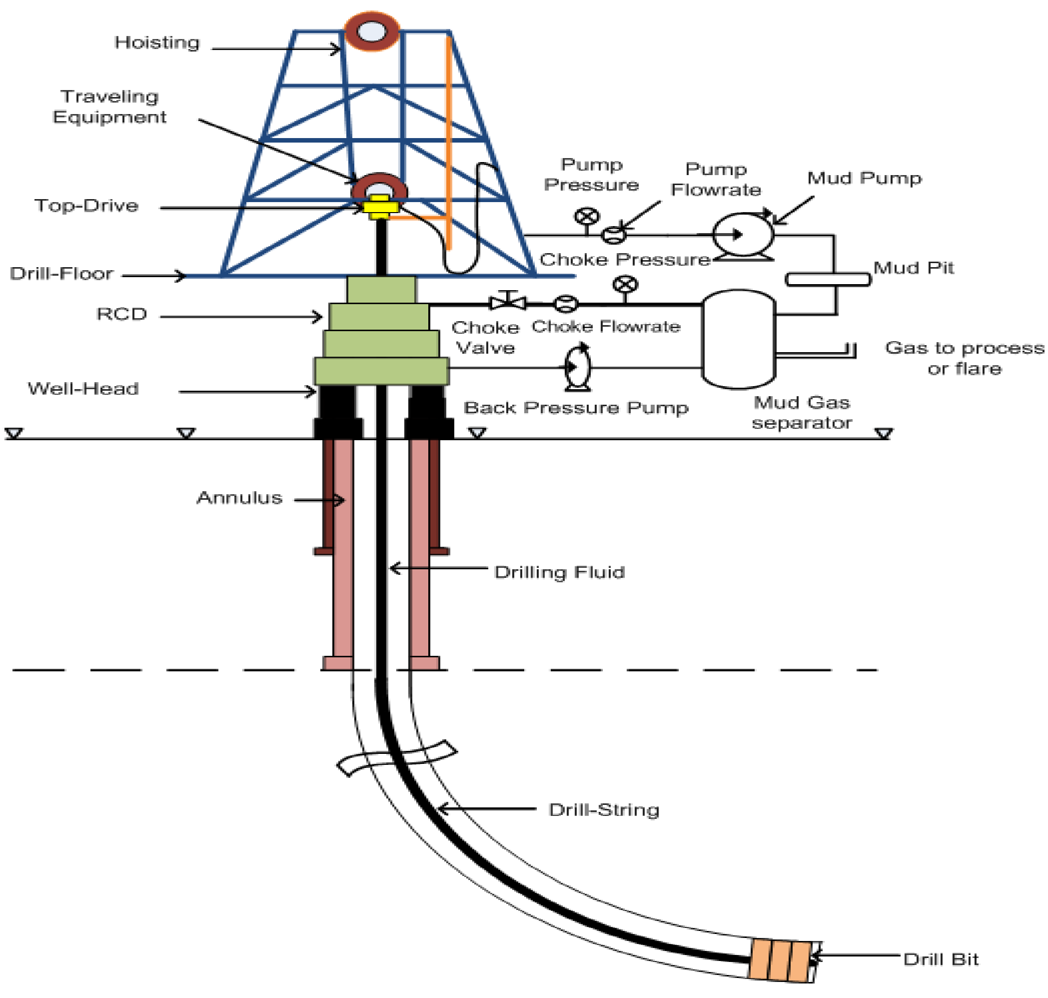


Figure 2.1: Schematic representation of MPD drilling (Zhou and Krstic, 2016)

2.3 Method

2.3.1 Problem Formulation

In MPD, there are three states; pump pressure (P_p), choke pressure (P_c), and bit flow rate (q_{bit}). Pump pressure and choke pressure are the available top-side measurements whereas bit flow rate is an unmeasured state; kick (q_k) is considered as an unknown input. Our objective is to estimate both the known and the unknown states and input simultaneously. The hydraulic model of an MPD system is given as follows (E. Hauge et al., 2013):

State vector, $X = [P_p, P_c, q_{bit}]^T$; Measurement vector, $y = [P_p, P_c]^T$; Unknown input= q_k

$$X_{k+1} = f(X_k) + q_k + w_k \qquad (2.7)$$

$$y_k = g(X_k) + v_k \qquad (2.8)$$

Where, f is the nonlinear system equation, $w_k \approx N(0, W_k)$ is the Gaussian process noise, and $r_k \approx N(0, \mathrm{R}_k)$ is the Gaussian measurement noise. Process and measurement noises are assumed to be uncorrelated. In our work, we represent the unknown input as part of the state vector, and estimate its magnitude along with other states simultaneously. The states and unknown inputs are concatenated into a combined state vector, and the corresponding dynamic model is written as:

$$\begin{bmatrix} P_{\mathrm{p},(k+1)} \\ P_{\mathrm{c},(k+1)} \\ q_{\mathrm{bit},(k+1)} \\ q_{\mathrm{k},(k+1)} \end{bmatrix} = \begin{bmatrix} f_1(P_{p,(k)}) \\ f_2(P_{c,(k)}, q_{\mathrm{k},(k)}) \\ f_3(q_{bit,(k)}) \\ q_{\mathrm{k},(k)} \end{bmatrix} \quad \text{……..…...….} \tag{2.9}$$

2.3.2 Observer

We implemented UKF as an observer for state and unknown input estimation purpose. UKF is the extension of the unscented transformation (UT) (Wan and Van Der Merwe, 2000). The UT is a method used for calculating the statistics (mean and covariance) of a random variable which undergoes a nonlinear transformation. UKF can deal with the nonlinearity directly without linearizing the nonlinear model. In UKF, state distribution is specified by a weighted set of deterministically chosen sampled points called sigma points. It captures the true mean and the covariance of the Gaussian random variable and also captures the posterior mean and covariance accurately up to the 3rd order (Taylor series expansion) in a nonlinear system. In our case, we considered that process and measurement noises are purely additive to reduce the computational complexity by reducing the number of sigma points.

For a nonlinear-discrete time system, there are two stages of UKF (Mahdianfar et al., 2013b): Prediction, and Update. Below we describe these two stages:

2.3.2.1 Prediction

Step 1: Initial value of state and covariance are selected.

Step 2: The set of sigma points are created based on the present state covariance applying the following equation-

$$\chi_{k-1} = [m_{k-1} \ldots m_{k-1}] + \sqrt{c}\,[0\ \sqrt{P_{k-1}}\ \text{-}\sqrt{P_{k-1}}] \quad \text{(2.10)}$$

Here χ is the matrix of sigma points and $c = \alpha^2 (n + k)$.

α and k are tuning parameters. α determines the spread of sigma points around m, and generally, it should be a small number. $k \geq 0$ should be selected to guarantee the semi-positive definiteness of the covariance matrix, and whereas *n* is the dimension of the state vector (Kandepu et al., 2008).

Step 3: The transformed set is calculated by translating each sigma point through model, and then predicted mean and covariance are calculated

$$\hat{X}_k = f(\chi_{k-1}, k-1) \quad \text{(2.11)}$$

$$m_k^- = \hat{X}_k\, w_m \quad \text{(2.12)}$$

$$P_k^- = \hat{X}_k\, W [\hat{X}_k]^T + Q_{k-1} \quad \text{(2.13)}$$

Here Q_k is the process covariance matrix. Vector w_m and matrix W can be defined as follows:

$$w_m = [W_m^{(0)} \; ... \; W_m^{(2n)}]^{\,T} \qquad \text{……………………………..…..……..………...…. (2.14)}$$

$$W = (I - [w_m \; ... \; w_m]) \times diag(W_c^{(0)} \; ... \; W_c^{(2n)}) \times (I - [w_m \; ... \; w_m])^T \qquad \text{………….….. (2.15)}$$

Where,

$$\begin{aligned}
W_m^{(0)} &= \frac{\lambda}{(n+\lambda)} \\
W_c^{(0)} &= \frac{\lambda}{(n+\lambda)+(1-\alpha^2+\beta)} \\
W_m^{(i)} &= \frac{\lambda}{2(n+\lambda)}, \; i=1,...,2n \\
W_c^{(i)} &= \frac{\lambda}{2(n+\lambda)}, \; i=1,...,2n
\end{aligned}$$

$\lambda = \alpha^2(n+k) - n$ is a scaling parameter

2.3.2.2 Updating

Step 4: New Sigma points are calculated from using following equation -

$$\chi_k^- = [m_k^- \; ... \; m_k^-] + \sqrt{c}\,[0 \; \sqrt{P_k^-} \; -\sqrt{P_k^-}] \qquad \text{…………………..………..……..……. (2.16)}$$

Step 5: New sigma points are passed through the measurement equation.

$$Y_k^- = g(\chi_k^-, k) \qquad \text{………………………….…………………………………...…. (2.17)}$$

The predicted mean μ_k and covariance of the measurement S_k are computed by-

$$\mu_k = Y_k^- w_m \quad \text{(2.18)}$$

$$S_k = Y_k^- W [Y_k^-]^T + R_k \quad \text{(2.19)}$$

Here, R_k is the measurement covariance matrix. Cross-covariance of state and measurement C_k is computed as follows-

$$C_k = X_k^- W [Y_k^-]^T \quad \text{(2.20)}$$

Kalman Gain is calculated as,

$$K_k = C_k S_k^{-1} \quad \text{(2.21)}$$

Step 6: The updated state mean m_k and covariance P_k is computed conditional to the measurement y_k.

$$m_k = m_k^- + K_k [y_k - \mu_k] \quad \text{(2.22)}$$

$$P_k = P_k^- - K_k S_k K_k^T \quad \text{(2.23)}$$

Updated state mean and covariance act as an initial value for the next time step. The algorithm of UKF can be represented by the flow chart in Figure 2.2:

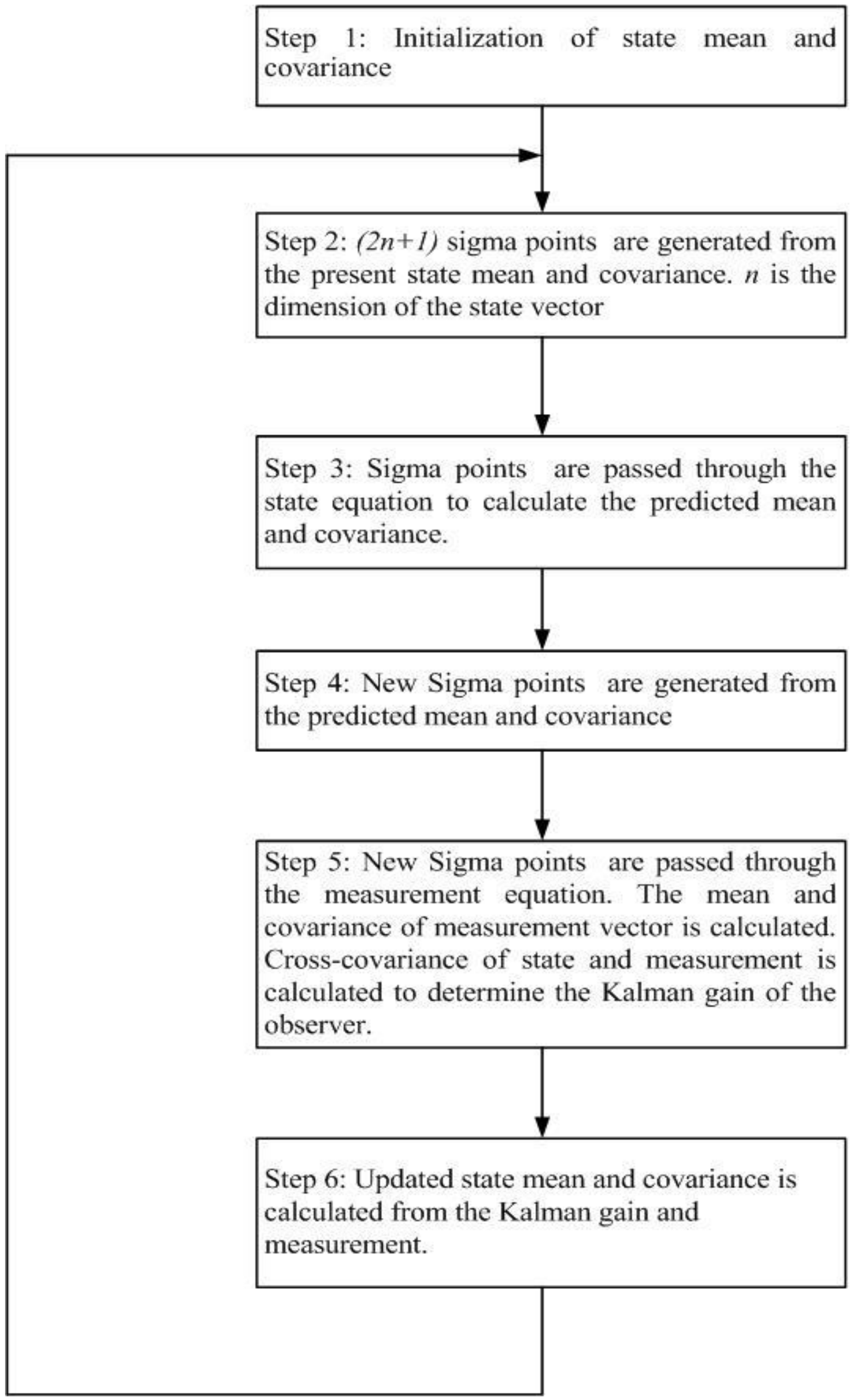


Figure 2.2: The UKF algorithm flowchart

2.4 Results and Discussion

The effectiveness of the proposed method is demonstrated through three case studies. For the first study, the simulation model of an MPD system was used with different process and measurement noise scenarios (Kaasa and Stamnes 2012). Next, experimental data from a laboratory scale MPD system were used for the second case study. Finally, field data from a drilling rig operating in Western Canada was used to validate the unknown input observer.

2.4.1 Simulated MPD model

MPD system was simulated based on the hydraulic model described in Section 2.2. Model parameters used for simulation are summarized in Table 2.1. UKF was implemented on the simulated MPD system to estimate the hidden states (i.e., bit flowrate) and unknown input (i.e., gas influx rate). The robustness of the proposed methodology was demonstrated through three different process and measurement noise scenarios. In this simulation, the augmented process had both model mismatch and measurement noise as per our design.

Measurement noise remained unchanged for all cases, while the model mismatch was changed from low to a high level to check the efficacy of the estimator. Static drilling conditions were considered; as such volumes in drillstring and annulus were unchanged throughout the simulation. Drilling fluid was also considered unchanged in the simulation. For each scenario, mud was pumped at the rate of 1200 LPM, and the choke opening was 30 percent.

Table 2.1: Simulated MPD system parameters (Nandan & Imtiaz, 2017b)

Parameter	**Value**	**Unit**
Volume of annulus (V_a)	89.9456	m^3
Volume of drillstring (V_d)	25.5960	m^3
Total vertical depth (TVD)	3500	m
Mass parameter (M)	8.04×10^8	kg/ m^3
Bulk modulus in annulus (β_a)	2.3×10^9	Pa
Bulk modulus in drillstring (β_d)	2.3×10^9	Pa
Density in drillstring (ρ_d)	1300	kg/ m^3
Density in annulus (ρ_a)	1300	kg/ m^3
Friction factor in drillstring (f_d)	1.65×10^{10}	S^2/m^6
Friction factor in annulus (f_a)	2.08×10^9	S^2/m^6
Choke discharge coefficient (C_d)	0.6	-

Choke discharge area (A_0)	2×10^{-3}	m^2
Choke downstream pressure (P_0)	1.013×10^{5}	Pa
Flow rate (Q_p)	1200	LPM

For the first scenario, the process covariance matrix, Q, was set to = diag [50 50 0.000005 0.000005], and the pump pressure and choke pressure were affected by additive measurement noise with a covariance R= diag [500000 500000]. In this simulation, a kick was simulated at 200s, and that led to a sudden change in pump pressure and choke pressure. The observer was able to estimate the hidden state and unknown input simultaneously based on the pump pressure and choke pressure measurements. After 350s, the kick was removed from the system, and the process became normal again.

Filtered and estimated states and inputs along with actual states, are illustrated in Figure 2.3 and Figure 2.4**.** For the second scenario, the process model mismatch was increased from low to medium noise level with a covariance Q= diag [50000 50000 0.00005 0.00005], and other conditions were unchanged. The corresponding results are shown in Figures 5 and 6. As shown in Figure 2.5 and Figure. 2.6, a high level of process model mismatch affected both the unknown state and input estimation. However, the proposed estimator efficiently estimated the unknown state and unknown input.

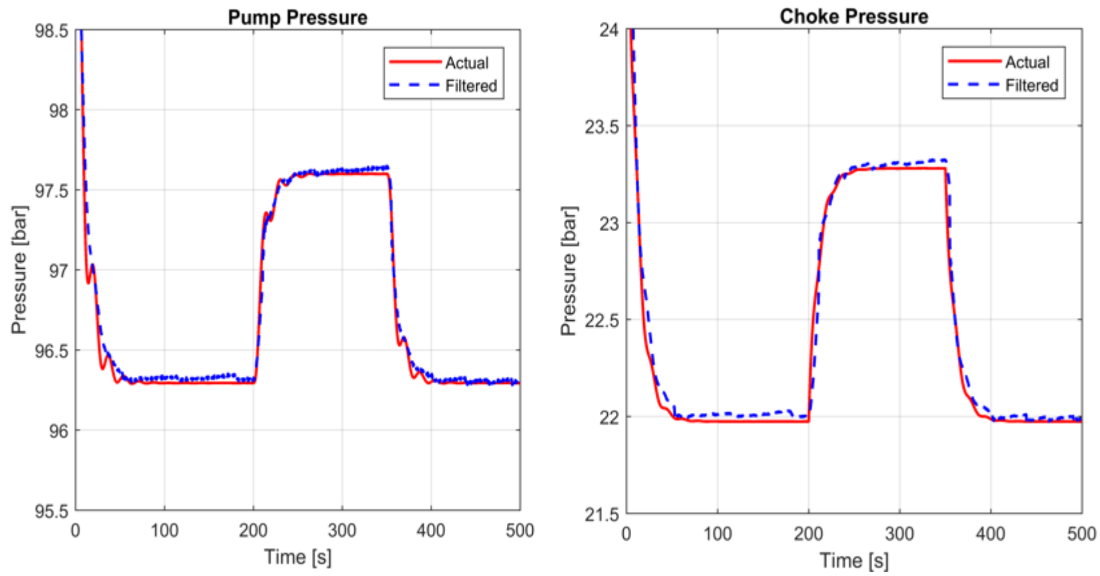


Figure 2.3: Filtered and actual states for the low noise scenario

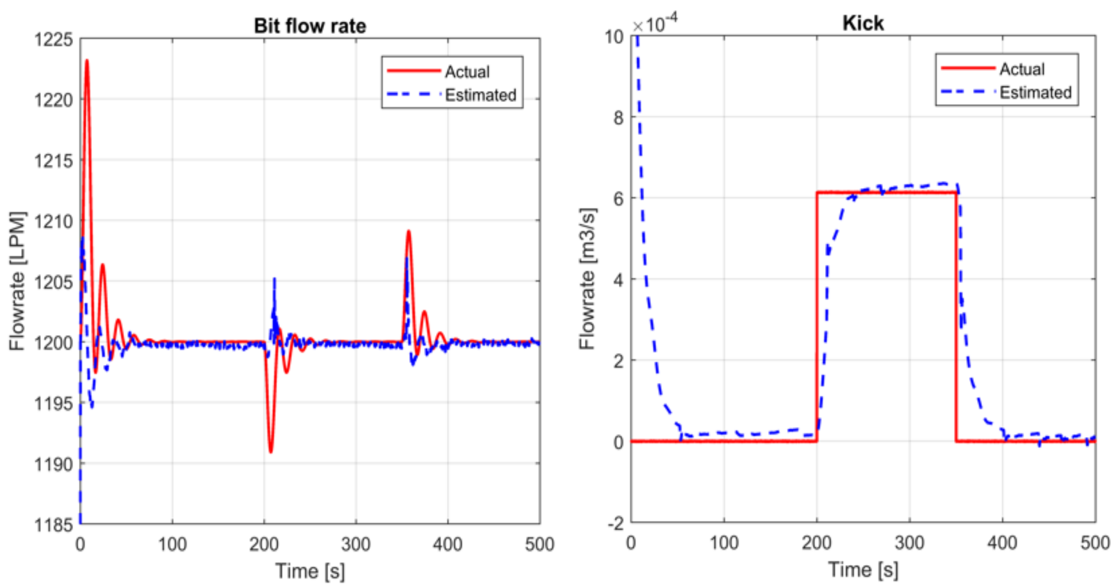


Figure 2.4: Estimated and actual states and inputs for the low noise scenario

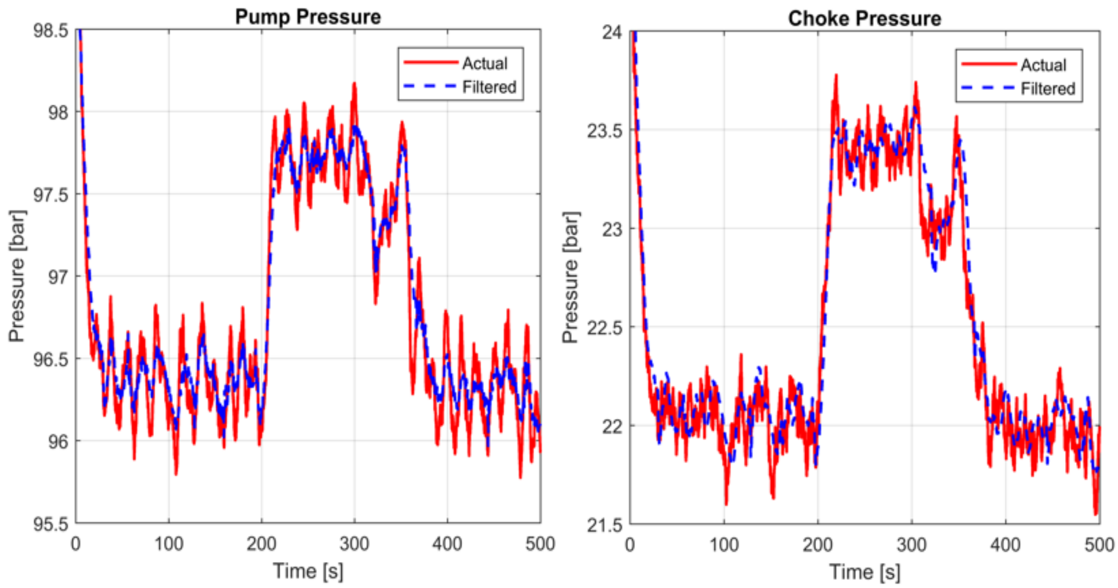


Figure 2.5: Filtered and Actual states for high noise scenario

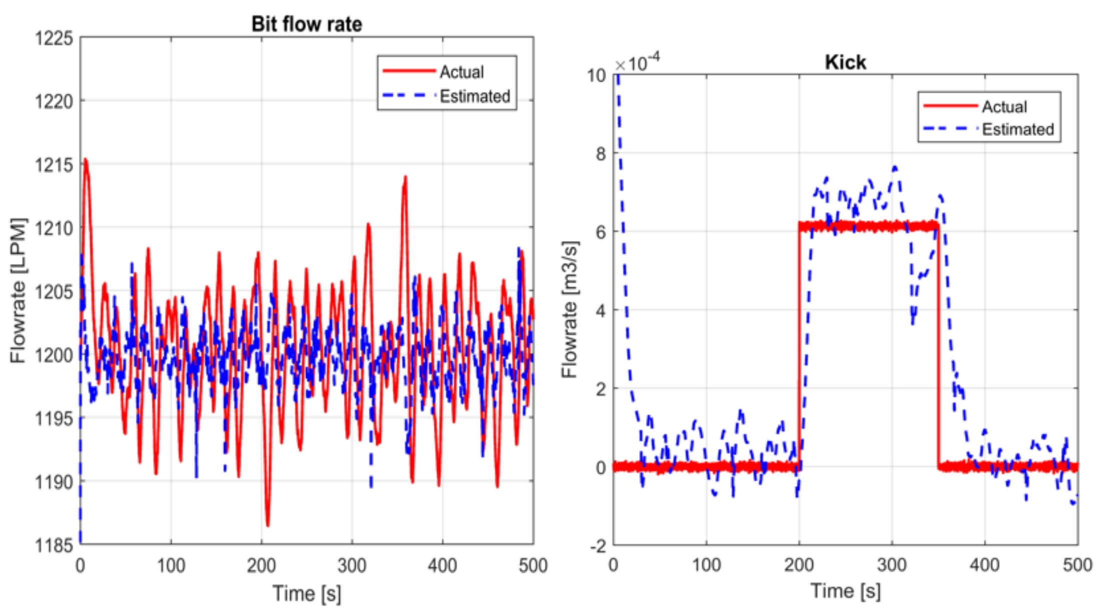


Figure 2.6: Estimated and actual states and inputs for high noise scenario

2.4.2 Simulated closed loop MPD model

A simple PI controller was implemented to test the observer in a closed loop system. The model parameters remained the same as in Table 2.1. Initially, the choke opening was 30 percent, and the pump flow rate was fixed at 1200 LPM. In this case study, the covariance of the system noise was Q= diag [50 50 0.000005 0.000005], and the pump pressure and choke pressure were affected by additive measurement noise with a covariance R= diag [500000 500000]. A kick was encountered at the 250th second.

The controller was able to mitigate the kick at 290 seconds. New choke opening was 21.47 percent after kick mitigation. Kick control and choke opening percentage is presented in Figure 2.7**.** Filtered and estimated state and input, along with actual states, are presented in Figure 2.8 and Figure 2.9**.** Our main objective was to detect the unknown kick, which was achieved, as shown in Figure 2.9**.**

Estimation of the kick is dependent on choke pressure change. In a closed loop scenario, as long as the pressure set point is unchanged, there is influx into the system and kick can be estimated accurately. However, as the pressure was increased after the kick detection to mitigate the kick, the observer is no longer valid, therefore Figure 2.9 (b) is showing the estimated kick signal only for the period when kick magnitude was increasing.

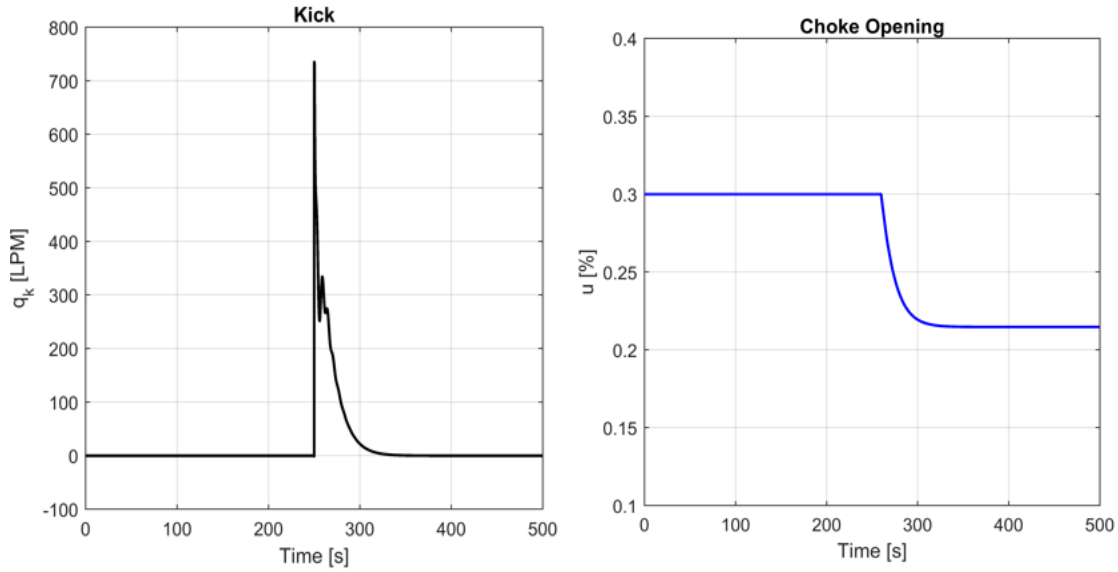


Figure 2.7: Kick mitigation in a closed loop MPD system

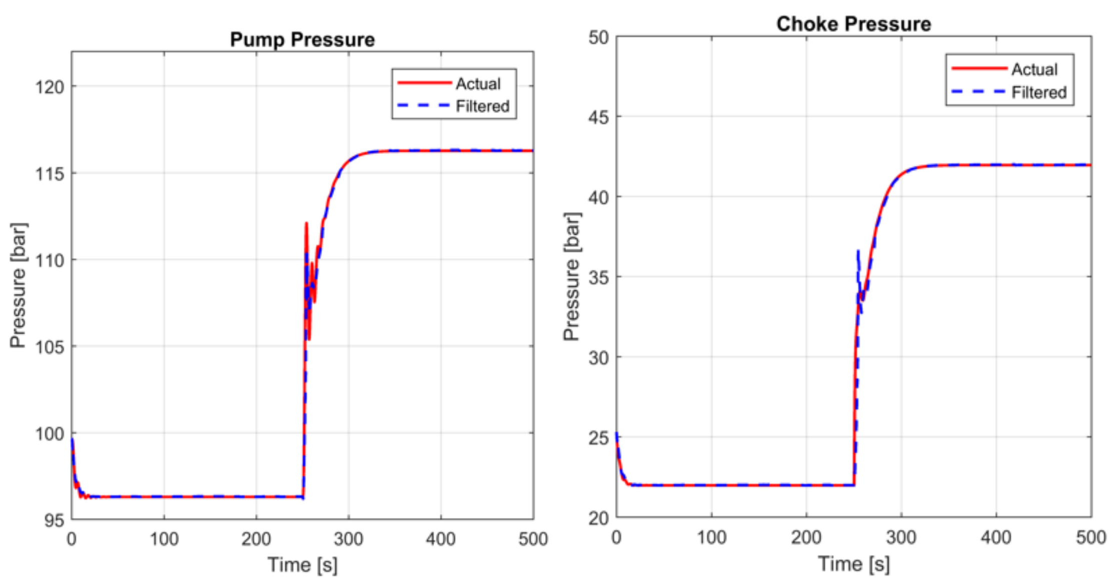
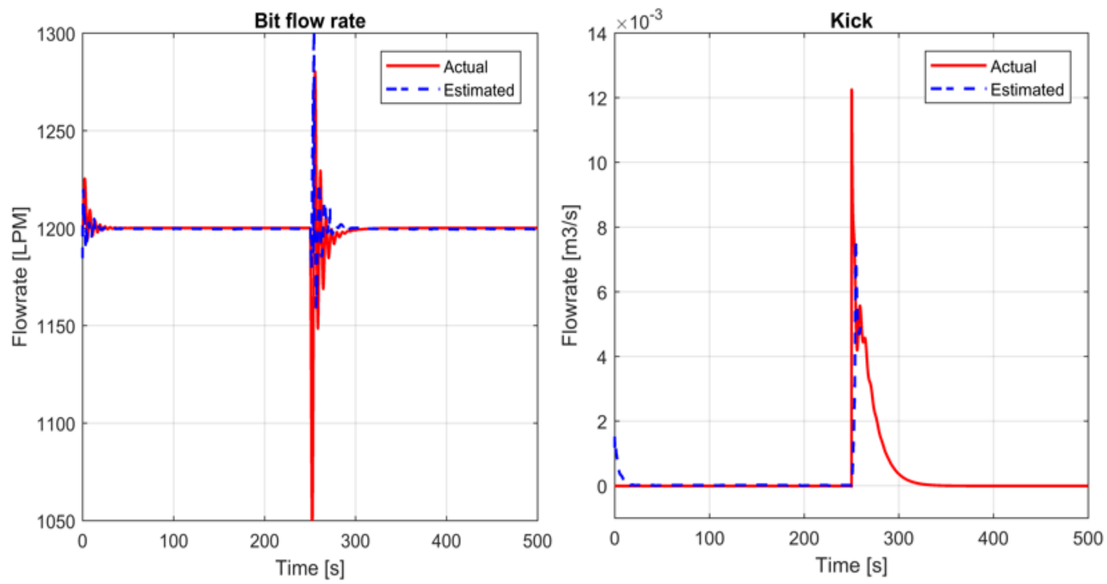


Figure 2.8: Filtered and actual states and inputs in a closed loop MPD system



(a) **(b)**

Figure 2.9: Estimated and actual states and inputs in a closed loop MPD system

2.4.3 MPD Experimental Setup

A lab scale MPD setup was developed by Amin (2017) in the process engineering facility at Memorial University of Newfoundland. The 16.5 ft concentric flow loop was created to replicate the MPD operation. The inner pipe section represents the drill string, and the outer annular section represents the annular casing of a well. As shown in Figure 2.10**,** the experimental setup is equipped with 8 pressure transmitters, 4 flow meters, and 2 control valves. Drilling fluid is pumped using a progressing cavity pump.

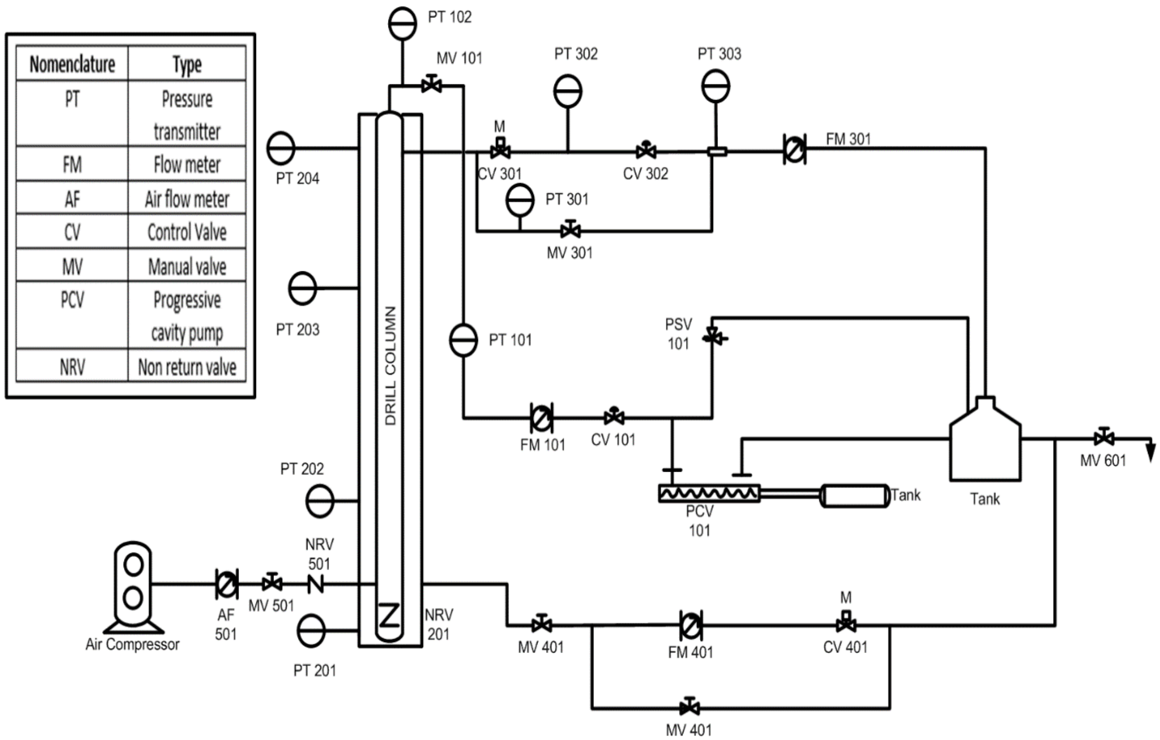


Figure 2.10: Schematic diagram of the experimental setup (Amin, 2017)

A variable frequency drive controls the pump pressure and the flowrates. An air compressor supplies gas in the system, which we considered as a kick for our system. An open loop experiment was performed on this setup and the experimental data was collected by MATLAB. Water was considered as drilling fluid. Pump pressure and choke pressure were measured by PT102 and PT 302, respectively. The pump flow rate was fixed at 40 LPM and choke opening was 50% throughout the operation. The other parameters are given in Table 2.2.

Table 2.2: Experimental setup parameters

Parameter	Value	Unit
Volume of annulus (V_a)	0.01518	m^3
Volume of drill string (V_d)	0.0054	m^3
Total vertical depth (TVD)	4.75	m
Mass parameter (M)	8.4×10^8	Kg/ m^3
Bulk modulus in annulus (β_a)	2.15×10^9	Pa
Bulk modulus in drillstring (β_d)	2.15×10^9	Pa
Density in drillstring (ρ_d)	1000	Kg/ m^3
Density in annulus (ρ_a)	1000	Kg/ m^3
Friction factor in drillstring (f_d)	47147.21	S^2/m^6
Friction factor in annulus (f_a)	43680.9	S^2/m^6
Choke discharge coefficient (C_d)	0.6	-
Choke discharge area (A_0)	0.00028	m^2
Choke downstream pressure (P_0)	1.013×10^5	Pa
Flow rate (Q_p)	40	LPM

A gas kick was injected into the annular section at the 120th second of operations by the air compressor. The magnitude of the kick was recorded by the airflow meter, AF 501. For this current study, we only compared the unknown input as there was no flow meter available to record the bit flow rate. The pressure transmitter captured the change in the pressure instantaneously, but the flow meter took approximately 20 seconds to display the variation. The gas injection was stopped at 290th second. Figure 2.11 shows the actual and filtered states of the process. Figure 2.12 illustrates the estimated and actual unknown input of the system. The applied algorithm estimated kick from the choke pressure, as such the estimated kick was observed 20 seconds prior to the actual kick reached the surface flowmeter shown in Figure 2.12. The proposed method was able to determine the magnitude of the kick accurately.

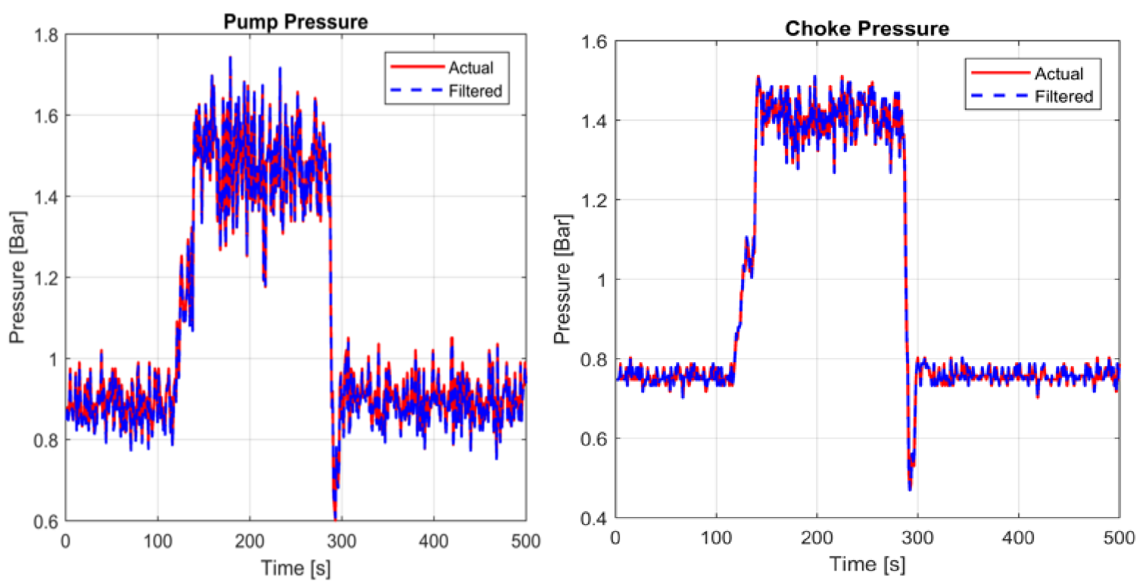


Figure 2.11: Filtered and actual states for experimental data

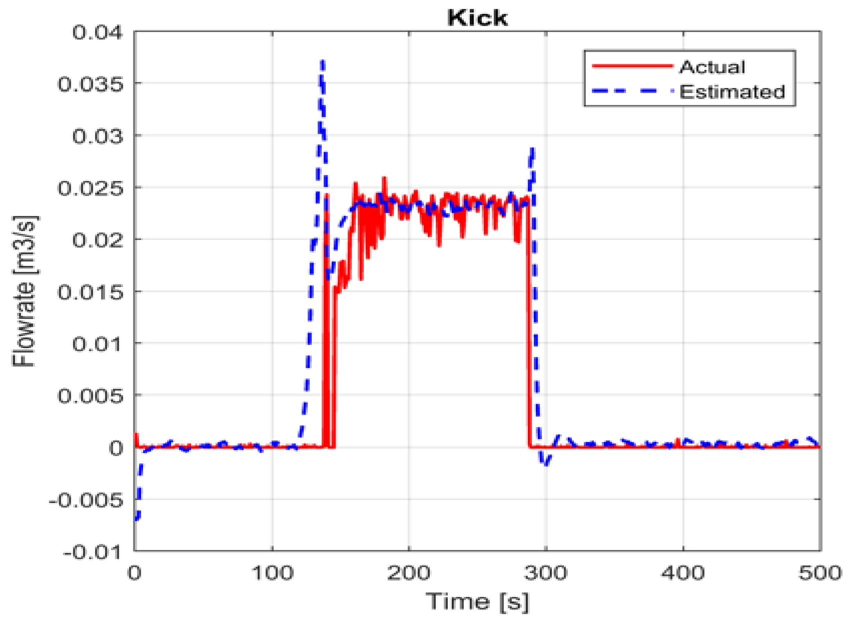


Figure 2.12: Estimated and actual unknown input for experimental data

2.4.4 Implementation in a field case study

The proposed method was tested on real data collected from an actual MPD operation that was taking place in Western Canada. From the drilling data, the measured depth (MD) was available for every second. The MD was used to calculate the true vertical depth and other changing parameters, e.g., annular volume, drill string volume, etc. for the drilling system. Other measured variables available from the surface sensors, pump flow rates and choke flow rates were used directly in the UKF algorithm.

The pump pressure was estimated as the difference between the standpipe pressure and the choke pressure. Friction factors were calculated from pipe specifications. The well parameters are given in Table 2.3

Table 2.3: Field parameters from the rig operating in Western Canada

Parameter	Value	Unit
Measured Depth (MD)	3671.2-3768.6	m
Volume of annulus (V_a)	0.00739*MD+27.172	m^3
Volume of drill string (V_d)	0.00739*MD	m^3
Bulk modulus in annulus (β_a)	1.3×10^9	Pa
Bulk modulus in drillstring (β_d)	1.3×10^9	Pa
Density in drillstring (ρ_d)	1240	Kg/ m^3
Density in annulus (ρ_a)	1240	Kg/ m^3
Choke downstream pressure (P_0)	1.013×10^5	Pa
Flow rate (Q_p)	1	m^3/ min

Figure 2.13, and Figure 2.14 shows the time trends of the data. Presence of gas influx was observed throughout the operation. For the current study, sample data set over 4000 s were selected, mainly ensuring the presence of kick. In this period, the gas influx was noticed on three different occasions: 1190, 2200, and 3300. On all of the three occasions, immediately prior to the change reflected in the flowrate, pressure transmitter displayed fluctuations. The change was first detected in the pump pressure, as the gas enters the annular section pump is suddenly working against a compressible fluid; as a result, a sharp decrease in pump pressure is observed. Due to this, while the gas flow was detected at 1100 second, the pump pressure change was detected much earlier at 950 second. This dip in

pump pressure is followed by a spike in pressure in the annular section. As more gas enters into the system, the annular pressure increases and the increased pressure is reflected by a sharp change in the choke pressure. This pressure signature of the pump and choke pressure indicates that it is possible to estimate the reservoir kick earlier than the flow measurements using the pressure signal. The UKF designed in the previous section used the measurements from the available sensors on the surface of the drilling rig and estimated the kick magnitude. In this unknown input estimator UKF, pump pressure and choke pressure are the measured states and the gas influx to the annular section is the unmeasured state. The UKF only filters these two signals. Figure 2.13 shows the actual and filtered pressure signals of the MPD system. The measured gas influx rate (i.e. gas kick) and the estimated gas influx rate are shown in Figure 2.14. As expected, the estimated kick was observed approximately 150 seconds ahead of its detection by the flow sensor. This clearly shows that the estimation of the kick using pressure measurement is beneficial.

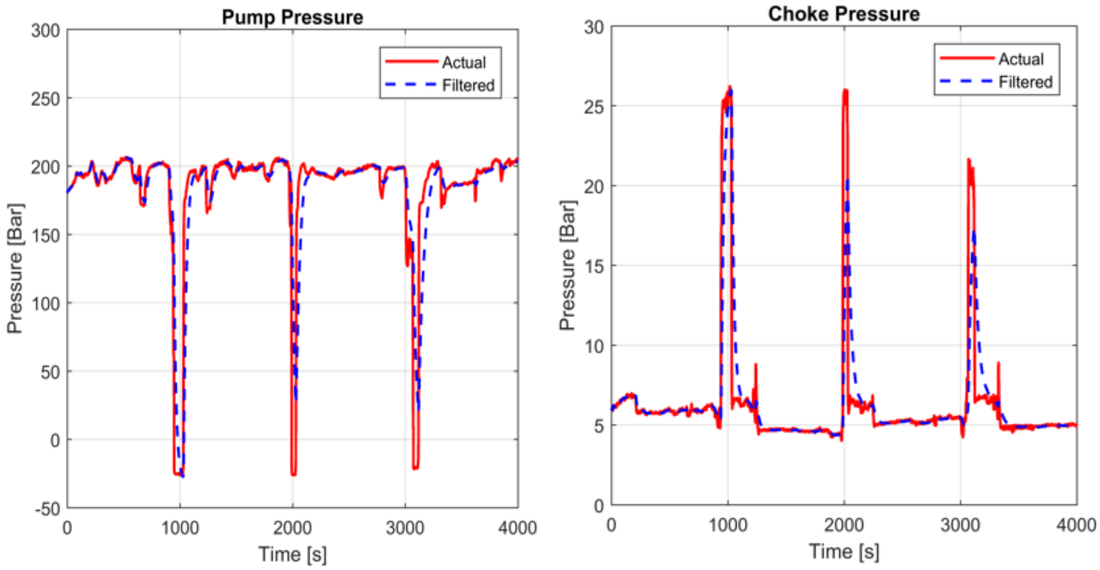


Figure 2.13: Filtered and actual states for field data

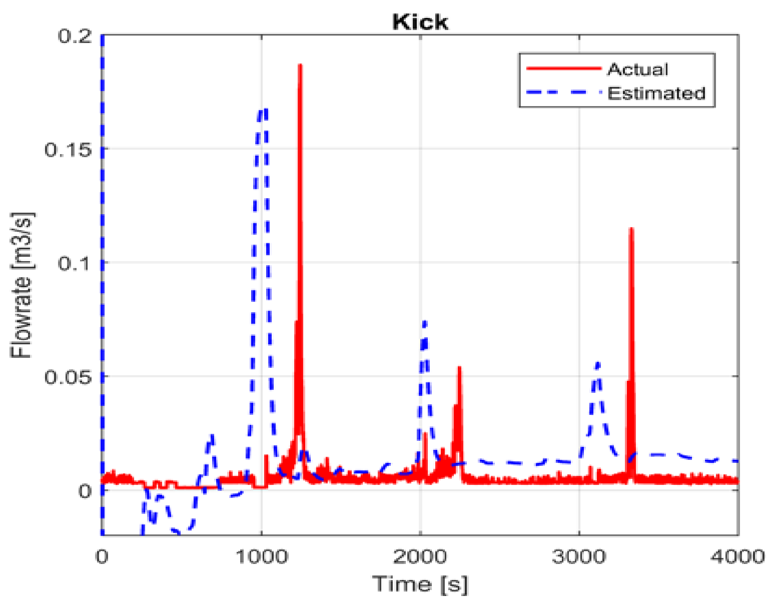


Figure 2.14: Estimated and actual unknown input for field data

2.5 Conclusion

In this paper, we presented UKF as a simultaneous estimator of hidden states (i.e., bit flowrate) and unknown input (i.e., reservoir influx). It was observed from the simulation, lab scale, and field case study that UKF is able to successfully estimate the bit flow and gas kick. UKF was found to be robust in the presence of significant measurement noise and plant model mismatch. It was observed that kick detection and estimation from the pressure leads to early detection of kick compared to the surface flow sensors. Both experimental data and field case study validated the findings.

In the experimental case study, the kick was detected 20 seconds before the actual kick appeared in surface flowmeter, and kick detection was approximately 150 seconds earlier for the field case study. Early estimation and detection of kick improve the performance of the kick mitigation process significantly and can play an important role in the increase of the safety and efficacy of a drilling operation. Different drilling operations such as: pipe extension scenario, no pump flow etc. can be used for further validation. Temperature effects need to be considered as well.

Acknowledgement

The authors would like to thank the Natural Sciences and Engineering Research Council (NSERC) of Canada for financial support.

Nomenclature

α = tuning parameters of sigma points
β_a = bulk modulus in annulus, Pa

β_d = Bulk modulus in drillstring, Pa
λ = scaling parameter
ρ_a = Density in annulus, Kg/ m^3
ρ_d = Density in drillstring, Kg/ m^3
σ_w = wall shear stress. Pa
χ = sigma points
A_0 = choke discharge area, m^2
C_d = choke discharge coefficient
f_a = friction factor in annulus, S^2/m^6
f_d = friction factor in drillstring, S^2/m^6
g = gravity, m/s^2
H_{TVD} = total vertical depth, m
M = mass parameter, Kg/ m^3
P_{bh} = bottomhole pressure, Pa, Bar
P_c = choke pressure, Pa, Bar
P_o = choke downstream pressure, Pa, Bar
P_p = pump pressure, Pa, Bar
q_{bit} = bit flowrate, m^3/s, LPM
q_c = choke flowrate, m^3/s, LPM
q_k = kick, m^3/s, LPM
q_p = pump flowrate, m^3/s, LPM
V_a = volume of annulus, m^3
V_d = volume of drillstring, m^3

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Chapter 3

Real time kick monitoring and management in the managed pressure drilling operation

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Abstract

The sudden influx of reservoir fluids (i.e., reservoir kick) into the drilling annulus is one of the common abnormal events encountered in the drilling operation. A kick can lead to a blowout, causing loss of lives, assets, and damage to the environment. This study presents a framework for real time kick monitoring and management in managed pressure drilling (MPD) operation. The proposed framework consists of three distinct steps: the unscented Kalman filter (UKF) is used to detect and estimate the kick's severity; the estimated severity and optimal control theory is used to calculate the time to mitigate the kick in the best case scenario; based on total predicted influx and pressure rise in the system generate a warning and activate the mitigation strategy. Thus, the proposed method can estimate, monitor, and manage kick in real time, enhancing the safety and efficiency of the MPD operation. The robustness of the developed method were validated using a simulated MPD system. Implementation of the proposed approach into a pilot scale experimental setup

demonstrate its applicability. The proposed monitoring framework delivered good outcomes in both case studies.

Keywords: Kick; MPD; Observer; Risk; Alarm.

3.1. Introduction

The need for hydrocarbon will continue to exist in the foreseeable future. However, many of the convenient wells have already been used for the extraction of oil and gas. These used sources affect the nearby wells by creating a smaller pressure window for operation (Møgster et al., 2013). Maintaining the bottomhole pressure (BHP) within this permissible range while drilling in a narrow pressure margin is exceptionally challenging (Nandan and Imtiaz, 2016). Kick is known as an influx of reservoir fluid that happens when the reservoir pressure exceeds the BHP. On the other hand, drilling fluid will be lost to formation if BHP exceeds the fracture pressure. An unmitigated kick may result in a catastrophic accident causing significant damage to the environment and human lives. The Macondo incident in the Gulf of Mexico is a prime example of this kind of undesired events (Hauge et al., 2013).

Drilling operation is associated with risk, and to ensure safety while drilling, accurate pressure control throughout the wellbore is required. Drilling at greater depth may require pipe extension, creating significant pressure fluctuation. Besides, the annular pressure profile changes due to the drill-pipe connection, tripping, swab, and surge operation. These activities add additional complexity during a drilling operation (Siahaan et al., 2012). Under this above mentioned scenarios, MPD has emerged as a powerful method to control the annular pressure profile precisely. MPD operates in a closed pressurized mud circulation system offering higher flexibility and precision than the conventional method. Automation in MPD has increased the efficiency and safety of the process by eliminating the risk of human error (Breyholtz et al., 2010). The automated MPD system relies on accurate measurement of each state and variable. Mud density, viscosity are uncertainties in operation. Frictional loss is dependent on mud density, viscosity, pressure, length, and diameters. So, these factors increases the uncertainties in the drilling operations. Besides, accurate measurements are not available in the bottomhole region because of the greater depth. The estimation of these unmeasured states and unknown inputs such as kick are crucial to enhance the performance of the MPD system. So, an observer is required to estimate the unknown kick in the system. Kalman filter based estimation is the most widely used approach for unknown state estimation (Julier and Uhlmann, 2004).

Significant research has been conducted on estimation and controller design for the MPD system. Stamnes et al. (2008) and Stamnes et al. (2009) estimated BHP in a well by implementing a Lyapunov based adaptive observer dealing with unknown frictions and density. Real field data verified the findings by comparing the estimated BHP to the actual BHP. Zhou et al. (2010) proposed a novel observer by estimating kick, and reservoir pressure from the difference of the predicted flow rates and actual flow rates. Zhou et al. (2011) extended his previous work on observers for kick detection and attenuation applying a switching based controller. Nandan and Imtiaz (2017) used a similar technique for the bit flow rate and reservoir pressure prediction and implemented a nonlinear model predictive controller (NMPC) with kick mitigation. Zhou and Nygaard (2010) implemented an adaptive observer to estimate downhole pressure during a drilling operation. Kaasa and Stamnes (2012) developed a simplified hydraulics model to capture the dominating hydraulics of the MPD system and used topside measurements and downhole measurements to calibrate the uncertain parameters in the annulus. Sui et al. (2012) estimated BHP during drilling and pipe connection operation by implementing a moving horizon (MHE) based observer. The method improved the conventional MHE approach by including the state's and parameter's constraints and noise filtering. Espen et al. (2012) considered kick and its location in a linearized MPD system as unknown parameters and estimated using a stable adaptive observer. Nygaard et al. (2007) applied UKF for state estimation and implemented NMPC to control the well pressure. UKF based estimation method was applied by Gravdal et al. (2010) to predict the essential parameters in a well-flow model. Topside and BHP measurements were used for the calibration of friction factors. The parameters were updated every thirty seconds by estimating the BHP. Three case studies were shown to verify the method. Mahdianfar et al. (2013) designed a joint UKF to simultaneously estimate states and unknown parameters in a well. They considered friction factors and bulk modulus as unknown parameters. These parameters were combined in a state vector and were estimated simultaneously with the states using available topside measurements.

An advanced dynamic risk based maintenance strategy using a Bayesian approach was presented in Pui et al. (2017) to create a risk profile for the offshore MPD system for rotating control device (RCD) and blowout preventer (BOP). The applied framework minimized the operational maintenance by mitigating the risks and identifying the critical components in the MPD system. Abimbola and Khan (2018) developed a risk based warning system using loss function (LF) to provide real time blowout risk analysis by estimating operational risks for drilling operations. The researchers provided standard criteria of the measured parameter from absolute bottom-hole pressure to pressure gradients. Though some work has been done on dynamic risk assessment of MPD systems, these methods lack some prediction ability as the probability of a blowout, or catastrophic event is calculated from the measured signal. Also, none of the methods take the controller capability into consideration. We propose to develop a robust warning system based on the real time operational data (Beyond Energy Services and Technology Corp, 2018). The developed warning system is independent of the controller and can deal with the unmeasured kick as well.

The rest of the paper is organized as follows: the model development for the MPD system is illustrated in Section 3.2, followed by the problem formulation and methodology in Section 3.3. The simulation results and the experimental results are presented in Section 3.4 with concluding remarks in Section 3.5.

3.2. Problem Formulation

In a mathematical model of an MPD system, there are two measured states, namely, pump pressure (Pp), and choke pressure (Pc), and one unmeasured state, bit flow rate (qbit). The kick (qkick) is considered as an unknown input in the model. The relationships among the states and the inputs for an MPD system are governed by the system hydraulics. Kaasa and Stamnes (2012) developed the hydraulics model of the MPD system from the mass and momentum balance equations. In this work, we used the model for developing the monitoring system, including state estimation. The model is briefly described in this section. Drill string and annular mud return section are the control volumes of an MPD system. The hydraulics model for these control volumes can be written as:

$$\dot{P}_p = \frac{\beta_d}{V_d}(q_p - q_{bit}) \quad \text{(3.1)}$$

$$\dot{P}_c = \frac{\beta_a}{V_a}(q_{bit} - q_c + q_k) \quad \text{(3.2)}$$

$$\dot{q}_{bit} = \frac{1}{M}(P_p - P_c - f_d q_p^2 - f_a q_{bit}^2 - (\rho_a - \rho_d) g h_{TVD}) \quad \text{(3.3)}$$

$$P_{bh} = P_c + Pf_a + \rho_a g h_{TVD} \quad \text{(3.4)}$$

$$q_c = u_c K_c sign(P_c - P_0)\sqrt{|P_c - P_0|} \quad \text{(3.5)}$$

$$q_k = K_p(P_{res} - P_{bh}) \quad \text{(3.6)}$$

βd and βa are the symbols of the bulk moduli of mud in drill string and annulus, respectively and ρd and ρa for the mud densities. Drill string volume and annulus volume are presented as Vd, and Va respectively; frictional loss coefficients in the drill string and the annulus are shown as fd and fa respectively. In the state space form, the model can be expressed as

$$X_{k+1} = f(X_k) + q_k + w_k \qquad (3.7)$$

$$y_k = g(X_k) + v_k \qquad (3.8)$$

State vector, $X = [P_p, P_c, q_{bit}]^T$; Measurement vector, $y = [P_p, P_c]^T$; Unknown input= q_{kick}

Where, f is the nonlinear system equation, $w_k \approx N(0, W_k)$ is the Gaussian process noise, and $r_k \approx N(0, R_k)$ is the Gaussian measurement noise. Process and measurement noises are assumed to be uncorrelated.

Our objective is to estimate the kick from the available top side measurements by applying the UKF. Based on the kick, the impact of a kick in the system will be calculated and compared with operability conditions for monitoring and control purposes. Section 3.3 describes the methodology in detail.

3.3 Methodology on real time kick monitoring and management

Real time and predictive warning systems can play a significant role in increasing process safety. Varga et al. (2010) proposed a novel concept for a predictive alarm management system. They identified the stable and unstable operating conditions of a process. A warning was generated when the state's value crossed the controllable region, which was determined by the Lyapunov's secondary stability analysis of the state variables. The proposed method was applied to two industrial benchmark problems. A design based on operability constraints and state estimators were presented for model predictive safety system in Ahooyi et al. (2016). A real time receding horizon operability analysis was done to identify the predicted operational hazards. An extended Luenberger observer (ELO) was used to estimate the present and future state variables. The alarm was generated based on the controller's capacity to mitigate the extreme value of a predicted state. In the real world, process variables are interconnected. So optimizing one extreme state using one manipulated variable may cause other variables to exceed the safety limit. A risk based alarm design was proposed by Ahmed et al. (2011). The present and future risks associated with the system variables were evaluated to generate alarms in the system. Researchers prioritized the alarms based on the severity and provided operator actions to mitigate the risk.

There is no significant work has been done on real time kick management for the MPD system. Our research work addressed this issue by developing a framework for real time kick monitoring and management system. It requires detection and accurate estimation of kick and a robust warning system. There are mainly three steps to achieve our goal described as follows:

- Implementation of UKF to estimate the unmeasured kick in the system. The estimation was done using the available topside measurements: flow rate at the pump, pump pressure, and choke pressure.

- Optimal control output to mitigate the kick was estimated using an optimizer. A moving horizon predictor was used to predict kick size for a short duration to calculate the required time to mitigate the kick.

- The total predicted kick volume entered during the mitigation time was calculated. The fluctuation of pressure due to kick was computed. A warning system was created based on the industry standard well operation matrix.

Figure 3.1 shows the overall methodology for risk based monitoring. Followed by the flow chart a detailed description of each step is provided.

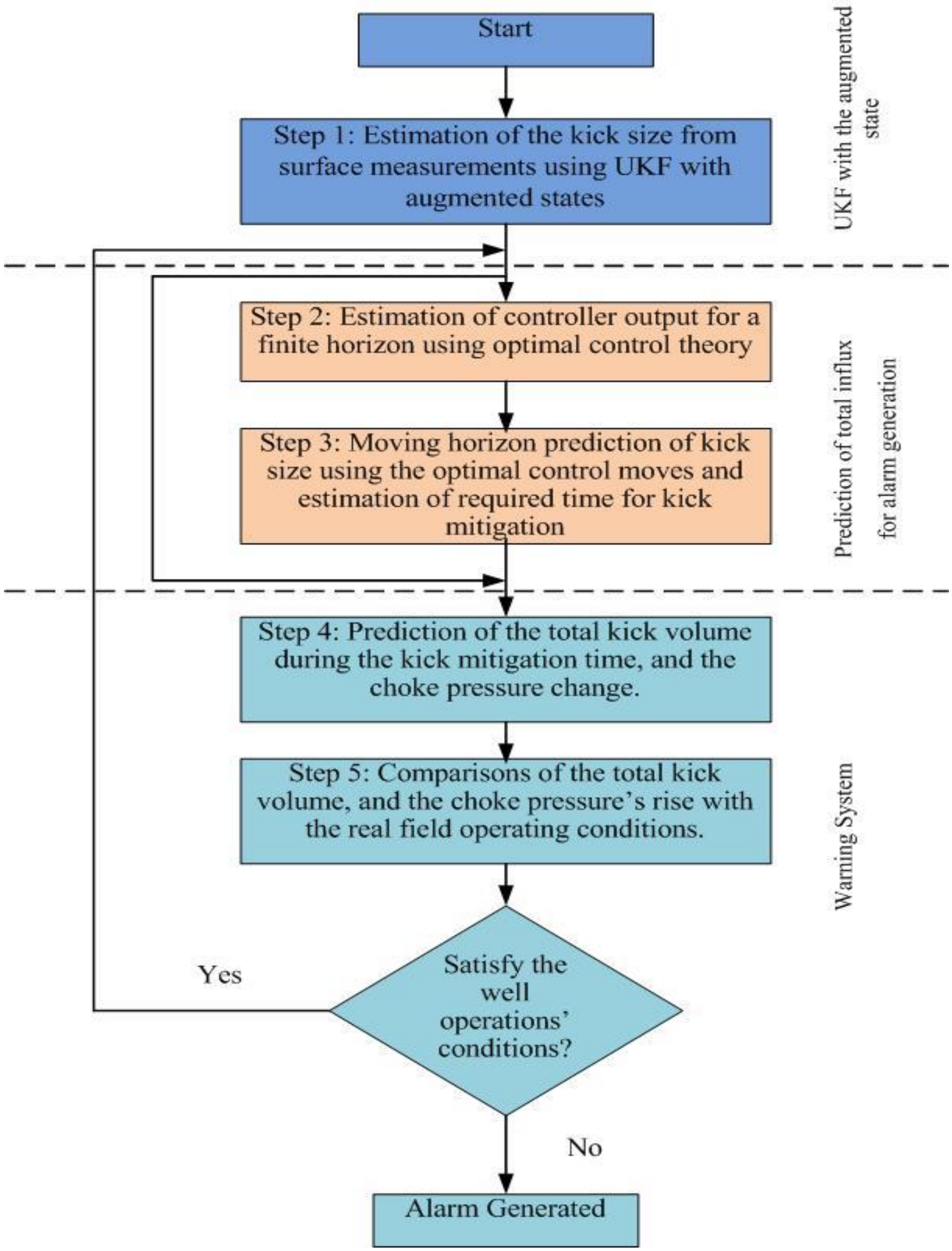


Figure 3.1: Implementation steps of real time kick monitoring

3.3.1 UKF with the Augmented States

UKF is a widely used state estimator for nonlinear systems (Gravdal et al., 2010). In this work, our objective is to estimate states pump pressure (Pp), choke pressure (Pc), bit flow rate (q_{bit}) and the unknown input to the system, reservoir influx (q_{kick}). In order to estimate the unknown states, the states and the unknown inputs are placed into an augmented state vector. After augmenting the reservoir influx into the state vector, the augmented state transition matrix looks as in Equation (3.9).

$$\begin{bmatrix} P_{p,(k+1)} \\ P_{c,(k+1)} \\ q_{bit,(k+1)} \\ q_{kick,(k+1)} \end{bmatrix} = \begin{bmatrix} f_1(P_{p,(k)}) \\ f_2(P_{c,(k)}, q_{kick,(k)}) \\ f_3(q_{bit,(k)}) \\ q_{kick,(k)} \end{bmatrix} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.9)$$

The UKF is an extension of the unscented transformation (UT), a method used for calculating the statistics (mean and covariance) of a random variable in a nonlinear transformation (Wan and Van Der Merwe, 2000). Deterministically chosen sigma points are used for state distribution to capture the true mean and the covariance of the Gaussian random variable and calculate the posterior mean and covariance. These measurements can be done accurately up to the 3rd order (Taylor series expansion) in a nonlinear system. There are two stages of UKF (Mahdianfar et al., 2013): Prediction, and Update. Below we describe these two stages:

3.3.1.1 Prediction

Step 1: A set of initial values of state, m_{k-1} and covariance, P_{k-1} are selected.

Step 2: The set of sigma points are generated based on the present state covariance by the following equation-

$$\chi_{k-1} = [m_{k-1} \; ... \; m_{k-1}] + \sqrt{c}\; [0 \; \sqrt{P_{k-1}} \; -\sqrt{P_{k-1}}] \qquad (3.10)$$

Here, χ is the matrix of sigma points and $c = \alpha^2 (n+k)$. α and *k* are tuning parameters used for sigma points' spread specifications , and *n* is the dimension of the state vector (Kandepu et al., 2008).

Step 3: Sigma points are transferred through model to calculate the predicted mean and covariance by using the following equation:

$$\hat{X}_k = f(\chi_{k-1}, k-1) \qquad (3.11)$$

$$m_k^- = \hat{X}_k \, w_m \qquad (3.12)$$

$$P_k^- = \hat{X}_k W [\hat{X}_k]^T + Q_{k-1} \qquad (3.13)$$

Here, Q_k is the process covariance matrix. Vector w_m and matrix W can be described as follows:

.

$$W_m^{(0)} = \frac{\lambda}{(n+\lambda)}$$

$$W_c^{(0)} = \frac{\lambda}{(n+\lambda)+(1-\alpha^2+\beta)}$$

$$W_m^{(i)} = \frac{\lambda}{2(n+\lambda)},\ i=1,...,2n$$

$$W_c^{(i)} = \frac{\lambda}{2(n+\lambda)},\ i=1,...,2n$$

$\lambda = \alpha^2(n+k)-n$ is a scaling parameter.

3.3.1.2 Updating

Step 4: New Sigma points are generated from the following equation -

$$\chi_k^- = [m_k^- \ ... \ m_k^-] + \sqrt{c}\ [0\ \sqrt{P_k^-}\ \text{-}\sqrt{P_k^-}\ ] \qquad \text{…………......…. (3.14)}$$

Step 5: New sigma points are transferred in the measurement equation.

$$Y_k^- = g(\chi_k^-, k) \qquad \text{……………………………………...…. (3.15)}$$

The predicted mean μ_k and covariance of the measurement S_k are calculated by the following equation-

$$\mu_k = Y_k^- w_m \qquad \text{…………………….…………………...…. (3.16)}$$

$$S_k = Y_k^- W [Y_k^-]^T + R_k \qquad \text{…………………………......…. (3.17)}$$

Here, R_k is the measurement covariance matrix. Cross-covariance of state and measurement C_k is calculated as follows-

$$C_k = X_k^- W [Y_k^-]^T \quad \text{……………….……….……...…. (3.18)}$$

Kalman Gain is calculated by the following equation-

$$K_k = C_k S_k^{-1} \quad \text{….……………………...…... (3.19)}$$

Step 6: The updated state mean m_k and covariance P_k is computed based on the measurement y_k .

$$m_k = m_k^- + K_k [y_k - \mu_k] \quad \text{………………….……......……... (3.20)}$$

$$P_k = P_k^- - K_k S_k K_k^T \quad \text{……………….……...…………... (3.21)}$$

Updated state mean and covariance act as an initial values for the next time step.

3.3.2 Prediction of total influx for alarm generation

Once the kick has been detected, and the initial kick size has been estimated, the next step is to calculate the total size of influx into the system. However, as the controller will try to mitigate the kick in the system, the controller effect needs to be accounted for in the calculation. In order to make a monitoring system independent of the controller, we calculated the influx size assuming an optimal controller response. Therefore, the estimated influx size will be a conservative estimate and makes the monitoring system robust. Choke valve opening (uc) was considered as the manipulated variable. The cost function minimizes the difference between the upper kick limit and predicted kick over the prediction horizon, keeping the choke valve deviation within the acceptable limits (Nandan and Imtiaz, 2017). The cost function can be written as:

$$J = \min_{u_c} \sum_{K=k}^{k+m} \gamma_1 (\hat{q}_k (K) - q_k^{set} (K))^2 + \gamma_2 \Delta u_c^2 \quad \text{…………………..} \ (3.22)$$

Where $\gamma_1 \in \mathbf{R}$ and $\gamma_2 \in \mathbf{R}$ are weighing constants and m is the prediction horizon. Kick and input constraints can be defined as:

$$q_k^{min} \le q_k \le q_k^{max} \quad \text{…………………………….……….} \ (3.23)$$

$$u_c^{min} \le u_c \le u_c^{max} \quad \text{…………………………………..} \ (3.24)$$

When the kick enters the system, it affects the states and is reflected by the change in the pressure measurements. The controller takes action to keep the kick below the threshold limit. The time required to mitigate the kick back into the safe region was calculated. This time was used for total kick volume for real time kick management.

3.3.3 Warning Generation

The warning system is based on total influx volume and the pressure in the annular section of the drilling rig. The total volume can be identified by integrating the volumetric flow rate of kick until the kick is fully mitigated.

$$Total\_Volume = \int_{0}^{T=mitigation\_time} q_{kick\_predicted}\, dT \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (3.25)$$

The change in surface choke pressure is calculated from the increase in pressure from the stable surface pressure during the influx.

$$P_{choke(increment)} = P_{choke(kick)} - P_{choke(normal)} \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (3.26)$$

We used an industry standard guideline for setting the alarm threshold. The MPD well operation matrix from the Beyond Energy Corporation is presented in Figure (3.2). The matrix provides the necessary guidelines for actions in an MPD system based on operating conditions. The warning system and the management of the well for different influx scenarios are given in the risk matrix. Prediction of the influx volume in real time will provide a precise quantitative measure to an operator to activate appropriate mitigation action based on the guideline.

MPD well control matrix (Rotating from 0 to 150 RPM)					
Maximum Surface Back pressure (SBP) for stripping: 70 Bar (70% of dynamic RCD limit)		Surface Pressure Indicator			
		SBP while drilling	SBP during connections	During well control, No rotation, no pipe movement	Maximum SBP Limit
		0-42.5 Bar(0 RPM≤ 100 RPM)	Based on RPM to left- 50 Bar	50-100 Bar	>100 Bar
		0-17 Bar (≥100 RPM≤ 150 RPM)			
Influx Indicator	No Influx	Manageable	Manageable	Cease drilling, adjust drilling parameters to increase BHP	Shut in on Rig's Blow out preventer
	(0≤ 750 Liters)	Cease drilling, adjust drilling parameters to increase BHP	Cease drilling, adjust drilling parameters to increase BHP	Cease drilling, adjust drilling parameters to increase BHP	Shut in on Rig's Blow out preventer
	(≥750 Liters≤ 1500 Liters)	Cease drilling, adjust drilling parameters to increase BHP	Cease drilling, adjust drilling parameters to increase BHP	Shut in on Rig's Blow out preventer	Shut in on Rig's Blow out preventer
	(>3000 Liters)	Shut in on Rig's Blow out preventer	Shut in on Rig's Blow out preventer	Shut in on Rig's Blow out preventer	Shut in on Rig's Blow out preventer

Figure 3.2: MPD well control matrix (Beyond Energy Services and Technology Corp, 2018)

3.4. Implementation of the methodology

The effectiveness of the proposed methodology is demonstrated through two case studies: a simulation model of an MPD system (Kaasa and Stamnes, 2012) and on a laboratory scale MPD system.

3.4.1. Simulated system

MPD system was simulated based on the hydraulic model described in Section 3.2. A Proportional Integral (PI) controller was implemented to mitigate the kick. Model parameters used for simulation are presented in Table 3.1. In this case study, the covariance of the system noise was Q= diag [50 50 5×10^-6 5×10^-6], and measurement noise with a covariance R= diag [5×10^6 5×10^6] was added with pump pressure, and choke pressure. Volumes in drillstring and annulus and drilling fluid were unchanged throughout the simulation. Mud was pumped at a rate of 1200 LPM, and initially, the choke opening was at 30 percent. We introduced two kicks into the system, one with a magnitude of 550 LPM and the other 24 LPM. The performance of the monitoring system is described in the result section.

Table 3.1: Simulated MPD system parameters (Nandan and Imtiaz, 2017)

Parameter	Value	Unit
Volume of annulus (V_a)	90	m^3
Volume of drillstring (V_d)	25.6	m^3
Total vertical depth (TVD)	3500	m
Mass parameter (M)	8.04×10^8	Kg/ m^3
Bulk modulus in annulus (β_a)	2.3×10^9	Pa
Bulk modulus in drillstring (β_d)	2.3×10^9	Pa
Density in drillstring (ρ_d)	1300	Kg/ m^3
Density in annulus (ρ_a)	1300	Kg/ m^3
Friction factor in drillstring (f_d)	1.65×10^{10}	S^2/m^6
Friction factor in annulus (f_a)	2.08×10^9	S^2/m^6
Choke discharge coefficient (C_d)	0.6	-

Choke discharge area (A_0)	2×10^{-3}	m^2
Choke downstream pressure (P_0)	1.013×10^{5}	Pa
Flow rate (Q_p)	1200	LPM

3.4.2. Experimental Setup

The proposed methodology was implemented on a lab scale MPD setup located in the process engineering facility at Memorial University of Newfoundland (Amin, 2017). The setup is a pipe in a pipe system simulating the annular volume and the drillstring. The vertical length in the experimental setup is 16.5 ft, and it can only monitor the flow behavior of a static drillstring. The schematic of the experimental setup is given in Figure 3.3. As shown in the diagram, the experimental setup has eight pressure transmitters, four flow meters, and two control valves. A progressing cavity pump supplies the drilling fluid, which can be controlled by a variable frequency drive. For our experiment, we considered water as drilling fluid. The kick was introduced in the setup by an air compressor injecting air into the annular section. A PI controller was implemented to perform the closed loop operation, and the experimental data was collected by MATLAB. Communication between the MPD plant and MATLAB is established using ADAM 5000TCP/IP, OPC Server, and MATLAB OPC toolbox. PT102 is used to measure the pump pressure, and PT302 is for choke pressure measurement. The pump flow rate was fixed at 60 LPM throughout the operation. Initially, the choke opening was at 55 percent, and however, it changed due to the control action. The rest of the parameters are given in Table 3.2. We also tested the experimental setup for a wide range of kicks. The results of two representative kicks are presented in the next section.

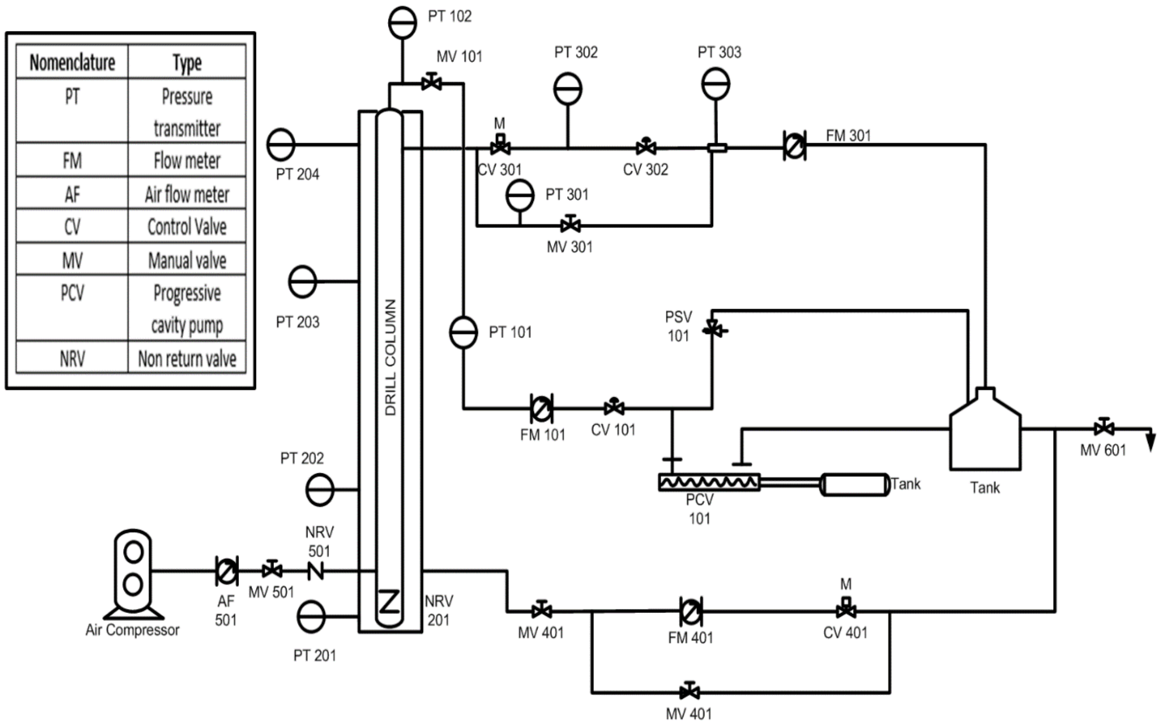


Figure 3.3: Schematic diagram of the experimental setup (Amin, 2017)

Table 3.2: Experimental setup parameters

Parameter	Value	Unit
Volume of annulus (V_a)	0.01518	m^3
Volume of drill string (V_d)	0.0054	m^3
Total vertical depth (TVD)	4.75	m
Mass parameter (M)	8.4×10^8	Kg/ m^3
Bulk modulus in annulus (β_a)	2.15×10^9	Pa
Bulk modulus in drillstring (β_d)	2.15×10^9	Pa

Friction factor in drillstring (f_d)	47147.21	S^2/m^6
Friction factor in annulus (f_a)	43680.9	S^2/m^6
Choke discharge coefficient (C_d)	0.6	-
Choke downstream pressure (P_0)	1.013×10^5	Pa

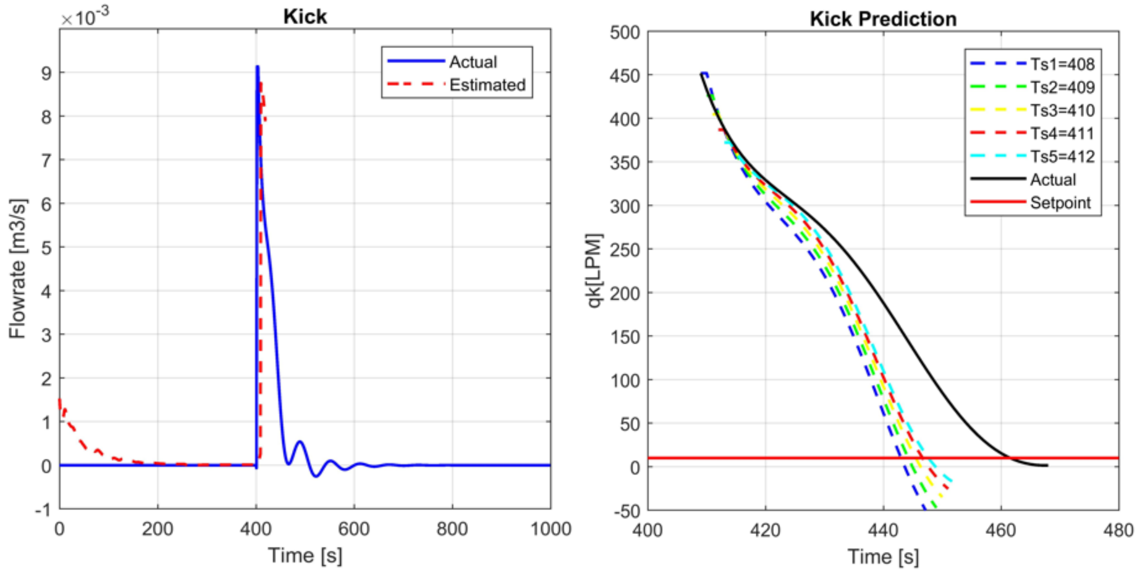
3.5. Results and discussions

Kicks with different magnitudes were introduced to the simulated system and the experimental system to test the warning system. The experiments and the results from the warning system are summarized below.

3.5.1 Simulation Results

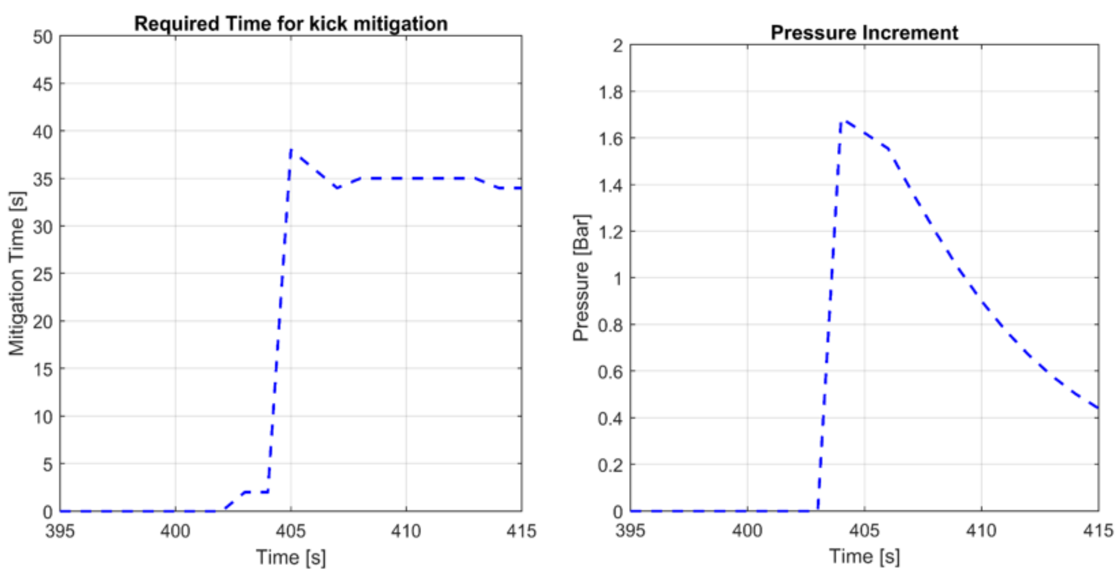
For the first scenario in the simulated study, a kick was introduced at 400 seconds that led to a sudden change in pump pressure and choke pressure. UKF was able to estimate the kick size based on the pump pressure and choke pressure measurements. Our initial goal was achieved by detecting the unknown kick, as shown in Figure 3.4(a). In the observer, kick size estimation is dependent on choke pressure variations. The kick was estimated as long as the pressure set point was unchanged. As the pressure set point was changed after the kick detection to mitigate the kick, the UKF estimate was no longer valid. The reason for this limitation is, as reservoir fluid influx into the control volume, the pressure inside the MPD system increases. Thus there is a positive correlation between the flow and the fluid influx. On the other hand, when the pressure set point is increased, the system pressure increases; however, the rate of influx into the system decreases. Thus there is an inverse response in the system. The observer is not able to capture this inverse response.

The estimated kick was utilized for predicting the influx in the system for the entire monitoring horizon. We selected our monitoring time horizon from 395 seconds to 415 seconds. As shown in Figure 3.4(b), predicted kick values are presented from five different sample points starting from 408. In this simulation study, we considered 10 LPM as the safe limit for the kick in the system. Required time for kick mitigation based on the optimal control action at a different point in time were calculated and presented in Figure 3.5(a). The total influx volume into the system and incremental pressure were calculated following procedure described in Section 3.3. The predicted influx volume and the overpressure were compared with the operational risk matrix presented in Figure (3.2). The total kick volume crossed the safety zone at 405 and entered the critical zone, as presented in Figure 3.5(c). The alarm for shut down operation was generated at 405. The proposed framework was able to estimate the unknown kick and identify the suitable operating conditions with the predicted kick. Real time kick management was achieved as the alarm was generated within 5 seconds of the kick.

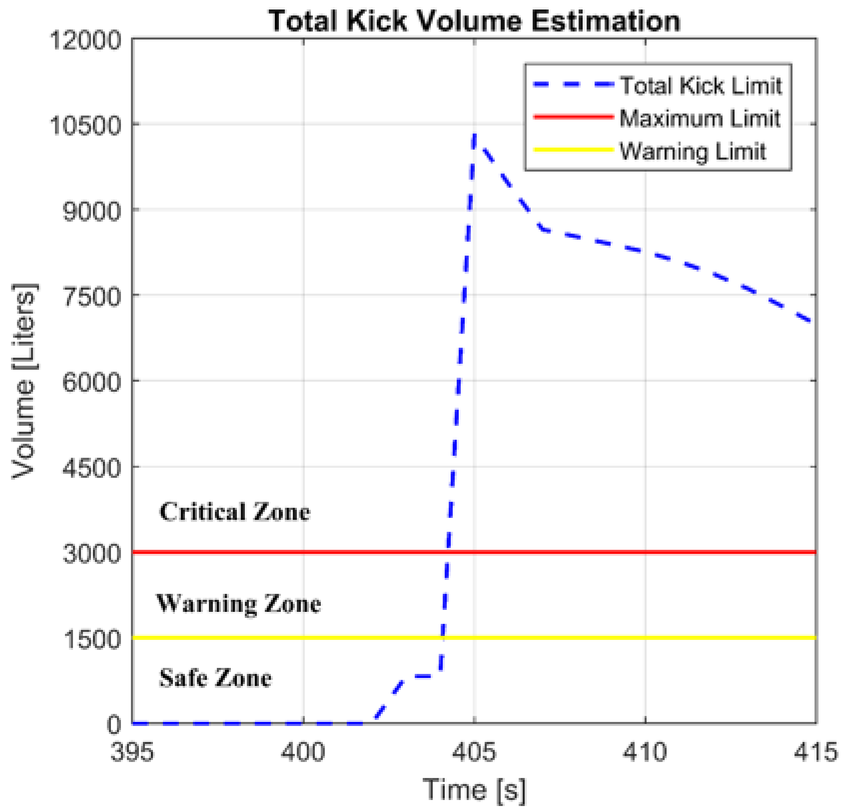


(a) (b)

Figure 3.4: (a) Estimated and actual kick in a closed loop MPD system. (b) Predicted Kick from different time samples in the monitoring horizon



(a) (b)

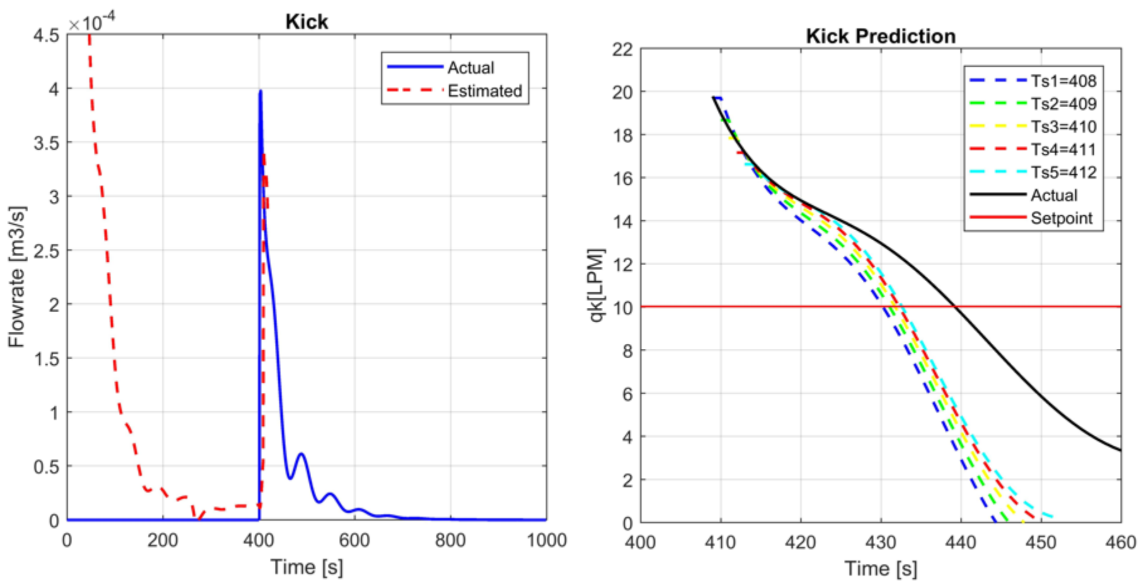


(c)

Figure 3.5: (a) Required time to mitigate kick. (b) Pressure increment due to kick. (c) Total kick volume estimation

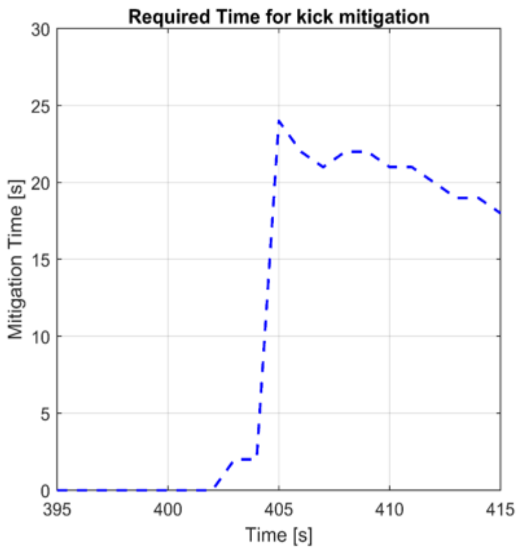
For the second scenario, a kick of a smaller magnitude was introduced at 400 seconds. Model parameters remained the same as in Table 3.1, system noise and measurement noise were kept unchanged. The pump flow rate was 1200 LPM, and the choke opening was 30 percent. UKF was able to detect the kick and estimate the magnitude of the kick, as shown in Figure 3.6(a). A similar approach was taken to predict the kick in the same monitoring horizon. The predicted kicks from different time samples are presented in Figure 3.6(b).

As shown in Figure 3.7(a), the optimizer required less time to mitigate the kick into the safety limit because of having a smaller kick magnitude. As presented in Figure 3.7(b), 3.7(c), the pressure increment, and the total volume, were less than that for the previous scenario. The total kick volume remained within the safety zone during the monitoring time. As such, no alarm was generated for this scenario.

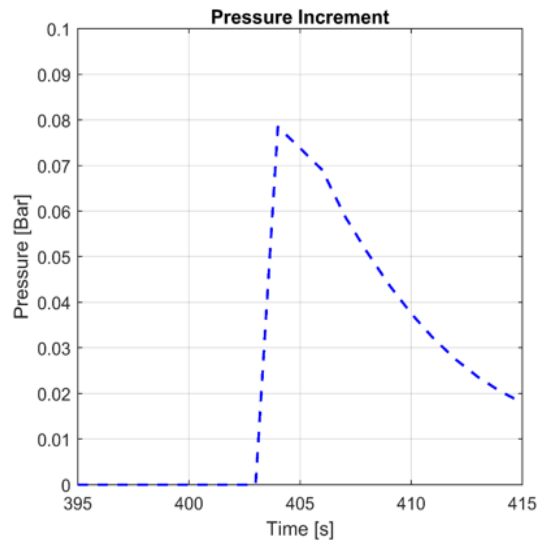


(a) (b)

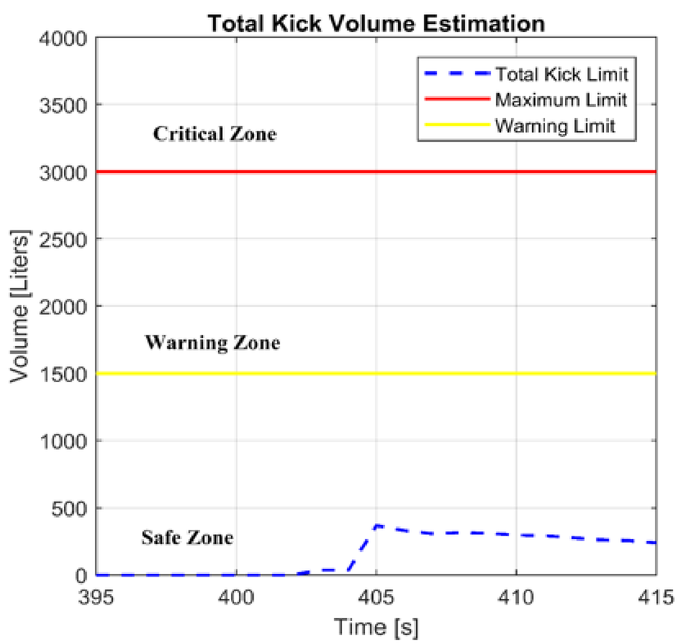
Figure 3.6: (a) Estimated and actual kick in a closed loop MPD system. (b) Predicted kick from different time samples in the monitoring horizon



(a)



(b)

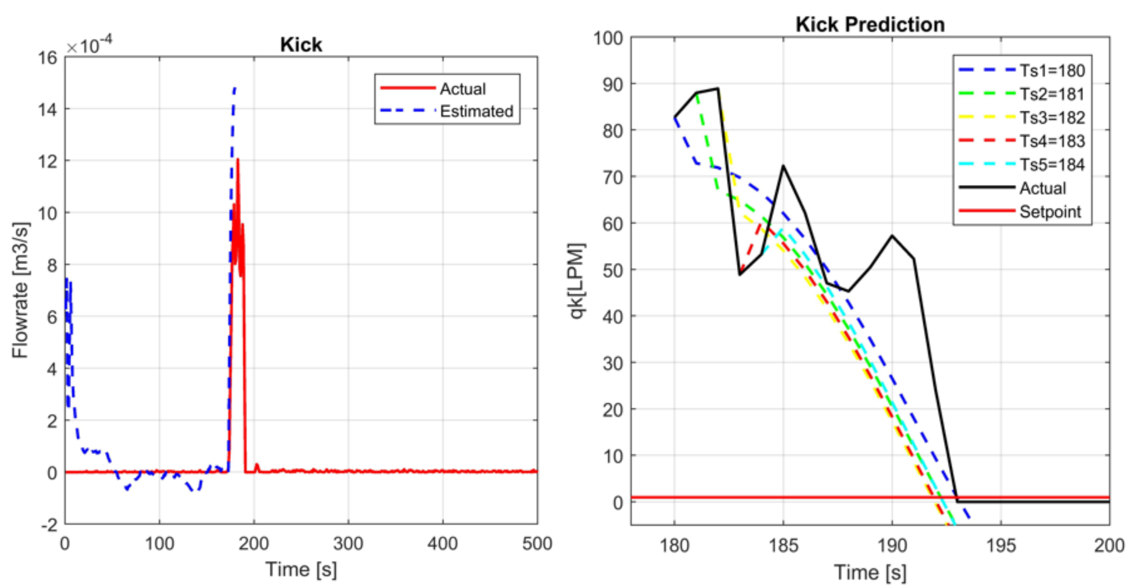


(c)

Figure 3.7: (a) Required time to mitigate kick. (b) Pressure increment due to kick. (c) Total kick volume estimation

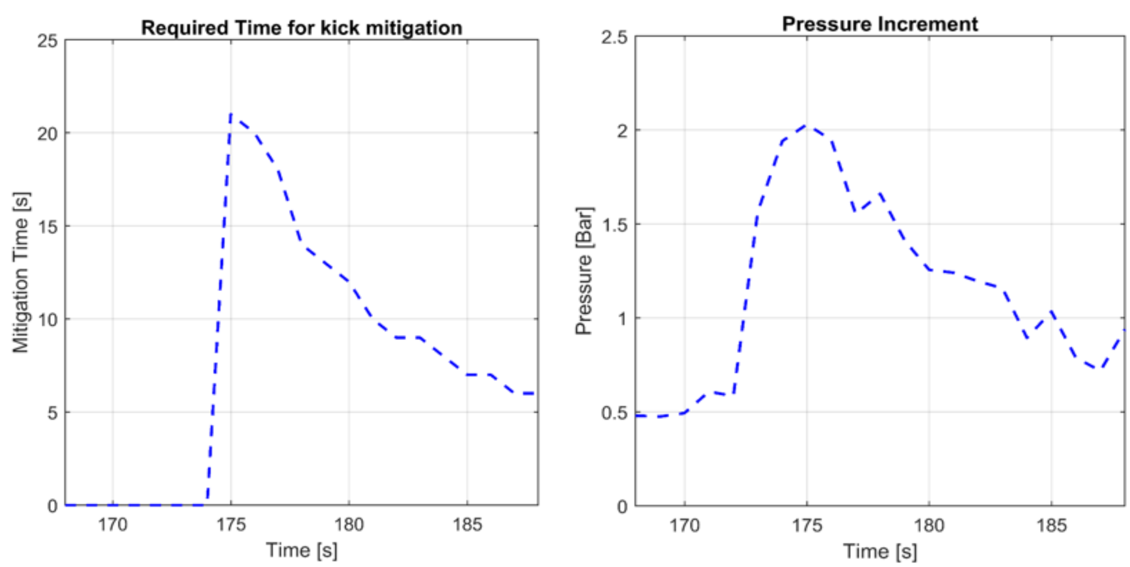
3.5.2 Experimental Results

Two kick scenarios are considered for experimental evaluation. For the first scenario, a gas kick was injected into the annular section at 173 seconds by the air compressor. The gas influx led to an instantaneous change in the choke pressure. The controller took action and mitigated the kick. For our experimental case study, the safety limit for kick was considered 1 LPM. As presented in Figure 3.8(a), the observer has successfully detected the kick and identified the magnitude of the disturbance. Kick prediction for the next 100 seconds was made using the estimated kick value. Kick prediction from 5 different sample points with the actual kick is presented in Figure 3.8(b). The total influx volume to the system and the pressure increment were calculated as described in Section 3.3. The results were compared with the conditions presented in Figure (3.3). Since the experimental setup is a small size replica of the MPD operation, the industrial guideline is not applicable to the system. We adjusted the limits to suit the experimental setup. The total kick volume crossed the safety zone at 175 seconds and entered the critical zone, as presented in Figure 3.9(c). So, the alarm for shut down operation was generated at 175 seconds. The alarm was generated within 2 seconds of the kick encountered, creating a real time warning scenario.

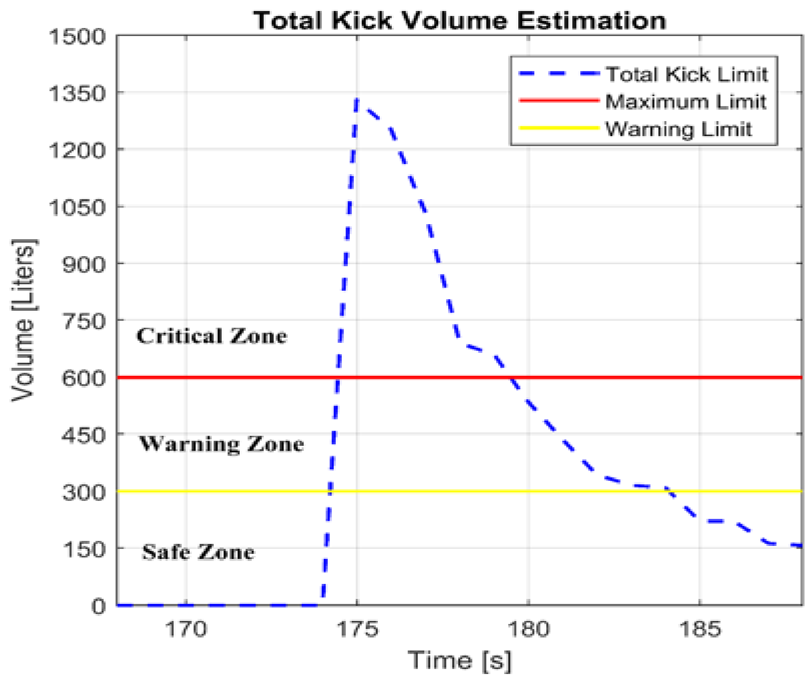


(a) (b)

Figure 3.8: (a) Estimated and actual kick in a closed loop MPD system. (b) Predicted Kick from different time in the monitoring horizon



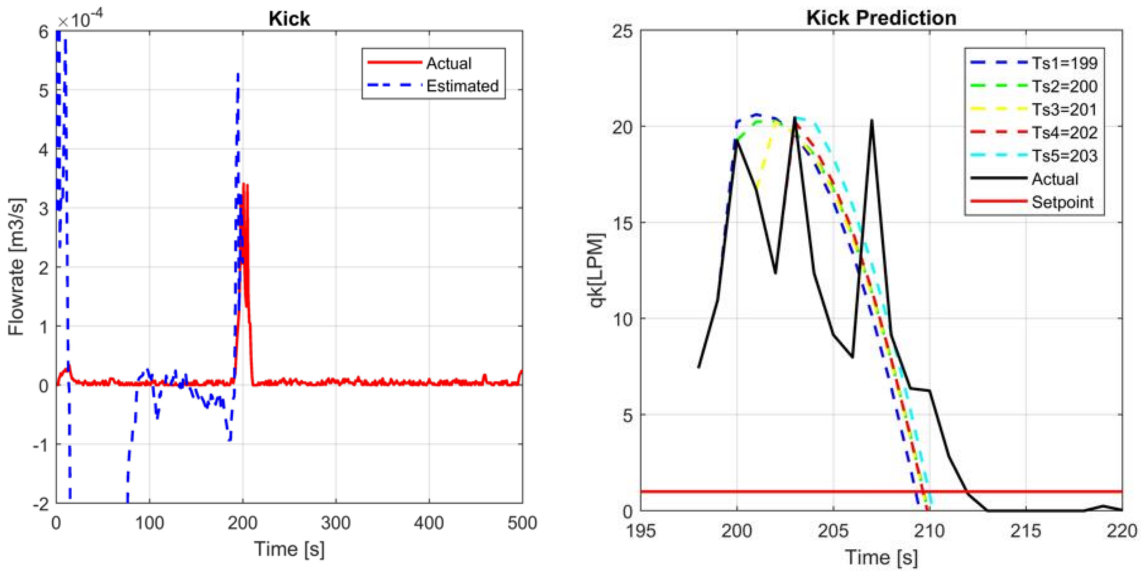
(a) (b)



(c)

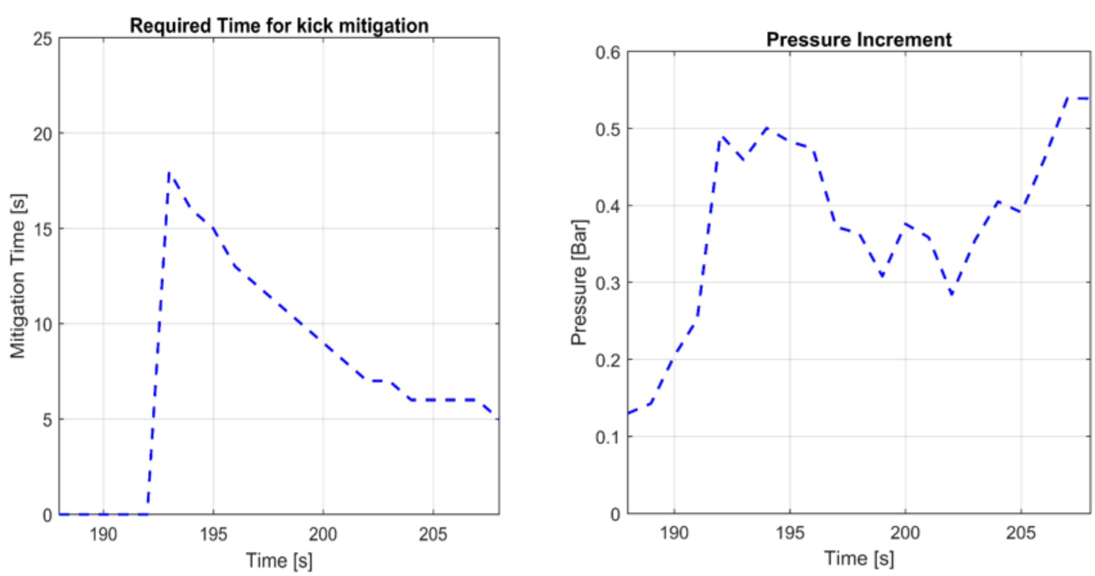
Figure 3.9: (a) Required time to mitigate kick. (b) Pressure increment due to kick. (c) Total kick volume estimation

For the second scenario, a kick of smaller magnitude was injected in the MPD setup at 192 seconds. Operating conditions remained unchanged for this experiment. UKF detected and estimated the kick, as presented in Figure 3.10(a). The estimated kick size was used to predict the influx size for the next 100 seconds. Predicted kick from different sample points, starting at 199 seconds, is given in Figure 3.10(b). Mitigation of predicted kick was achieved quicker due to the smaller kick size, as shown in Figure 3.11(a). These impacted the total kick volume and the pressure increment. As displayed in Figure 3.11(c), the total volume entered the warning zone at 193 seconds. For this kick scenario, the system generates a warning alarm to the operators to take necessary actions for kick mitigation.

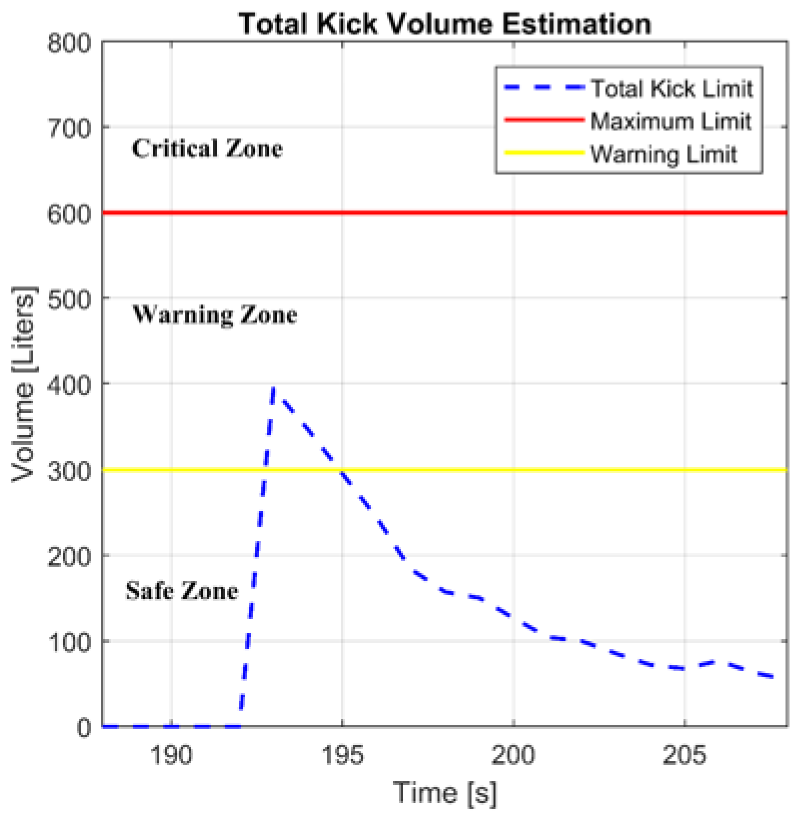


(a) (b)

Figure 3.10: (a) Estimated and actual kick in a closed loop MPD system. (b) Predicted Kick from different time in the monitoring horizon



(a) (b)



(c)

Figure 3.11: (a) Required time to mitigate kick. (b) Pressure increment due to kick. (c) Total kick volume estimation

3.6 Conclusions

A real time framework to estimate, monitor, and manage kick in an MPD system have been presented. The monitoring system uses the surface measurements to detect the kick. UKF detected and estimated the kick's magnitude effectively. The main feature of the monitoring system is its predictive nature and the ability to take the controller action into account. The monitoring system is also controller independent. It assumes an optimal controller. As such, it provides the best case scenario and is conservative in issuing an alarm. The proposed warning system is based on an industrial MPD well control matrix so that it can be comparable with the practical warning conditions. However, the alarm sensitivity can be increased or decreased by manipulating the alarm threshold depending on the philosophy of operation. Two case studies validate the proposed approach. In the simulated case study with field scale dimensions, an alarm was generated within 5 seconds of the actual kick. For the experimental study, the alarm was issued within 2 seconds.

3.6. Acknowledgment

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Chapter 4

Summary Conclusions and Future work scopes

4.1 Conclusion

The objective was to develop a framework for real time kick estimation and monitoring in MPD system. UKF was implemented as a simultaneous estimator of hidden states (i.e., bit flow rate) and unmeasured disturbance (i.e., reservoir influx). The estimated kick is further processed to calculate the time to mitigate the kick by the controller. The monitoring system used optimal control method, so it was controller independent. The proposed warning system is based on an industrial MPD well control matrix so that it can be comparable with the practical warning conditions. Some of the key findings are-

- UKF performed effectively in the presence of significant measurement noise and plant model mismatch. Three case studies validated the findings.
- Kick detection and estimation from the pressure leads to an early detection of kick compared to the surface flow sensors. In the experimental case study, the kick was detected 20 seconds before the actual kick appeared in surface flow meter, and kick detection was approximately 150 seconds earlier for the field case study.

- A real time framework to estimate, monitor, and manage kick in an MPD system was achieved. In the simulated case study, an alarm was generated within the 5 seconds of actual kick, and for the experimental study, the alarm was issued within 2 seconds.
- The proposed monitoring system has the predictive nature and can take the controller action into account. It assumes an optimal controller. As such, it provides the best case scenario and is conservative in issuing an alarm.

4.2 Future Work Scopes

Some future recommendations are highlighted below:

- A two-phase MPD model can be considered for a better representation of the real life MPD system.
- Temperature effects need to be considered in future studies.
- Different drilling operations such as: pipe extension scenario, no pump flow etc. can be used for further validation.
- Development of a user friendly graphical user interface for better alarm visualization (e.g. VT SCADA software).

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Appendix

The model is based on three fundamental equations. These are –

- Equation of State
- Equation of Continuity (mass conservation)
- Equation of Motion

A.1 Equation of State

The density of drilling mud depends on pressure and temperature. The equation of state for the density can be written as -

$$\rho = (P, T) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(A.1)}$$

The linearized representation can be done for a small change of density (Kaasa and Stamnes, 2012).

$$\rho = \rho_0 + \frac{\partial \rho}{\partial P}(P - P_0) + \frac{\partial \rho}{\partial T}(T - T_0) \quad \ldots\ldots\ldots \text{(A.2)}$$

The temperature difference can be neglected considering isothermal condition

$$\rho = \rho_0 + \frac{\partial \rho}{\partial P}(P - P_0) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(A.3)}$$

Bulk modulus is a numerical constant which is used to determine the compressibility of a fluid (White, 2011).

$$\beta = -(1/V)\frac{\partial P}{\partial V} = \rho \frac{\partial P}{\partial \rho} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(A.4)}$$

From equation (A.3),

$$\rho = \rho_0 + \frac{\rho_0}{\beta}(P - P_0) \quad \text{.......................... (A.5)}$$

Drilling fluid gets affected by the friction created by straight pipe, bend pipe, curved pipe, choke valve, and tees. This factors impact the dynamics of flow along the main flow path.

A.1.1. Friction

- Head losses
- Minor losses

A.1.2 Head Losses

Head losses is used to determine the energy losses in sections consisting of straight pipes.

$$\frac{\partial F}{\partial x} = S(x)\frac{\partial}{\partial x}(\sigma_w) \quad \text{.................................... (A.6)}$$

$$\sigma_w = f\,\frac{1}{4}\frac{\rho}{2}v^2 \quad \text{.. (A.7)}$$

σ_w = Wall shear stress. For a pipe flow, f is dimensionless, and is used to determine the roughness of the pipe resistance (White, 2011).

2.1.3 Minor Losses

Minor losses occur at a pipe entrance or exit, sudden expansion or contraction, bends, elbows, tees, and other fittings (White, 2011).

$$\Delta P = K_L \frac{1}{2} \rho v^2 \quad \text{.......................................} \quad (A.8)$$

For the incompressible flow, pressure drop

$$K_L = \frac{\Delta P}{\frac{1}{2} \rho v^2} \quad \text{.......................................} \quad (A.9)$$

K_L is an empirical loss coefficient, and dimensionless,

Choke valve in the MPD system can cause minor loss, and the size of the loss can be a significant portion of resistance in the system. The velocity of the flow, $v = C_d \sqrt{\frac{2(P_c - P_0)}{\rho}}$

C_d = Discharge coefficient of the valve.

Choke valve flow rate, $q_c = v \times A(x) = C_d A(x) \sqrt{\frac{2(P_c - P_0)}{\rho}}$ .... (A.10)

The pressure loss due to friction is the sum of the minor losses and the head losses. The friction loss in the straight pipe can be obtained from equation (A.6),

$$\frac{\partial F}{\partial x} = S(x) \frac{1}{4} f \frac{\rho}{2} v^2 \quad \text{..................................} \quad (A.11)$$

The minor losses can be related to friction gradient

$$\frac{\partial F}{\partial x} = A(x) \frac{\partial K}{\partial x} \frac{\rho}{2} v^2 \quad \text{.......................................} \quad (A.12)$$

So the total system loss can be represented as -

$$\frac{\partial F_F}{\partial x} = \frac{1}{4} fS(x)\frac{\rho}{2}(\frac{q}{A(x)})^2 + \frac{\partial K}{\partial x} A(x)\frac{\rho}{2}(\frac{q}{A(x)})^2 \quad \text{………… (A.13)}$$

A.2 Equation of Continuity (mass conservation)

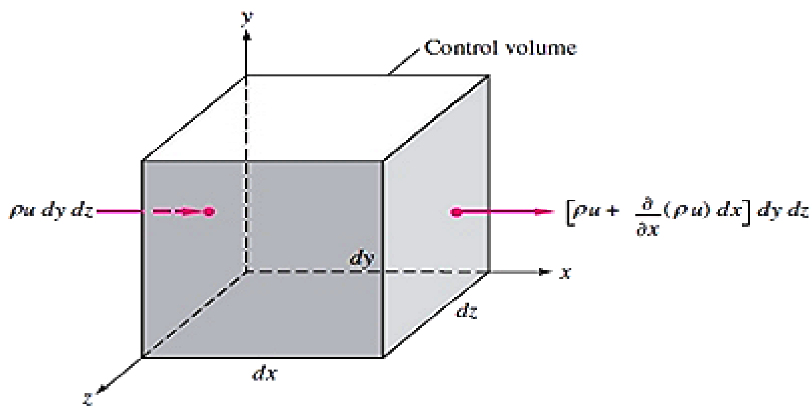

Figure A.1: Elemental Cartesian fixed control volume showing the inlet and outlet mass flows on the x faces (White, 2011)

Considering one dimensional flow in the x-direction,

$$\frac{\partial \rho}{\partial t} + \frac{\partial}{\partial x}(\rho u) = 0 \quad \text{…………………………………..…… (A.14)}$$

The continuity function is integrated over a deformable control volume (Kaasa and Stamnes, 2012).

$$\frac{\partial}{\partial t}(\int_0^L \rho A(x)dx) = \sum m_{in} - \sum m_{out} \quad \text{……………………………….. (A.15)}$$

Where $m = \int_0^L \bar{\rho}(p)A(x)dx = \rho(\bar{p})V$

V= Total volume in the well

A(x) = Area in the well

From equation (A.15),

$$\dot{m} = \sum m_{in} - \sum m_{out} \quad \text{...} \quad (A.16)$$

Density of the well is not constant but can be approximated as average density. The average density is dependent on pressure variations in the well.

$$\bar{\rho}(p) = \frac{1}{V}\int_0^L \rho(x,p)A(x)dx \quad \text{..} \quad (A.17)$$

$$\dot{m} = \frac{\partial m}{\partial t} = \frac{\partial \bar{\rho}(p)V}{\partial t} = V\frac{\partial \bar{\rho}(p)}{\partial t} + \bar{\rho}(p)\frac{\partial V}{\partial t} \quad \text{...........................} \quad (A.18)$$

Inserting the bulk modulus in the equation (A.18),

$$\dot{m} = \bar{\rho}(p)\frac{V}{\beta}\frac{\partial \rho}{\partial t} + \bar{\rho}(p)\frac{\partial V}{\partial t} = \rho(\frac{V}{\beta}\dot{\bar{P}} + \dot{V}) \quad \text{...............................} \quad (A.19)$$

From equation (A.16),

$$\bar{\rho}(p)(\frac{V}{\beta}\dot{\bar{P}} + \dot{V}) = \sum m_{in} - \sum m_{out} \quad \text{............................} \quad (A.20)$$

$$(\frac{V}{\beta}\dot{\bar{P}} + \dot{V}) = \sum q_{in} - \sum q_{out} \quad \text{...........................} \quad (A.21)$$

Where,

$$\frac{1}{\bar{\rho}(p)}\sum m_{in} = \sum q_{in}$$

$$\frac{1}{\bar{\rho}(p)}\sum m_{out} = \sum q_{out}$$

The well is considered as two separate subsystems (two different control volumes), the drill string and the annular mud return section. Drilling fluid enters the drillstring under pump pressure P_p with a flow rate of q_p. The drilling fluid passes through the bit with a flow rate of q_{bit}. It flows through the annular control volume under the choke pressure P_c and at flow rate q_c. So equation (A.7) becomes,

$$\frac{V_D}{\beta}\dot{P}_p = q_p - q_{bit} - \dot{V}_D \qquad \text{(Subsystem 1)}$$

$$\frac{V_A}{\beta}\dot{P}_c = q_{bit} + q_{kick} + q_b - q_c - \dot{V}_A \qquad \text{(Subsystem 2)}$$

A.3 Equation of Motion

The momentum balance is obtained by using Newton's second law of motion (Zhou et al., 2011). For the one dimensional flow,

$$\sum F = \rho\frac{\partial V_s}{\partial t}A(x)dx \qquad \text{…………………………………………..………… (A.22)}$$

The sum of the forces acting on the fluid will consist of two different type of forces, body forces and surface forces.

$$\sum F = F_{surface} + F_{gravity}$$

Surfaces forces are the sum of the hydrostatic pressure, and friction forces (viscous stress) due to motion (White, 2017).

$$F_{surface} = -\frac{\partial p}{\partial x} A dx - \frac{\partial F_F}{\partial x} dx$$

$$F_{gravity} = \rho g \sin\theta = \rho g \frac{\partial h}{\partial x}$$

From the equation (A.22),

$$\rho \frac{\partial V_s}{\partial t} A(x) dx = -\frac{\partial p}{\partial x} A(x) dx - \frac{\partial F_F}{\partial x} dx + \rho g \frac{\partial h}{\partial x} A(x) dx$$

$$\rho \frac{\partial V_s}{\partial t} dx = -\partial p - \frac{1}{A(x)} \frac{\partial F_F}{\partial x} dx + \rho g \partial h \quad \text{……………………. (A.23)}$$

This is a reduced form of Navier-Stokes equation (White, 2011). Due to one directional flow, $V_s = \frac{\partial x}{\partial t}$. Equation (23) is integrated over a control volume L.

$$\int_0^l \frac{\rho}{A(x)} \frac{\partial q}{\partial t} dx = -\int_{p(0)}^{p(l)} \partial p - \int_0^l \frac{1}{A(x)} \frac{\partial F_F}{\partial x} dx + \int_{h(0)}^{h(l)} \rho g \partial h$$

$$\int_0^l \frac{\rho}{A(x)} \frac{\partial q}{\partial t} dx = p(0) - p(l) - \int_0^l \frac{1}{A(x)} \frac{\partial F_F}{\partial x} dx + \rho g [h(l) - h(0)] \quad \text{……. (A.24)}$$

Inserting the expression for friction drop in equation (A.24),

$$\int_0^l \frac{\rho}{A(x)} \frac{\partial q}{\partial t} dx = p(0) - p(l) - \int_0^l \frac{1}{A(x)} \frac{1}{4} f S(x) \frac{\rho}{2} \left(\frac{q}{A(x)(x)}\right)^2 + \frac{\partial K}{\partial x} A(x) \frac{\rho}{2} \left(\frac{q}{A(x)}\right)^2 dx + \rho g [h(l) - h(0)]$$

$$\int_0^l \frac{\rho}{A(x)} \frac{\partial q}{\partial t} dx = p(0) - p(l) - F |q| q + \rho g [h(l) - h(0)] \quad \text{……………………………...…… (A.25)}$$

Where $F = \frac{\rho}{2}(\int_0^l \frac{\partial K}{\partial x}\frac{1}{A(x)^2}dx + \int_0^l \frac{1}{4}\frac{S(x)}{A(x)^3}dx)$

For the annulus section, $\int_0^l \frac{\rho}{A(x)}\frac{\partial q}{\partial t}dx = M_a \dot{q}_a$ …………………………………….…… (A.26)

Flow through the annulus is consist of the flow through the bit and influx of the reservoir.

$$M_a \dot{q}_a = P_{bit} - P_c - F_a |(q_{bit} + q_{res})|(q_{bit} + q_{res}) - \rho_a g h_{bit} \quad \text{(A.27)}$$

$$P_{bit} = P_c + F_a |(q_{bit} + q_{res})|(q_{bit} + q_{res}) + M_a(\dot{q}_{bit} + \dot{q}_{res}) + \rho_a g h_{bit} \quad \text{(A.28)}$$

For the drilling section, $\int_0^{ld} \frac{\rho}{A(x)}\frac{\partial q}{\partial t}dx = M_d \dot{q}_d$

$$M_d \dot{q}_d = P_p - P_{bit} - F_d |q_d| q_d + \rho_d g h_{bit} \quad \text{(A.29)}$$

$$P_{bit} = P_p - F_d |q_{bit}| q_{bit} - M_d \dot{q}_{bit} + \rho_d g h_{bit} \quad \text{(A.30)}$$

Adding equation (A.28) and (A.30) together,

$$M_a \dot{q}_a + M_d \dot{q}_d = P_{bit} - P_c - F_a |(q_{bit} + q_{res})|(q_{bit} + q_{res}) + M_a(\dot{q}_{bit} + \dot{q}_{res}) + \rho_a g h_{bit} + P_p - F_d |q_{bit}| q_{bit} - P_{bit} + \rho_d g h_{bit}$$

$$M \dot{q}_{bit} = P_p - P_c - F_a |(q_{bit} + q_{res})|(q_{bit} + q_{res}) - F_d |q_{bit}| q_{bit} + (\rho_d - \rho_a) g h_{bit}$$

So the MPD model can be summarized as:

$$\frac{V_d}{\beta}\dot{P}_p = q_p - q_{bit} - \dot{V}_d$$

$$\frac{V_A}{\beta}\dot{P}_c = q_{bit} + q_{kick} + q_b - q_c - \dot{V}_A$$

$$M\dot{q}_{bit} = P_p - P_c - F_a\,|(q_{bit} + q_{res})|(q_{bit} + q_{res}) - F_d\,|q_{bit}|\,q_{bit} + (\rho_d - \rho_a)gh_{bit}$$

$$q_c = C_d A(x)\sqrt{\frac{2(P_c - P_0)}{\rho}}$$