Development of a Digital Twin Based Real-Time Drilling Optimization and Control System

By

©Mohammed Mokhtar Said

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Abstract

The Oil and Gas industry suffers from a unique problem. The activity of the industry, and subsequently the retention of highly qualified personnel is closely tied to the oil price. Economic factors that are beyond the control of operators, govern the experience level of employees in all levels of the industry. The recent development of digital technologies presents an excellent opportunity for the industry to overcome the loss of experience accompanied by every downturn, and the increased rate of incidents accompanying every resurgence. This thesis consists of four articles discussing two different topics. These include i) developing a digital twin-based drilling optimization and control system, and ii) developing laboratory facilities for validating field scale experiments. The first article presents the theoretical development of a digital twin-based control system for drilling rigs. It starts with how the industry evolved the concepts of integrated operations, and real time support centers, and follows by how to construct the proposed digital-twin-based automation solution. The second article expands on a single component of the digital twin-based system. It discusses the development of an auto driller system based on optimal control theory. The article consists of an extensive literary review of drilling optimization, followed by developing a modified version of mechanical specific energy to be used as an objective function, development of a simple drilling model to be used as part of the controller, and development of a model predictive controller that optimizes the selection of drilling parameters. The model predictive controller was shown to be successful through simulations but had some performance limitations due to the complexity of the bit rock coupling term in the drilling model. The third and fourth articles discuss the development of a hardware in the loop drilling simulator. The articles describe the design of the system, the development of its operating systems, and experimental validation of its performance. The articles also discuss the development of Bond Graph models that were used for planning of experiments and components of the simulators control system. The thesis is concluded by recommendations on how to improve the proposed automation system and expand the capabilities of the simulator.

To My Family

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Co-Authorship Statement

I Mohamed Mokhtar Said, hold a principal author status for all the manuscript chapters (Chapter 2-5) in this dissertation. However, each manuscript is co-authored by my supervisors and co-researchers, whose contributions have facilitated the development of this work as described below.

- Paper 1 in Chapter 2: M. M. Said, Rick Pilgrim, Dr. G. Rideout, Dr. S. Butt "Theoretical development of a digital-twin based automation system for oil well drilling rigs" I was the primary author, Rick Pilgrim provided their research proposals to be incorporated as part of proposed digital twin system, and Dr. G. Rideout, Dr. S. Butt provided guidance, reviewing, and editing, and supervision. (Presented at SPE 22CET Calgary, Alberta, Canada).
- Paper 2 in Chapter 3: M. M. Said, Dr G. Rideout, Dr. S. Butt "Development of an Auto-Driller System Based on Optimal Control Theory" I was the primary author, and Dr. G. Rideout, Dr. S. Butt provided guidance, reviewing, and editing, and supervision. (Submitted to Upstream Oil and Gas Technology)
- Paper 3 in Chapter 4: M. M. Said, Farid Arvani, Dr. G. Rideout, Dr. S. Butt "Development and Implementation of a Hardware in the Loop Drilling Simulator" I was the primary author, Farid Arvani shared all his work on the drilling simulator to be used as a foundation for my work, and Dr. G. Rideout, Dr. S. Butt provided guidance, reviewing and editing, and supervision. (Submitted to Upstream Oil and Gas Technology)
- Paper 4 in Chapter 5: M. M. Said, Dr G. Rideout, Dr. S. Butt "Bond Graph Modeling of the Hybrid Pneumatic/Hydraulic Axial Motion Component of a Physical Drilling Simulator" I was the primary author, and Dr. G. Rideout, Dr. S. Butt provided guidance, reviewing, and editing, and supervision. (Presented at ICBGM'2018, Bordeaux, France).

Mohammed Mokhtar Said   Date

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List of Abbreviations

ALARA	As Low As Reasonably Possible
ANN	Artificial Neural Networks
AUV	autonomous underwater vehicles
AVD	active vibration damper
BHA	Bottom Hole Assembly
BHP	Bottom Hole Pressure
BLS	Bureau of Labor Statistics’
BOP	blow out preventers
BSEE	US Bureau of Safety and Environmental Enforcement
CCS	confined compressive strength
CFD	computational fluid dynamics
CFOI	Census of Fatal Occupational Injuries
DAS	Drilling Advisory System
DDE	delay differential equations
DEM	Discrete Element Method
DOC	depth of cut
DOT	drill off tests
DSE	Drilling specific energy
ECD	Equivalent Circulating Density
ESD	Emergency-Shut-Down
FBD	free body diagram
FDM	Finite Difference Method
FEM	Finite Element Method
FPGA	Field-Programmable Gate Array
HIL	Hardware in the loop
HIS	Bit hydraulic horsepower per square inch
HPHT	High-Pressure High-Temperature
HRSE	Hydro-Rotary Specific Energy
IOT	Internet of Things
KNN	K-Nearest Neighbor
LDS	Large Drilling Simulator
MODU	Mobile Offshore Drilling Unit
MPC	Model Predictive Control
MPD	Managed Pressure Drilling
MRF	magnetorheological fluid
MSE	Mechanical Specific Energy
MSI	Mechanical Specific Impulse
MWD	Measurment while drilling
NMPC	Nonlinear Model Predictive Control
NPT	non-productive time
ODE	Ordinary Differential Equations
PDE	Partial Differential Equation

PLC	Programmable Logic Controller
ROP	rate of penetration
ROTC	real time operations support center
RPM	Rotary Speed
RTOS	Real-Time Operating System
SCE	Solids Control Equipment
SMO	Sequential Minimal Optimization
TOB	Torque on bit
VARD	vibration assisted rotary drilling
VFD	Variable Frequency Drive
WITS	Wellsite Information Transfer Specification
WOB	Weight on Bit

List of Variables

A	Area
a	Bit Radius
C_a	Axial Damping Coefficient
C_p	Specific Heat at Constant Pressure
C_t	Torsonal Damping Coefficient
C_v	Specific Heat at Constant Volume
d	Depth of Cut
d_0	Initial Depth of Cut
D_c	Drill Collar Diameter in inch
D_p	Drill Pipe Diameter in inch
E	Internal Energy
h	Enthalpy
I	Drill String Inertia
K	Fluid Consistency
K	Maurer Bit Constant
K_a	Axial Stiffness
K_t	Torsonal Stiffness
l	Wear Flat Length
L_c	Drill Collar Length
L_p	Drill Pipe Length
M	Drill String Mass
$\dot{m}$	Mass Flow Rate
N	Bit Rotary Speed
n	Power Law Exponent
n	Number of Blades
p	Pressure
R	Universal Gas Constant
ROP	Rate of Penetration
T	Torque
t	Time
T_c	Cutting TOB
T_f	Friction TOB
T	Temperature
v	Velocity of Flow
V_0	Steady State ROP
V_m	Maximum Pipe Velocity
W	Weight onBit
W_0	Threshold Weight on Bit

W_0	Applied WOB
W_c	Cutting WOB
W_f	Friction WOB
γ	Cutter Orientation
ϵ	Rock Intrinsic Specific Energy
μ	Friction Coefficient
ξ	Cutter Inclination
σ	Rock Contact Pressure
Ω_0	Applied Rotary Speed
Ω_s	Initial Bit Angular Position

Chapter 1 Introduction

1.1 Background and Research Motivation

Drilling to explore and produce hydrocarbons in sensitive environments is a very challenging process under normal weather conditions. Steady increase in global demand for energy has pushed exploratory drilling farther offshore into deeper waters and harsher environments. The Arctic and North Atlantic are two environmentally sensitive regions that are rich in hydrocarbons, but the weather conditions are harsh; Arctic drilling is limited to summertime only, with a regulatory requirement that the operator is able to drill a relief well in the same drilling season in case of a blowout, while the North Atlantic is prone to severe storms and sea ice. The window of time available for operations is short and keeping a Mobile Offshore Drilling Unit (MODU) on location is expensive. A pressing need has arisen to reduce exploration cost and substantially reduce the risk to the environment. The conventional solution is to have the best people operate the best equipment to drill as fast as possible. The problem remains that even the best people make mistakes while working under this kind of pressure. Such mistakes can lead to injuries, loss of life, damage to equipment, or long-lasting environmental impact. The cyclic nature of the oil industry, where the rise and fall of oil price dictate the size of the work force, and state of operating equipment, has been a massive roadblock to always having the best people and equipment ready. This cyclic nature deters valuable experience that leaves the industry from returning when the industry booms and dissuades new talents from getting into the industry. The loss of valuable experience due to cost control measures can be clearly seen in incident rates as the industry restarts its growth phase, and the recommendation to overcome it is to rely more on automation [1]. The industry started to develop solutions that relied on digitalization, automation, and advisory systems to overcome the limitations imposed by economic constraints. The development of real time operations support centers (ROTC's) alleviated some of these issues [2-5] as it concentrated the experienced personnel in a single focal point, where they can support multiple simultaneous operations. Further developments focus on digitalizing and compiling expert knowledge in expert systems, in combination with various machine learning based models, that support the RTOC's and personnel on the rigs [6-9].

1.2 Problem statement

In recent years more attention has been directed to the automation of the drilling process. The continuing advancement of rig instrumentation, downhole sensors, third party surface logging equipment, and variable depth of cut bits, has continually complicated the optimization of the drilling process. Drillers must monitor data from their own consoles, mud logging screens, directional measurement while drilling, and logging while drilling data, as well as keep in mind the operating limit of every piece of equipment on surface and downhole. This information overload makes it almost impossible for a single person to optimize drilling performance. Systems that collect all this data and advice the drillers with optimum drilling parameters have been developed. When the drillers follow the systems advice, and the formation being drilled is relatively homogeneous, faster drilling rates are observed. In practice the formation drilled is non-homogeneous and is always changing, leading to frequent change in advised drilling parameters. The drillers find it difficult to keep up with the advice and drilling rates suffer [10-14].

1.3 Proposed solution

Optimality is universally present all around our everyday life; most processes are governed by optimization problems. The majority of the fundamental laws of physics can be cast in an optimization context. In engineering applications, optimality can be used as a design principle, and the benefit gained by optimization is often hard coded in the problem itself. Our current technology levels allow us to build a system that feeds advised optimum drilling parameters directly into rig equipment. Doing this will shift the attention of the drillers from faster drilling to safer drilling. It will also allow for a faster rate of penetration (ROP), longer bit runs, and better detection of kick precursors so that actions may be taken to prevent them from occurring. A kick is a well control problem in which the drilled formation pressure is higher than the hydrostatic pressure of the drilling fluid. When this occurs, the greater formation pressure forces formation fluids into the wellbore. This forced flow of formation fluids is called a kick. If the flow is stopped by the rig crew, the kick is killed, and operations can resume safely. An uncontrolled kick that increases in severity becomes a "blowout" which is a surface or subsurface uncontrolled release of formation fluids from a well [14-18].

Automation also allows for better utilization of the integrated operations business model, where all data becomes available in real time to all interested parties. The integrated operations model creates a virtual workspace through two-way video conferencing and live data streaming from the site to an integrated operations control center. The center processes all the data to evaluate key performance indicators in real time, update geological models, confirm stratigraphy, and predict pore pressures to provide management with the highest level of situational and environmental awareness, alongside with all previous well experience, the information can be analyzed and utilized by the operator's decision makers in real time to address problems as they are identified. By combining automation with the integrated operations approach, the operator is assured to take the best-informed decisions to increase efficiency and protect the environment [19]. Numerous studies have been performed to optimize drilling activities, aiming to maximize drilled footage and minimize drilling costs. Drilling optimization is achieved by pre-selecting the appropriate magnitudes of drilling parameters. Early studies in the literature focused on drilling optimization by analyzing performance post drilling. Drilling parameters were investigated off-site due to the limited ability of transferring data in real-time. Recent studies are oriented towards real-time optimization.

1.4 Research objective and scope

The overall goal of this research is to develop a digital twin based real-time drilling optimization control system, and drilling planning tool. The system should be able to process data from downhole sensors, surface equipment, and historical data from offset wells to produce optimum drilling parameters and apply the optimized parameters smoothly without inducing any unmitigated vibrations that may damage drilling tools. The starting point would be to identify the key performance metrics utilised by the industry to define optimal performance, and what has been done to ensure that optimal performance is achieved; this will include the selection and evaluation of high-fidelity drilling models to be used as a benchmark for drilling performance. These optimality conditions can then be cast as an optimization problem (non-linear programming problem) that can be solved to produce an optimum set point for drilling operations. The solutions found should then be verified by means of computer simulations. Moreover, the drilling technology lab at Memorial University has been developing a unique field scale hardware drilling simulator capable of running a hardware in the loop simulation [20], which has the drill string as a software model running on a computer and the bit-rock-interaction as part of the physical simulator. Completing the development of the system will allow for laboratory experiments to verify the theoretical components of the research.

1.5 Novelty of the proposed research

Control, optimization, and the use of digital twins in drilling operations have been studied in the literature over decades. However, using a digital twin as an optimization-based controller had not been explored. Optimization based controllers (optimal controllers and model predictive controllers) are especially suited for competing objective problems by optimizing a single objective function, which represent most of the problems faced by the drilling industry. The work presented in this thesis has two aims; to investigate the use of optimization-based controllers to generate optimal parameters at the supervisory level and feed those parameters into rig systems directly, and to develop experimental facilities able to reproduce representative field conditions economically.

1.6 Thesis Outline

Chapter 1 demonstrates the background, motivation, objectives, significance, and scope of research conducted in the current thesis.

Chapter 2 contains a review of the development of digitalization and the emergence of digital twin supported RTOC's, then identifies six different systems that can add great benefit to RTOS's if digitalized, and used to forecast drilling problems, and automate performance through numerical optimization. It also proposes validating the results using the experimental facilities developed later in the thesis

Chapter 3 focuses on the development of one of the six components proposed in chapter 2. It contains an extensive chronological review of drilling optimization, followed by the development and testing of an auto driller system based on optimal control theory.

Chapter 4 contains the development of the physical drilling simulator, and the results of the preliminary testing done to verify the system. It also shows how the simulator can reproduce conditions that will allow it to validate results from chapters 2 and 3. The simulator was developed by several team members, their works and contributions are cited throughout the chapter, the original work conducted for this thesis included the commissioning of the simulator, developing its operating system software, designing sealing assemblies for the rotary swivel and drill cell, installing the MPD system, and running validation experiments

Chapter 5 contains an experimentally verified bond graph model of the axial component of the drilling simulator, detailing the interaction between the hydraulic and pneumatic components of the system. This model is intended to be used as an experiment planning tool and can be used as part of the control system of the simulator if needed.

Chapter 6 presents the summary and recommendations for future work based on the completed research

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Chapter 2 Theoretical Development of a Digital-twin Based Automation System for Oil Well Drilling Rigs

Abstract

Advancements in digital technology and digitalization of industrial process have opened new frontiers for the oil and gas industry. The amount of historical data generated from drilled wells over the past decades of operations is currently being digitized. The processed data will provide operators with the option to make more informed decisions based on previous experiences. This will mitigate the constant loss of experience during industry downturns. The industry is combating this loss of experience through the innovative use of digitalization, integrated operations, and automation. Real time support centers operating under integrated operations business model are now utilizing digital twins (high fidelity models of the ongoing process being supported) to run forecasting simulations and compare results to digitalized historical data with the help of artificial intelligence and expert systems to aid with decision making and training junior staff. The existence of high-fidelity models, and digital twins is a solid foundation for automation. In this paper a review of the emergence of these technologies is used to identify where digital twins can be used as the foundation of automation solutions that would shift the focus of drilling crews from efficiency to operation and process safety.

2.1 Introduction

Over the past few decades, the digitalization of processes has revolutionized numerous industries. Significant improvements in processing power, data storage, connectivity, and sensor technology have created a surge in data driven applications, such as model based controllers, machine learning, and artificial intelligence. There is a huge potential for the oil and gas industry to leverage these applications to ensure a safer, more efficient, and profitable operating environment[1]. The World Economic Forum's Digital Transformation Initiative estimates that digitalization will create up to one trillion dollars of value for oil and gas producers over the next decade[2][3]. The latest trends in the world show that digitalization and automation will change the way companies operate and interact with their customers. Machine learning and artificial intelligence are increasing the levels of automation. This has a profound impact on areas such as offshore production management and integrity monitoring and maintenance, that has gained immense traction in the development of smart automated technologies in other related industries.

Increased development of automation system translates to increased efficiency and production for large scale industries. As such, industry leaders have a natural tendency to automate systems and processes that were once performed manually. A large percentage of today's activities could become automated. For example, simple repetitive tasks performed by workers such as tripping pipe in and out of hole, can be performed by robots. Drones and autonomous underwater vehicles (AUV) can address the health, safety and environmental challenges associated with operating in confined spaces, remote locations, subsea, and harsh environments that otherwise pose risks to human operators.

The development of automation solutions was largely accelerated by the increase in connectivity between people, machines, and the development of "The Internet of Things" (IOT). These developments are accelerating decision making and aid in remote control operations. [4]. This advancement of digital technology has facilitated the evolution of integrated operations control centers, and real time operations centers (RTOC's). Traditionally, when it came to field development, the oil and gas industry has organized disciplines and functions in self-contained independent "silos". This resulted in decisions being made inside these silos, without coordination with the other disciplines affected. Integrated Operations, then, evolved as a system that can incorporate all the silos and optimize the decision making in the organization (Figure 2-1). Integrated operations can be defined as new work processes which use real-time data to improve the collaboration between disciplines, organizations, companies, and locations to achieve safer, better, and faster decisions [5].

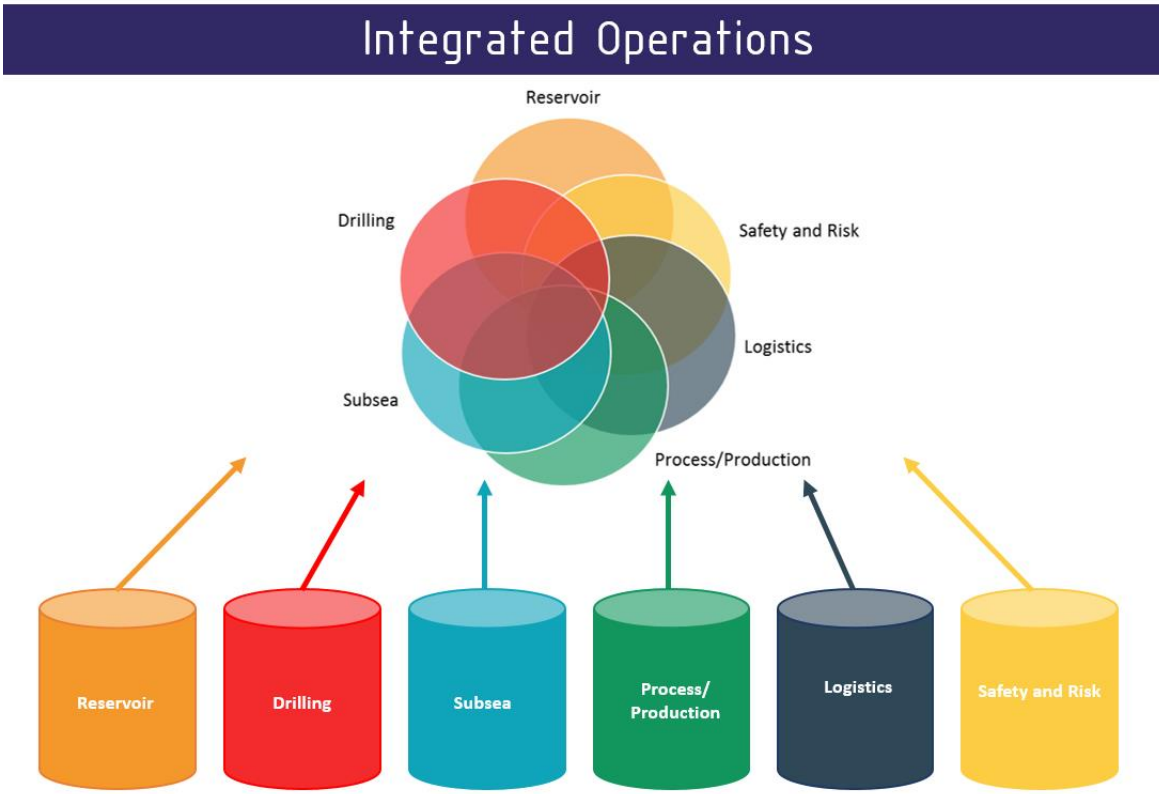

Figure 2-1: Integrated Operations Function Diagram

As drilling engineers continue to push the boundary of what is possible with more complicated wells, operation support centers evolved to be able to cater for the whole drilling cycle (planning, execution, and post drilling data analysis). For the planning phase, the concept of collaborative well design has emerged to overcome the limitations of the communication barrier between drilling engineers and geologists, geophysicists, and reservoir engineers involved in the well design. This newly birthed collaborative well planning has brought together all the stake holders to be an integral part of the well design, enabling drilling engineers to perform their design work on the well, while receiving instant feedback on any associated risk [6]. This process is described graphically in Figure 2-2.

Figure 2-2: Integrated Operations Control Centre Process Map

After the design phase is completed, from the drilling operations department point of view, a server is deployed on the rig and is connected to all service company's data acquisition systems. This server collects all drilling data from various service companies such as the drilling contractor, mud logging, drilling fluids, MWD, directional drilling, cementing, etc. and stores the data locally before it's transmission to the drilling support center via network. The drilling support center is then able to visualize the data through a web-based application. During drilling a well, a real-time support group monitors the streamed data from the rig site and is able to react immediately to any issue faced by the rig personnel. The staff manning an integrated operations control center are typically highly experienced individuals and are expected to interpret the data and identify any potential hazards while drilling to alert the team on the rig site and office-based teams. The senior staff can then act proactively, and they can call upon the expertise of any subject matter expert around the world in case a situation arises that requires that level of support [7][8]. The integrated operations approach has significantly improved how oil and gas companies operate their assets, but there are two significant drawbacks. The system is inherently reactive, as it detects problems in real time, which means the problems have already happened, and that the whole system in its core still relies on the experience of experts. This reliance is made severe by the cyclic nature of drilling activity, which is heavily influenced by oil price.

A close examination of Figure 2-3 shows that there is a drop in the oil price roughly every 5 years. [9], this drop is usually caused by an oversupply of produced oil. The oversupply is usually driven by technological advancements that were made possible by research funded by the booming oil price. This downturn is usually accompanied by a slowdown of drilling activity to cut back on costs, reduction in production rates, and staff layoffs. While cutting back operating costs for oil producers is a business decision necessary for maintaining a profitable business, it is one of the main contributors to the loss of valuable experience. Experts that exit the industry during downturns are not keen to return when the industry resumes, and fresh talent is usually reluctant to join the industry due to its long-term instability.

The greatest indicator of this experience loss is the rise in the rate of safety related incidents. During the period from 2003 to 2013, the U.S. oil and gas drilling industry grew significantly with a 71 % increase in the number of drilling rigs, the industry doubled the size of its workforce. The CDC analyzed the fatality events for the industry during this period using the data collected from the Bureau of Labor Statistics' (BLS) Census of Fatal Occupational Injuries (CFOI). It was found that the number of work-related fatalities in the industry increased 27.6%. A majority of the fatalities were attributed to transportation (479, [40.3%]) and contact with objects/equipment (308 [25.9%]), and more than 50% of the fatality cases reported were employed by well service providers (615 [51.7%]) [10]. Figure 2-4 shows the fatality data during this period. One of the most important recommendations of the CDC studies is the use of automation technologies to mitigate some of these fatalities. Interestingly, the correlation between fatality rates and oil price is evident in the visual correlation when comparing Figure 2-3 and Figure 2-4.

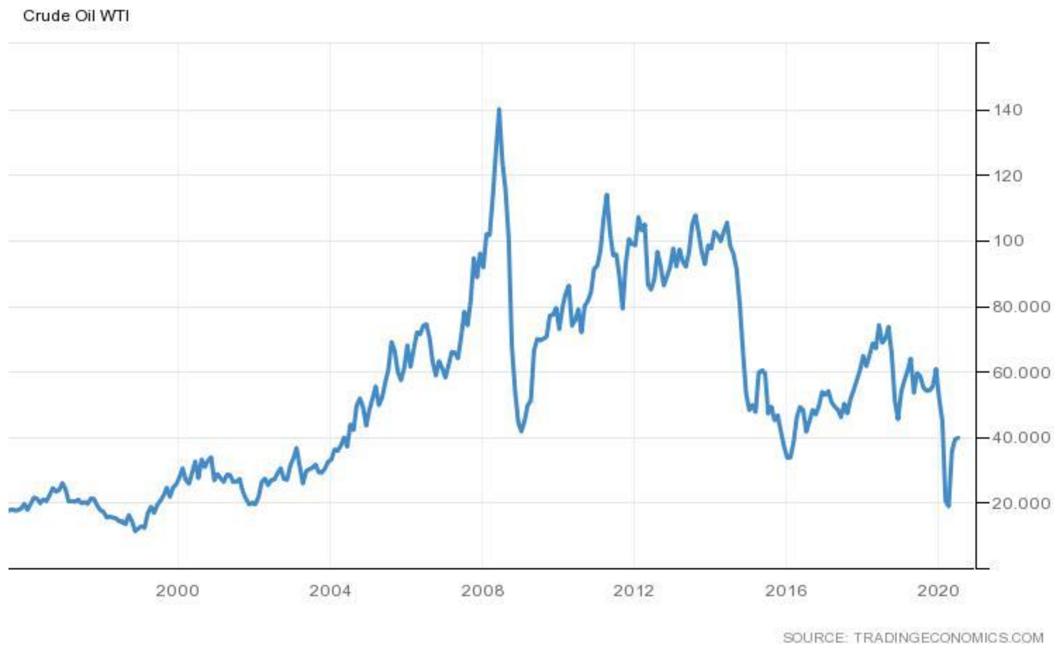

Figure 2-3 WTI Crude Price History [9]

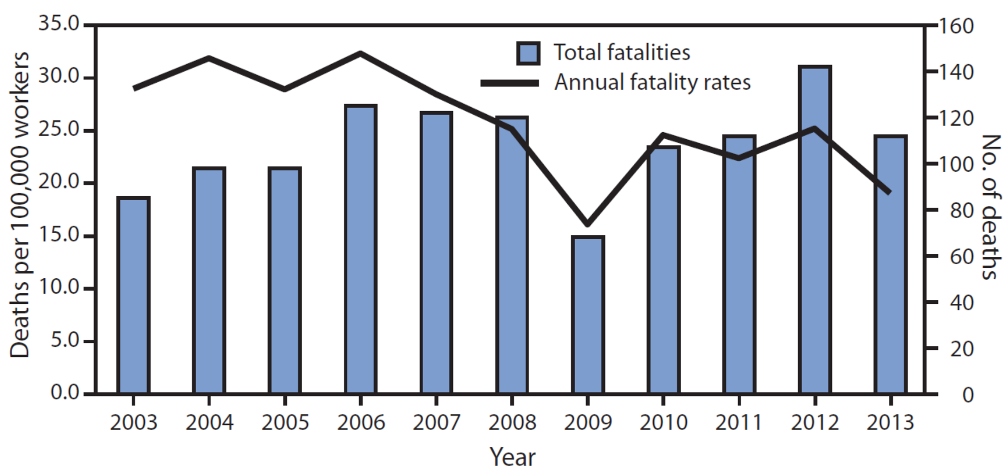

Figure 2-4 Fatalities during the 2003 to 2013 period [10]

Similar conclusions can be drawn from the rate of severe incidents. Since the mid-1970's the total number of blowouts per year has been relatively consistent averaging 0.54 blowouts for every 100 wells. Recently the number has increased to 1.45 blowouts per 100 wells, in the period after 2007 after a major drop in oil price the rate of blowouts per 100 wells start to spike as shown in Figure 2-5 and Figure 2-6 signifying the loss of experience after a drop in oil price [11] [12]. There is a direct correlation between oil price, crew experience, and incident rates.

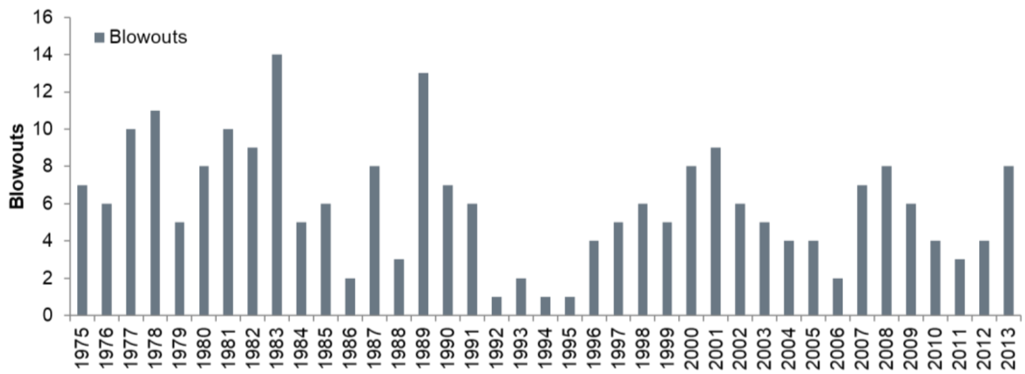

Figure 2-5 Offshore Gulf of Mexico Blowouts

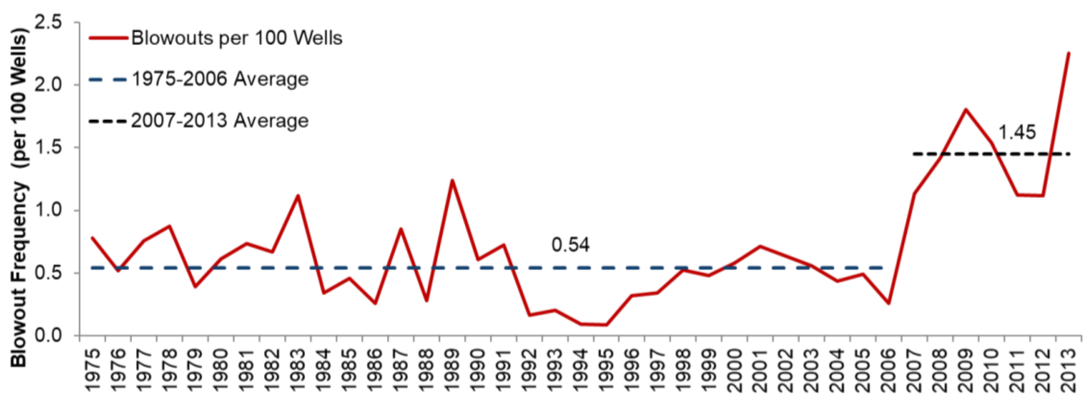

Figure 2-6 Offshore Gulf of Mexico Blowout Frequency

In the wake of the Macondo incident [13][14], the idea of using model predictive maintenance on blow out preventers (BOP's), to further increase the margin of operational safety, started to gain traction. The US Bureau of Safety and Environmental Enforcement (BSEE) started to require deep-water operators to gather real-time data from their BOP control systems and have the offshore data transmitted to experts on shore. When a few years earlier the only data available on BOP's was often just printouts of spread-sheets and graphs of pressure tests [13]. BOP real-time monitoring has been evolving over time. It was initially used for lessons learned and post-mortem analysis, then operators realized that there is value in obtaining the data early and analyzing it for warning signs to avert potential problems. The rewards for investing in monitoring and analysis are not just limited to moving from time-based repair schedules to systems based on actual wear. This type of maintenance scheme is obtained by accurately predicting when parts fail using sensory data, coined as maintenance by the numbers, which reduces maintenance costs by designing and manufacturing more reliable equipment and reducing the time lost due to equipment failures.

Another field that suffers greatly due to the loss of experience is the field of drilling optimization. Every year, millions of dollars are lost due to the improper selection of drilling parameters. Drilling performance optimization, or drilling at the minimum cost and highest productivity, has been sought after since the earliest days of establishing drilling engineering as a science. Several approaches have been tested with varying degrees of success. Most of these approaches have emerged as new data sources or higher data quality was made available due to the development of new and better sensors, and new technologies in general. The amount of data being generated on a modern rig is enough to overwhelm even the most experienced crew. The industry has recognized that as the amount of data being generated increases, it will be very difficult for the operators to follow it efficiently, and thus have turned to automation to solve this problem[15][16] [17].

The natural evolution of the integrated operations business model, and the industry being more and more reliant on automation to make up for the loss of experience, has started the new trends of relying on Digital Twins and Expert Systems. Digital Twins were introduced in 2003 by Michael Grieves at the University of Michigan as part of Grieves' Executive Course on Product Lifecycle Management [18] [19]. Simply put, a Digital Twin is a digital representation of a physical system as it mirrors the system in a digital capacity. Using advanced mathematical models and real time data from the system's various components, simulations of these components can be performed. This enables the operator to do more advanced and complex automated forecasting.

Forward-looking performance simulation services [20] can generate 'what-if' scenarios as well as predictive analytics in the wellbore. While real time data monitoring on running equipment, compared with model outputs from the Digital Twin, can prevent downtime by providing real time diagnostics, failure prediction, and early warnings for model predictive maintenance. The digital twin approach facilitates understanding complex operational systems and the prediction and detection of failures in equipment and in the drilling process, and it can provide early warnings before the operator gets into an undesirable situation [21][22].

Applications for this approach have started to show up across all disciplines of the oil and gas industry. A case study focusing on the digitalization of the Rumaila field [23] has shown that digitalization has changed the way the field was operated. Digital solutions have significantly improved efficiency by increasing the run life of equipment, improved reservoir management, and better tuned facilities with the added benefit of eliminating repetitive tasks, improving overall safety, and minimizing well downtime.

Multiple case studies examining the performance of a novel drilling application Digital Twin system have been recently tested and verified for over 10 years [6] [7] [8]. This system contains a single integrated solution for the entire drilling life cycle[24][25] and facilitates accurate decision making and results in measurable improvements in safety and efficiency key performance indicators. Additionally, there is a tremendous added benefit from having a Digital Twin system for training purposes. These systems would be beneficial for both engineers and work crews, thus increasing workplace efficiency. Two different training avenues are made available through Digital Twins.

Firstly, there is the familiarization with facility layouts and emergency procedures for evacuation and achieving competence in basic offshore egress. Research that assesses the level of competence gained through a virtual environment training program in basic offshore safety and investigates the training time required to reach competencies is currently being conducted. Experiments have demonstrated that the offshore egress learning objectives can be taught effectively using virtual reality training programs equipped with layouts of offshore facilities. Two main findings were observed; some individuals required more time in the virtual environment to reach the required level of competence, and the simulations should place more emphases on the procedures being taught in the training scenarios to ensure the training requirement were achieved[26][27].

Secondly, operational experience may be gained from commercial training simulator simulators [28] or academic simulators such as the Open Lab Online Simulator [29]. This type of simulator is a digital twin used in the offline mode for training and research purposes. Open Lab was designed specifically to be a user-friendly, high-fidelity, simulation environment. The system is already in use in the University of Stavanger, the University of Calgary, and with several industrial partners. It is primarily used for education, training, and research such as testing and calibration of predictive algorithms, training of drill crews to understand the effects of changing parameters in various drilling scenarios, illustration of and preparation for well behavior before drilling a new section, providing "what does good look like" data and illustrations to the driller before performing various operations, and presentation/learning tool of a drilling process for personnel without offshore practice.

In addition to RTOC's running Digital Twins, loss of experience is also mitigated using Expert Systems [30], an Artificial Intelligence method developed in 1965 by Edward Feigenbaum and Joshua Lederberg of Stanford University, to deal with problems in domains that require human expertise. The method is typically used in classification, diagnosis, monitoring, design, and scheduling problems.

An Expert System relies on a Knowledge Base and an inference engine to mimic human intelligence. The knowledge base contains an organized collection of facts about the problem being tackled, usually in the form of "if-then" rules, with an attached probability factor to deal with the uncertainty of the produced decisions. Knowledge Bases of an average Expert System would contain thousands of rules. The second component of an Expert System is the inference engine, which interprets and evaluates the facts in the Knowledge Base in order to provide an answer.

In addition to the if-then rules, which are also called production rules, Expert Systems can employ heuristic rules, or "rules of thumb," giving the system the ability to learn from experience. A Digital Twin augmented with an Expert System is an excellent aid to the rig and RTOC as it can produce recommendations that represent all the learnings from previous wells, reducing the reliance on human memory, or the full-time presence of an industry expert [30][31]. Expert systems have been developed to tackle drilling fluids and well control issues and are being developed for advice on common drilling practices[31] [32].

In this paper a theoretical understanding of how a Digital Twin based automation solution, can be constructed for several critical processes that are routinely carried out on any drilling unit. Creating a Digital Twin lies under the umbrella of modeling and simulation within the modern control theory as shown in Figure 2-7.

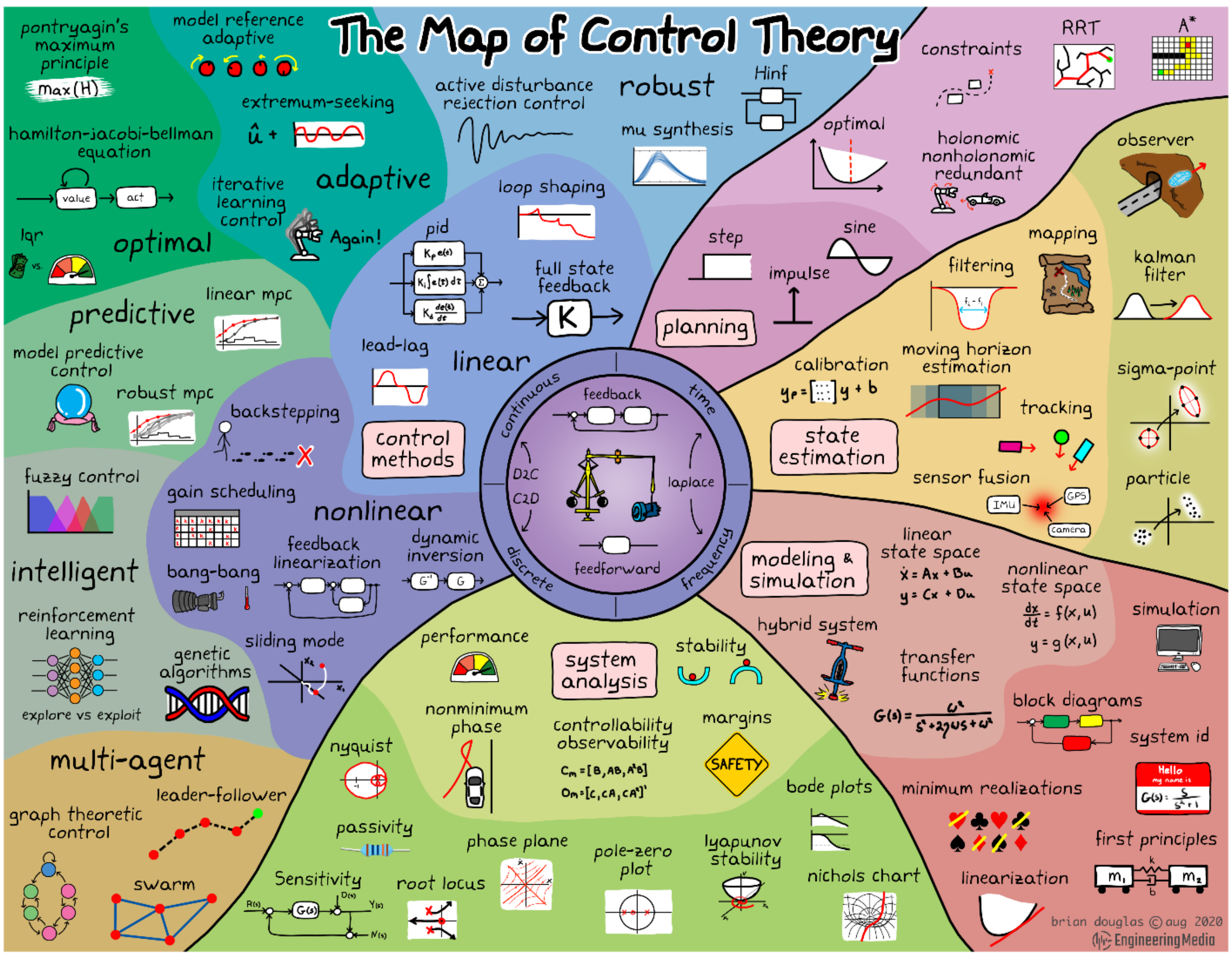

Figure 2-7 Map of Control Theory [33]

Digital twins currently utilized by the industry are composed of a multitude of models that combine in synergy to form the full system model. These sub-models can be categorized into one of three categories as shown in Figure 2-8. At the most basic level we find equipment models, these models make up the constituent sub models of the digital twin, and those can be used to predict equipment failure. Process models represent the next level of complexity, they consist of sub models that are combined to describe a specific operation. Process models usually represent interaction between equipment and the environment and are usually used to forecast process performance, these are the models that can be used for automation. System models, the most complicated models composed of multiple sub-models representing equipment, processes, and the environment. This category would include models for training simulators.

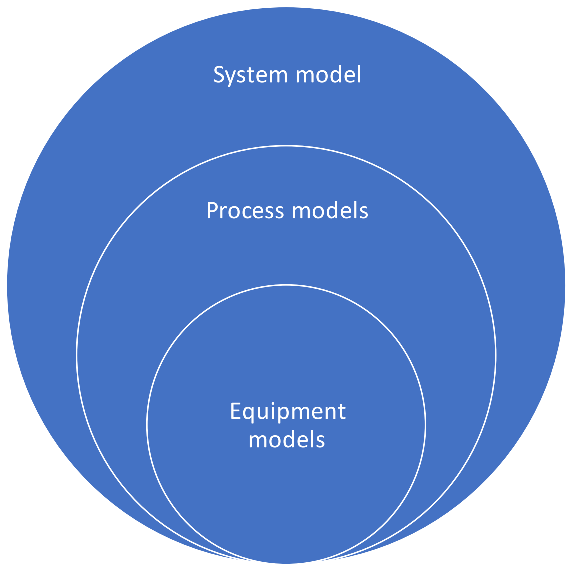

Figure 2-8 Digital twin model hierarchy

In the subsequent sections a discussion of the major process of interest on a MODU will be discussed and viewed as components of the proposed Digital Twin advisory and automation system. Then these components will be divided into different modules with a suitable controllers tailored for each application. Preference will be given to optimization-based controllers as they are more suited to deal with multi-input multi output problems that have competing objectives, such as most of the process on a drilling rig.

2.2 Digital Twin Modules

Determining Optimum Drilling Parameters

One of the most important applications for the proposed automation system is the ability to produce real-time control commands to the drilling rig. This will shift the role of the driller and tour pusher from focusing on drilling parameters to focusing on process safety. Coupling this automation with the mechanization of drilling equipment will reduce human contact with rotating equipment to an As Low as Reasonably Possible (ALARA) state. There is a very rich literature concerning the understanding and optimization of drilling performance, but the majority of these studies can by grouped into three major topics: direct correlation of performance with drilling parameters, direct correlation of performance with Mechanical Specific Energy (MSE) or one of its subsequent variants, and statistical correlation between a set of parameters and performance.

Direct correlation with drilling parameters was the earliest to emerge from researchers pursuing optimal performance. Studies conducted by Speer [34], Graham and Muench [35], Maurer [36], Galle and Woods [37], Young [38], Wilson and Bentsen [39], Warren [40], Bourdon et al described [41], Akgun [42], and E. Detournay [43] [44] have consistently shown that at perfect hole cleaning conditions, which means that all cuttings are removed from the bit face as soon as they are generated, increasing the Weight on Bit (WOB) and rotary speed will always increase the rate of penetration until a technical limit is reached at which no further improvement is attained. The plethora of models generated all agreed on this technical limit, called the founder point, but none presented a method to estimate it until 2021 when De Moura et al [45], [46] conducted experiments that clearly showed that the calibration constant included in Maurer's model[36] was dependent on the WOB. This modification converted the equations from a quadratic relationship between WOB and rate of penetration (ROP), into a cubic relation. The cubic relation has a global maximum point, which could be estimated mathematically, and estimates an optimum WOB for a specific bit type at a known hole size, rock strength, and rotary speed.

In 1965, Teale [47] developed the concept of Mechanical Specific Energy (MSE) and defined it as the mechanical work done to excavate a unit volume of rock. He found that there is a remarkable correlation between MSE and crushing strength of rock. Numerous researchers have studied the phenomenon such as Pessier and Fear [48], William and Jeff [49], Armenta, [50], Rashidi et al [51], Koederitz and Johnson[52], Dupriest et al [53], and Olalere et al[54] [55]. Researchers have used the original MSE formula developed by Teale and developed some variations of it including the effect of hydraulics to optimize drilling performance and predict pore pressure. Since MSE is inversely proportional to ROP, operators have trained the drilling crews to observe changes in MSE as they change drilling parameters. if the MSE value is decreasing in response to the changes then tis means a corresponding improvement in performance. This also meant that the technical limit, defined by the founder point previously discovered by the direct correlation with the drilling parameter studies, is synonymous with the minimum value of MSE. The most notable results were shown in Dupriest et al [53] showing that field applications of MSE monitoring has improved performance by 133% and that the founder point can be extended by proper engineering design as shown in Figure 2-9 .

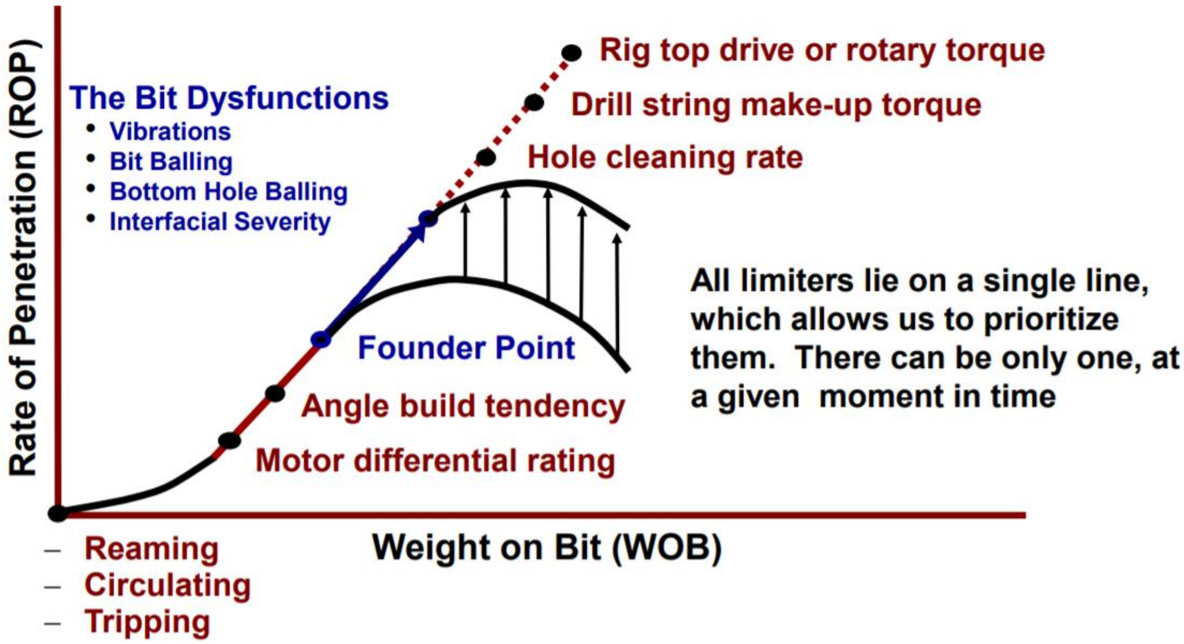

Figure 2-9 Improving design changes the founder point to higher values[53]

The third group of studies is mainly concerned with statistical correlation of drilling parameters with drilling performance. Reed [56] in 1972 used a Monte Carlo based model, Bourgoyne and Young [57] used a regression based model, later Maidla and Ohara [58] used a data set to calibrate the Bourgoyne and Young model for a specific field, and Eren [59] optimized the model further for effective functions at each data point. Alum and Egbon [60] also used regression analysis to connect ROP and fluid properties. Further down the line statistical approaches evolved into the use of artificial neural networks with the work of Yashodhan et al [61] and Jiang and Samuel [62].

Another aspect of optimization lies in the efficient transmission of power from the surface equipment to the bit, since all drilling performance models relate downhole WOB and rotary speed to performance, which can be related to surface parameters by a dynamic model of the drilling operation. Bit rock interaction, which is very well understood and documented as viewed by the presented literature, is a component of a larger system that is studied under drill string dynamics. One of the major limiters of drilling performance was found to be self-excited vibrations, these vibrations were found to be the root cause of early fatigue of drill pipes, premature failure of bits, and downhole tools, which accounted for 2–10% of well costs [63].

Ghasemloonia [64] published a very comprehensive review of vibration modeling and suppression methods, which included the history of drill string dynamics modeling and the challenges that are rising with the advent of new directional drilling methods and vibration assisted drilling.

The common factor between all performance and dynamics modeling methods is that they require at least an estimate of the rock strength to be effective. Geological modeling has been the cornerstone of the oil and gas industry since its infancy, and currently the industry has a large repository of logs and seismic surveys for almost every field being operated. The data, however, has a large degree of uncertainty for a well that is still being constructed, which requires accurate data for real-time optimization. This problem has been mitigated with the major advancements in logging while drilling technologies, namely the look ahead of the bit technologies [65]–[67] and the application of machine learning to estimate rock strength[68] [69], which can be used to obtain a fairly good estimate of the strength of the rock ahead of the bit.

The removal of the geological uncertainty reduces all the previously discussed optimization methods to bit characterization and drilling parameter selection. For simplicity, the assumption of perfect cleaning removes the flow rate and bit hydraulics optimization from the problem formulation. This provides us with a unique opportunity to combine all three major optimization methods into a single optimization problem. The empirical method for finding the founder point developed by De Moura et al [41] [42] is found to be in agreement with field drill off data published by Dupriest et al [53] shown in Figure 2-10.

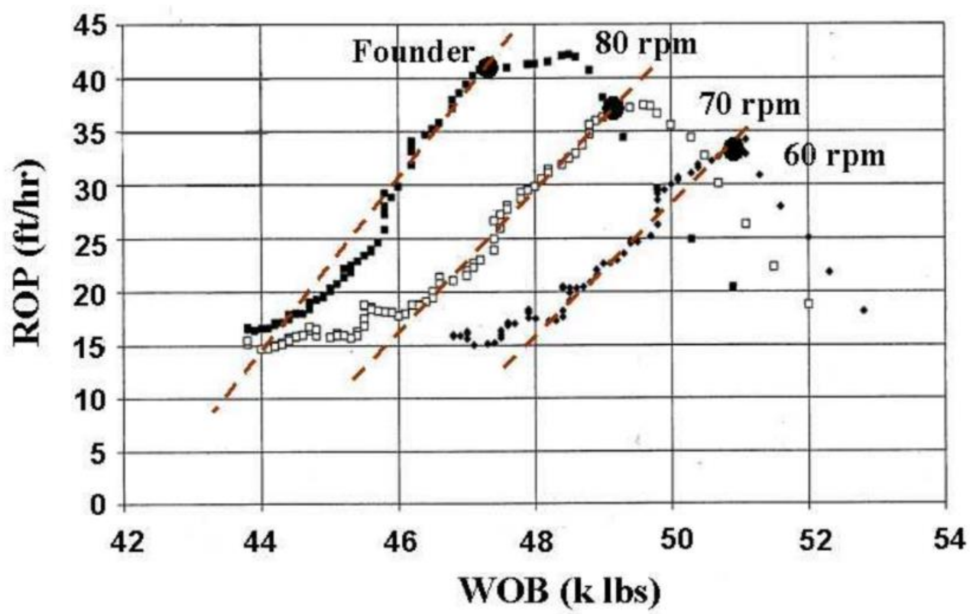

Figure 2-10 Drill off test data [53]

The same data was captured and used to calculate MSE values as shown in Figure 2-11, showing a correlation between max ROP and min MSE which coincides with the compressive strength of the rock as per Teale [47].

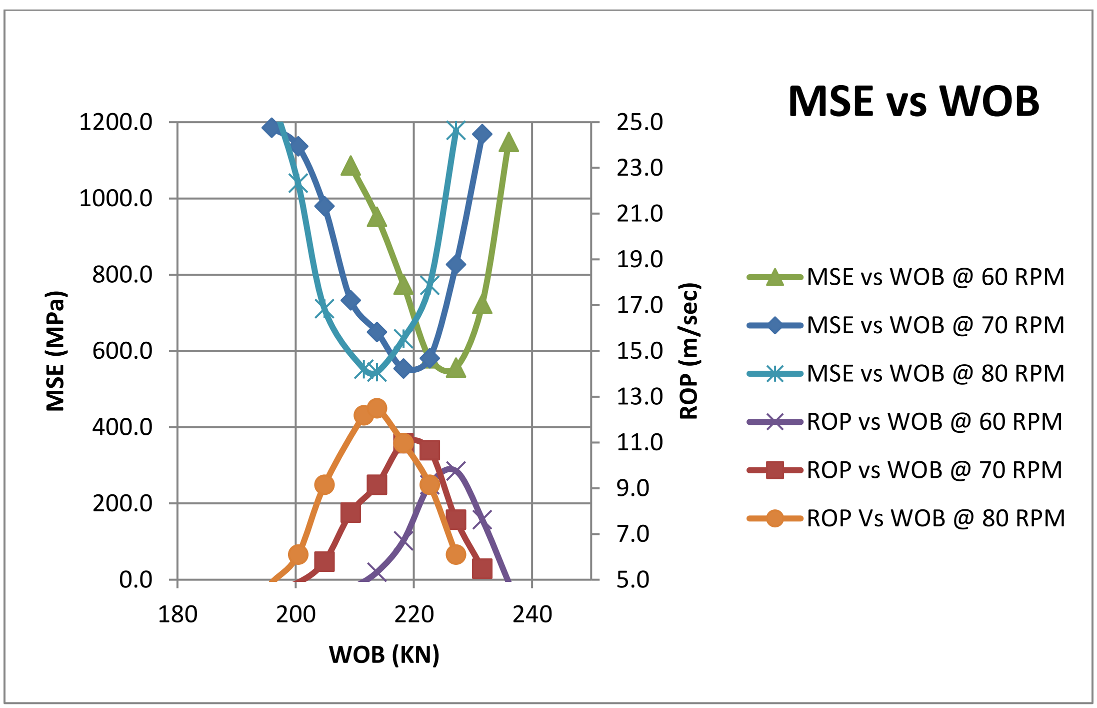

Figure 2-11 MSE and ROP against WOB at different rotary speeds

Since optimization for minimum MSE is a widely accepted industry practice, it will be used as the base for drilling optimization in the proposed digital twin-based system as well.

MSE is calculated as shown in Eq. 1.

$$\text{MSE} = \frac{W}{A} + \frac{120\ \pi\ N\ T}{A\ ROP} \qquad \textit{Eq. 1}$$

Where: W is the downhole WOB, A is the area of the bit, N is the rotary speed of the bit, T is the torque on the bit, and ROP is the Rate of Penetration.

Optimizing for minimum MSE requires the knowledge of the bottom hole WOB, bit rotary speed, torque on bit, and the ROP, all are function of the surface applied WOB and rotary speed and can be estimated through a high-fidelity model of the drilling operation (the Digital Twin). MSE can thus be used as either an objective function, or as a constraint, in combination with the high-fidelity model of the drilling process to optimize drilling performance. The objective of the optimization problem will be to find input values that produce a minimum MSE.

Pore Pressure Prediction and Managed Pressure Drilling (MPD)

Usually, drilling parameters are used to perform pore pressure predictions and they have the advantage of estimating the formation pressure at the bit at a relatively low cost. Methods like the d-exponent [70] or log data [71] have been frequently used and their drawbacks have long been noticed. A recent development in pore pressure prediction from the drilling parameters utilizes MSE and some variations of it to include the hydraulic component of drilling as well. Hydro-Mechanical Specific Energy (HMSE)[54], and Hydro-Rotary Specific Energy (HRSE) [55] are two such quantities. These performance indices are usually computed from the downhole measurements. However, a large percentage of historically available field data and present-day wells are in the form of surface measurements.

HRSE is the combination of axial, rotary, and hydraulic energies required to break and remove a unit volume of rock. This technique uses surface measured drilling parameters. Theoretically the effective stress state of the rock being drilled is an indication of pore pressure i.e., the higher the effective stress, the greater the total energy required to break and remove a unit volume of rocks. This directly correlates to the amount of energy consumed to excavate the rock. Abnormally pressurized intervals have a lower effective stress, and will not require the same energy to drill as normally pressurized zones at the same depth [55].

HMSE and HRSE were recently tested using the data from a vertical deep High-Pressure High-Temperature (HPHT) exploratory well in the Niger Delta Basin, where the main cause of over pressurization is under-compaction, and an excellent agreement between the predicted and measured formation pore pressure was found [54], [55]. Both techniques were shown to provide a reliable means of estimating the formation pore pressure from the drilling parameters in absence of reliable downhole measurements at relatively low cost. Additionally, it can be used as part of a control system that drives a managed pressure drilling (MPD) system.

The HMSE is calculated as shown in Eq. 2

$$\text{HMSE} = MSE + \frac{Hydraulic\ Energy}{Rock\ Volume\ Drilled}$$

$$\text{HMSE} = \frac{W}{A} + \frac{120\,\pi\,N\,T}{A\ \ ROP} + \frac{1154\ \ \Delta P_b\,Q}{A\,ROP} \qquad \textit{Eq. 2}$$

Where Q is the flow rate and ΔP_b is the pressure drop across the bit

The technique can be easily added on to an expanded formulation of the MSE performance optimization discussed earlier, monitoring the trend of HMSE, and detecting any deviation from the predicted optimized value should be used as an early warning for possible well control situations. This will expand the Digital Twin with pore pressure prediction and support for MPD applications.

Drilling Fluids and Solid Control Equipment Management

The importance of the monitoring and management of drilling fluid properties while drilling cannot be overemphasized. This is more prominent in fields where highly pressurized formations with tight pore pressure/fracture gradient windows are encountered. Among the most critical properties to monitor are the fluid density (mud weight), and the rheological properties (plastic viscosity, yield point, gel strength, and low shear rate viscosity) [72], as changes in these properties are early indicators of downhole problems. Traditionally the drilling fluids engineer performs a comprehensive fluid check at least once every 12 hours, while the rig crew monitors the fluid density and viscosity by checking the active mud every half an hour. If a deviation is detected in the simple density and viscosity checks, this usually triggers a more comprehensive test by the fluids engineer to troubleshoot the problem and apply the proper treatment. Recently, new sensor packages [73][74][75] have been developed that are capable of measuring drilling fluid properties in real time. The use of a real time fluids parameter monitoring system allowed for the early detection of drilling fluid related problems, such as increases in solids and chemical contaminations, and their impact on the Equivalent Circulating Density (ECD), which are mainly driven by buildup of drilled solids while drilling and mitigated by the efficient use of Solids Control Equipment (SCE). Thus, this method prevents prevalent drilling problems such as loss of circulation, and well control situations from occurring. Especially when used in combination with a managed pressure drilling system [76].

SCE health monitoring is generally done manually by the personnel onsite, namely the fluids engineer, solids control specialist, and rig hands. The fluids engineer usually evaluates the SCE daily to make sure it is running at peak efficiency. The conventional method to do so is regularly inspecting the equipment for screen tears and proper flow rates. The process is complemented by routinely checking the solids concentration of the drilling fluid, during the previously mentioned comprehensive fluid check. Through this, an efficiency figure is produced and it is used to estimate the amount of dilution fluid required to maintain the drilling fluids’ solids percentage at a desired level to maintain mud weight and ECD [72].

SCE efficiency is calculated on volumetric basis (Eq. 3). The initial volume of solids in the drilling fluid is measured at the beginning of an interval. The volume of rock excavated during that interval is calculated based on the depth of the bit at the beginning and end of the interval and the bit diameter. The amount of increase in solids in the drilling fluid is the amount of solids that the SCE failed to discard and got incorporated in the drilling fluid. The exact volume of the excavated rock that was incorporated in the drilling fluid can be calculated through multiplying the percent increase in the volume, by the total circulating volume of the drilling fluid. Maintaining the percentage of drilled solids below a specific maximum, usually below 5%, is desirable to maintain the optimal properties of a drilling fluid [77].

$$SCE\ Efficency = 1 - \frac{volume\ of\ solids\ added\ to\ drilling\ fluid}{Volume\ of\ excvated\ rock} \qquad Eq.\ 3$$

Since no SCE plant is perfect, a constant dilution stream of fresh mud is required. Utilizing these new sensors in combination with the ROP reading from rig sensors, we can monitor the performance of SCE and maintain dilution rates much more efficiently. By having sensors mounted at the discharge point of the shale shakers and in the suction pit of the active mud system, one can monitor the trend of solids build up at both locations to ultimately detect when SCE efficiency changes. This change might signify one of several things: a formation change that requires a change in screen size, broken screens that must be changed to maintain SCE efficiency, the requirement to adjust the decanting centrifuge, or changing the cones on a hydro cyclone system. The efficiency values can also provide us with required dilution rates related to current ROP to maintain optimum fluid properties[72] [77]. The approach described here can be used in combination with an expert system such as the one described in [32], to provide real time drilling fluids advice to the crews on the rig or in the RTOC.

Modeling Surge and Swab, Continuous Motion Tripping

Most drilling fluid service providers supply their customers with software that models Surge and Swab and gives a recommendation for tripping speeds based on Bottom Hole Assembly (BHA) configuration, hole profile and drilling fluid properties. A further service that was recently introduced is the ability to run these simulations in real-time while tripping to give the operator an estimate of downhole conditions.

These services are quite effective at mitigating serious well control situations, but their effectiveness relies heavily on the quality of data used in the simulations. Most simulations are run to provide the equivalent mud density on bottom while tripping in or out, in case of pulling out of hole, this assumes that the maximum pore pressure in the hole is at the total drilled depth of the well. This is not always the case as the highest pore pressure may be present anywhere in the drilled section and thus the equivalent density at the highest pore pressure will be less than the calculated one and may cause the well to be swabbed leading to a well control situation.

Two of the primary reasons for the loss of wellbore integrity are the combined effects of wellbore pressure fluctuations (Surge & Swab), as well as damage to the wellbore walls due to differential sticking of the drill pipe when stopped and started during a trip connection [78] [79]. It was also found that during tripping the -induced transient-stress and pore- pressure changes can be significant [80]. As shown in Figure 2-12, as the drill pipe starts and stops during the tripping operation, a secondary pressure transient is triggered. This pressure wave induces an increase (Surge) and decrease (Swab) of the Bottom Hole Pressure (BHP) and its simplest form is traditionally calculated in oil field units using the formula in Eq. 4 [81].

$$\Delta P = \left[\left(\frac{2.4\,V_m}{D_h - D_c}\frac{2n+1}{3n}\right)^n \frac{KL_c}{300(D_h - D_c)}\right] + \left[\left(\frac{2.4\,V_m}{D_h - D_p}\frac{2n+1}{3n}\right)^n \frac{KL_p}{300(D_h - D_p)}\right] \qquad \textit{Eq. 4}$$

Where n is the power law exponent, K is the fluid consistency, V_m is maximum pipe velocity, D_c is drill collar diameter in inch, D_p is drill pipe diameter in inch. D_h is hole diameter in inch, L_p is drill pipe length, and L_c is drill collar length.

The continued cycling of transient pressure can vary considerably in magnitude, depending on the acceleration of the drill string during starts and stops, and can have a fatiguing effect on the wellbore wall

[80] [82] [83]. The traditional mitigation measure for these well control situations and wellbore fatiguing is to control the running speed of the pipe in the hole to minimize surge and swab transient pressures. The most innovative approach to eliminate well control situations while tripping was the invention of the continuous tripping system. Continuous motion rigs, and continuous tripping systems move the pipe at constant speed, eliminating the transient pressures associated with stopping the pipe to break a connection.

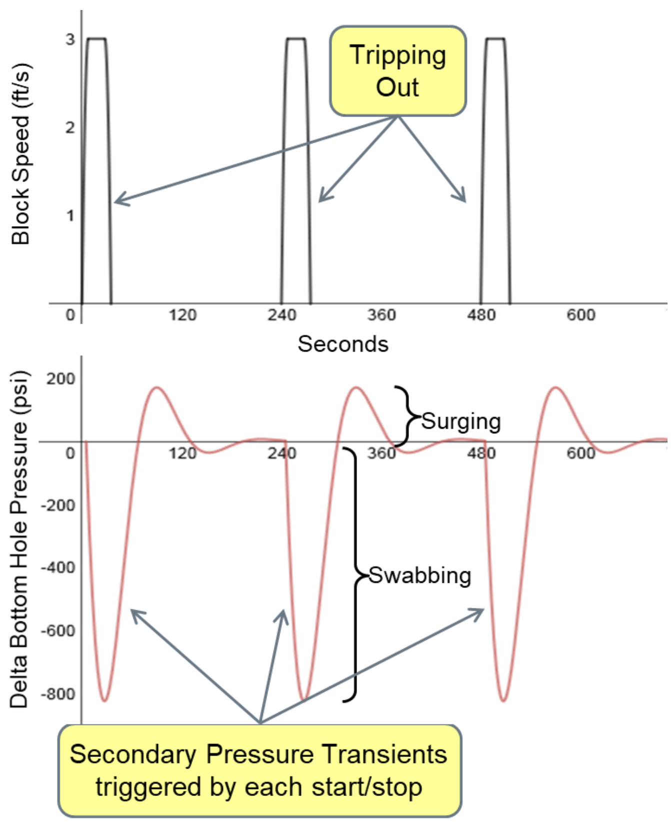

Figure 2-12 Pressure Transience While Tripping Out

A side-by-side comparison of the traditional tripping system and the continuous tripping system. which is a new configuration of existing drill floor components with the addition of a second set of power slips, is shown in Figure 2-13. The primary difference between the two systems is that continuous tripping system incorporates two lifting devices that are used alternately, transferring the drill string load between them while keeping the drill string in constant motion. The complete assembly comprises three parts, namely the elevator system, the racking system, and the continuous tripping machine. Models of the drilling fluid's behaviour, pore pressure/fracture gradient, and the systems' dynamics can be used to generate a value for the acceleration and sustained tripping speed of the traveling block that maintains a prescribed margin of safety that protects from swabbing the well while pulling out of hole or breaking the formation while running in hole. These values can be used to ensure the elimination of downhole transient pressure fluctuations.

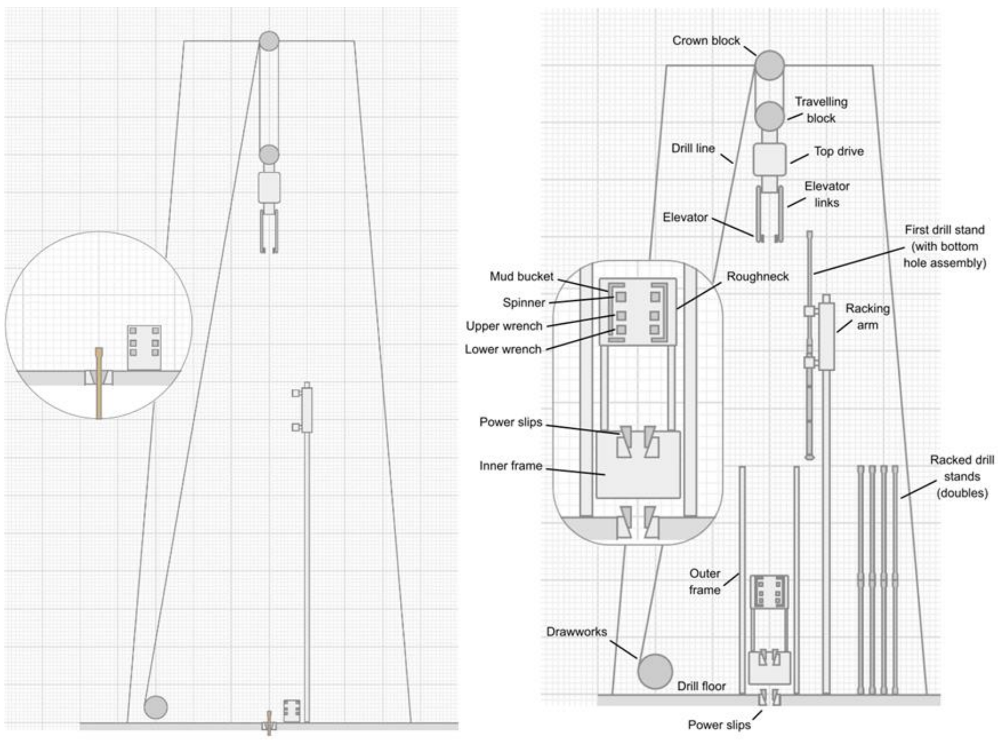

Figure 2-13 Conventional (left) and Continuous Tripping Systems (right)

Implementing a Digital Twin of the tripping process will allow for the use of a real-time simulation to predict under balance downhole conditions, and automating the process based on the Digital Twin will allow selecting the proper values for drill string acceleration, and sustained tripping speed that will minimize the effects of Surge and Swab, and the subsequent risk of fatiguing the well bore or inducing a well control situation.

Heave Compensation

Heave compensation systems are of great importance to the performance of deep-water drilling operations, especially for operations located in harsh open sea environments such as the North Atlantic [84] [85]. Rig heave is yet another source of undesired drill string vibration, and also causes Surge and Swab transient pressures which could lead to well control situations [86]. Modern drill bits require a constant WOB to maintain a stable bit rock contact. Since the 1970's there have been two types of heave compensators in use; passive and active heave compensators [84]. They are an essential component of any floating MODU as they minimize the fluctuation of the axial force on the drill string and the marine riser. Heave compensators use hydraulic and pneumatic mechanisms to compensate rig motion, but unfortunately, they cannot eliminate heave entirely due to physical system limitations such as nonlinear compliances and friction (Figure 2-14) [87]. The result of these limitations introduces frequency dependent lags in the phase of the compensating action. As a result of those lags, the passive systems would operate at a maximum efficiency of 40%, and the active systems would operate at an efficiency of 90-95% [88].

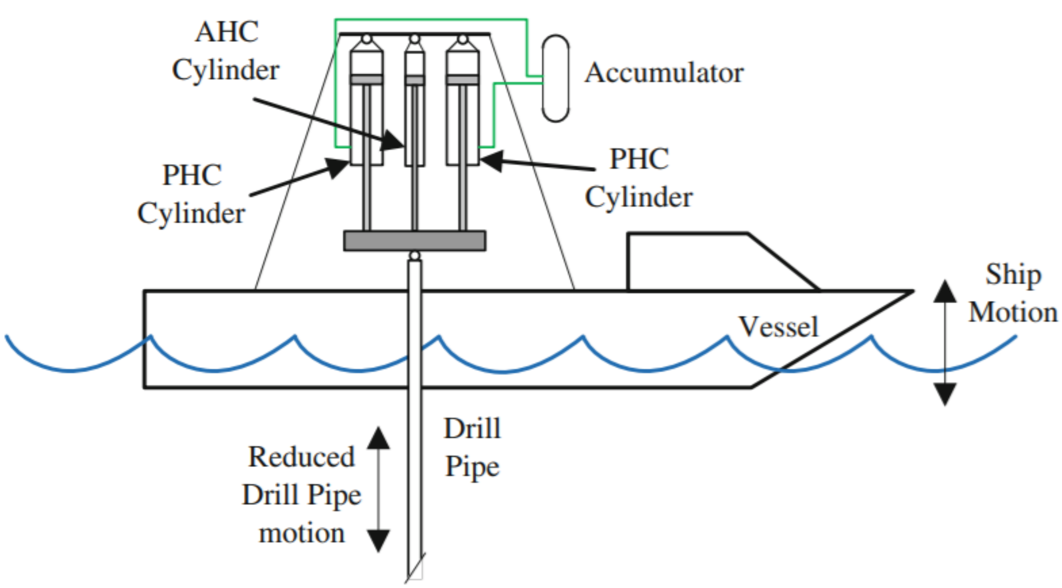

Figure 2-14 Semi-Active Heave Compensation System [87]

The dynamic load caused by heave motion is always transferred to the drill string if the load is greater than the compensator's capacity [89]. A simulation framework to study the coupled vibration between the rig heave and drill string was developed using Bond Graphs and the JONSWAP wave model [90]. Bond Graph theory is a unified dynamic system representation language that represents connections between multi-disciplinary elements seamlessly and explicitly as power flows, in the vector form, and gives a concise descriptions of complex systems [91]. The JONSWAP spectrum is a method that describes non-fully developed seas, as it represents wind-generated waves assuming a finite water depth and a limited fetch [92] [93]. Recent work has shown that a special Kalman filter can be used to estimate the disturbance terms affecting the system. The results showed that for external disturbances a reasonable attenuation rate with an acceptable control signal was obtained [94]. Combining the developed simulation framework with the proposed control approach in a Digital Twin will enhance the proposed MSE optimization, and Surge and Swab minimization Digital Twin proposed in the previous sections.

2.3 Implementation of the Automation System

Each of the modules discussed earlier can be considered as a sub-model of the digital twin system. These models are to be used in forward looking simulations during well planning and actual field operations. The simulations will support effective equipment maintenance and produce accurate predictions, when used in combination with an Expert System, to provide RTOC and field staff with recommendation. The data produced by the models can then be used for automation purposes as illustrated in the data flow in Figure 2-15.

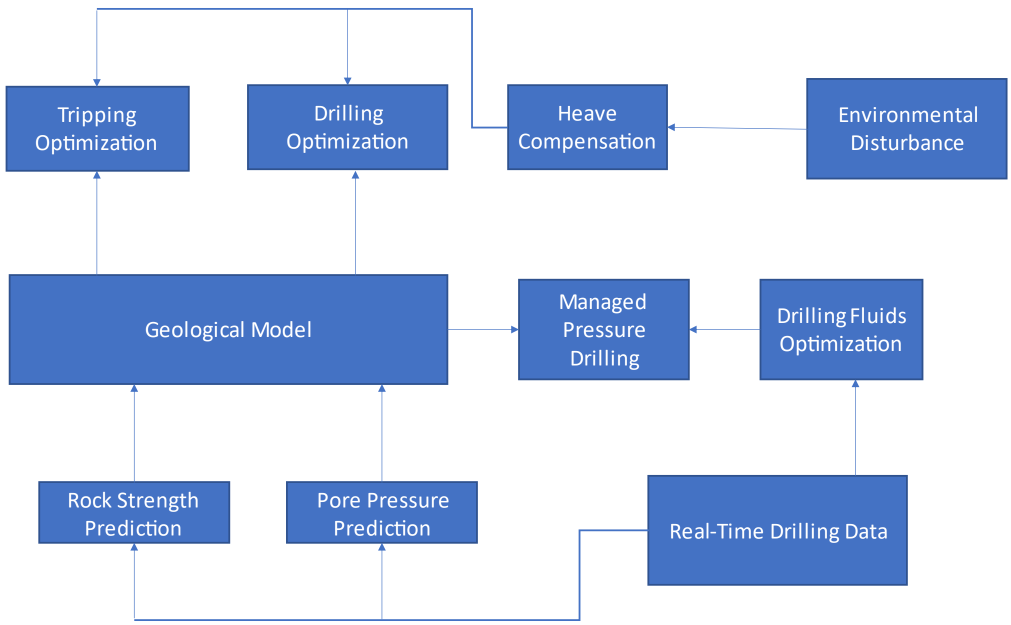

Figure 2-15 Data Flow in the Proposed System

The models can then be used to formulate the needed controllers, which consist of the following components in case of an optimization-based controller:

- An objective function, φ(W), that shall be minimized or maximized,
- Decision variables, W, that must be chosen, and
- Constraints that shall be respected, e.g., of the form G1 (W) = 0 (equality constraints) or G2 (W) ≥ 0 (inequality constraints).

Solving the optimization problem will generate an optimum set point that will guarantee the best performance. Development of these Digital Twin system can be started with simple software packages such as 20 Sim [95] to produce Bond Graph models, that can be later exported to MATLAB for further processing under the different control tool boxes. There is also the option of using open source toolboxes that run under MATLAB such as CasADi, which is a tool for nonlinear optimization and algorithmic differentiation [96]. It facilitates rapid and efficient implementation of different methods for numerical optimal control, both in an offline context and for Nonlinear Model Predictive Control (NMPC). It has been used to teach optimal control in graduate level courses, to solve optimization problems in science and engineering, as well as to implement new algorithms and software.

2.4 Experimental Validation of Developed Systems

Memorial University is home to a unique custom-built field scale drilling simulator. A general description of the field scale drilling simulator and its control system can be found in Figure 2-16 and Figure 2-17. The simulator uses a closed loop control system running a combination of linear and rotary actuators to simulate field conditions of complex drill strings, bit-rock, and rig environment interactions translating them into axial and torsional vibrations and compliances. It also includes a high-pressure drill cell and mud circulation system that are designed to simulate downhole mud pressure and pore pressure to simulate well control situations [97].

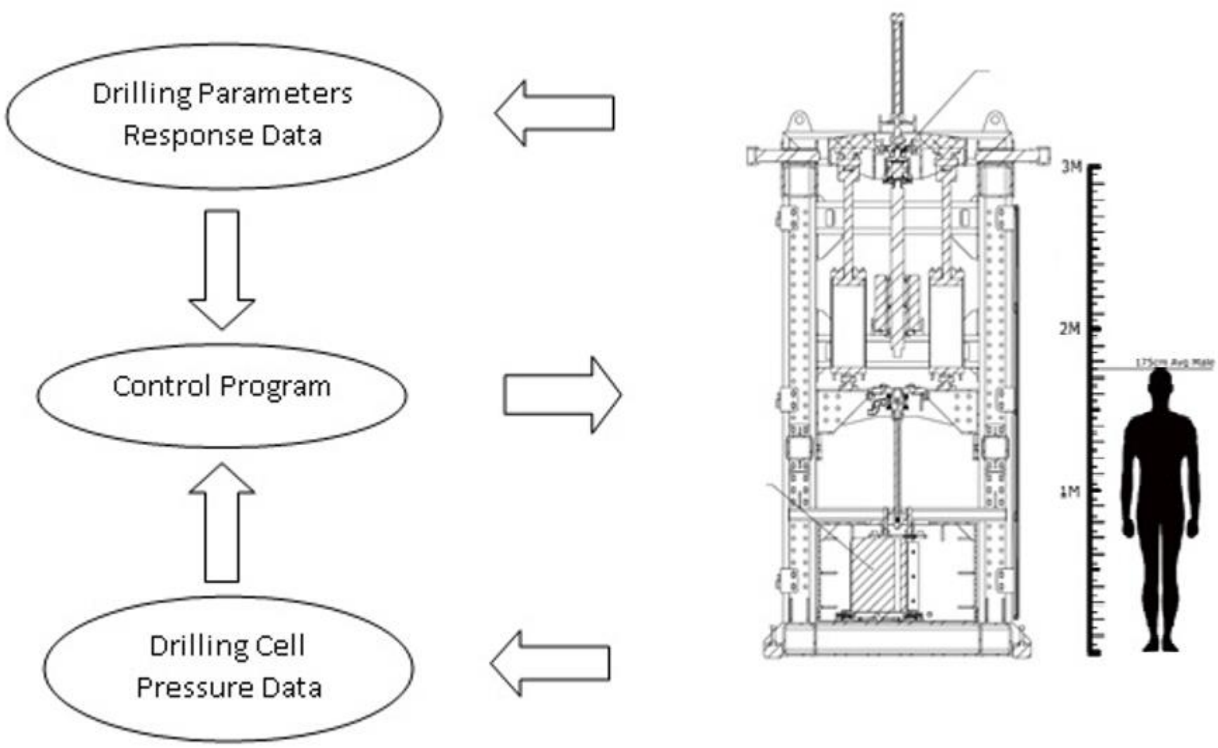

Figure 2-16 Field Scale Drilling Simulator

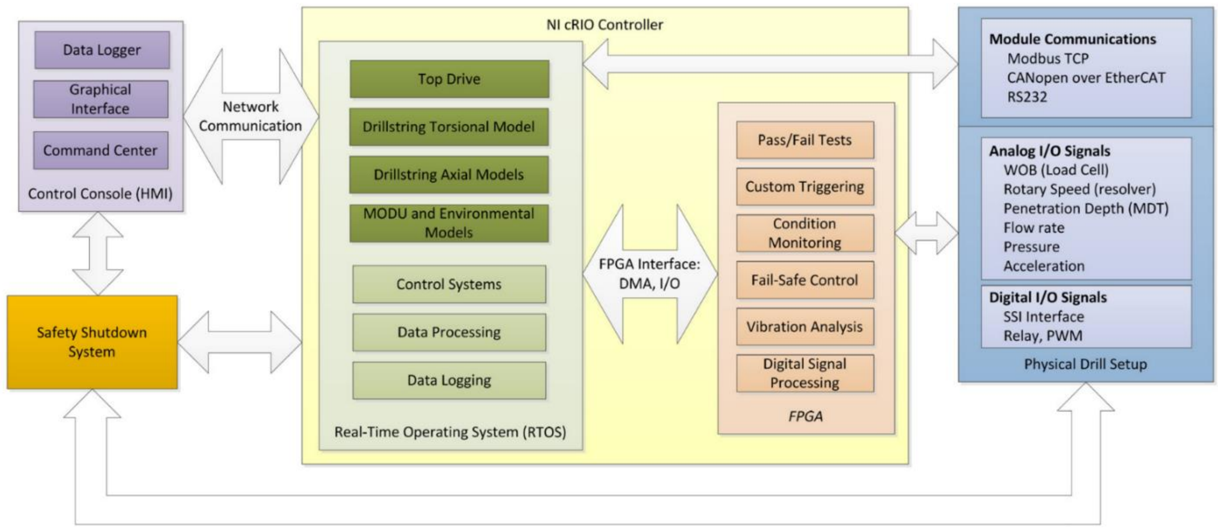

Figure 2-17 Control System of the Simulator

The field scale drilling simulator system is designed to physically simulate the bit-rock-mud portion of the drilling process while providing the response of the drill string vibrations and rig heave from numerical simulation. Since the system can accurately reproduce any downhole condition encountered in the field, it is an ideal testing platform for testing the proposed ROP optimization, vibration control, and pore pressure prediction problems using Digital Twins.

2.5 Conclusions and Future Work

A Digital Twin is a comprehensive, multi-component simulation that models the behavior of a real system to predict how that system will respond to various "what if" operational parameters and scenarios. The significant progress in digital technology had facilitated the rise of real time operation support centers and had a massive impact on the design and operation of oil and gas fields. The cyclic nature of the oil and gas industry had a strong impact on knowledge retention, as experienced personnel are forced out of the industry during down turns. The effects of the loss of experience are usually seen in the statistics, as rates of incidents increase as oil price increase after an extended downturn, and operations are started up with new crews that may not have the same level of experience. Augmenting real time operation support centers with Digital Twins and Expert Systems can help mitigate the effects of losing valuable personal experience lost during downturns. Digital Twins can be used in all stages of a well's life from design to abandonment, and they can be used as foundations of automation systems that shift the attention of drilling crews from fast operations to safe and efficient operations. Efficiency would be maintained by the Digital Twin based system to execute optimally calculated parameters and ensure vital equipment is maintained in optimal working conditions.

The major components of the proposed Digital Twin include i) drilling performance optimization for bit operating conditions, ii) pore pressure prediction and managed pressure drilling, iii) drilling fluids and solid control management, iv) controlling surge and swab for drill string tripping, and v) heave compensation. Separate models for each of these components have already been developed and tested using combinations of existing closed-form solutions and mechanical systems modelling based on Bond Graphs, Finite Element Method (FEM) models, Simulink, and others. Nonlinear programming formulations of optimization problems for these separate models can be developed which included an objective function that should be minimized or maximized, decision variables, and constraints. These formulations are then transferred to the MATLAB® environment to simulate various components and combinations of these components concurrently.

The major innovation of the digital twin to simulate drilling from an offshore floating MODU is the capability to evaluate the interactions of the various simulated components that, in past practice, would have been simulated independently. This provides the ability to evaluate "what if" scenarios over the overall drilling operations to better predict the impact of these scenarios on drilling operations.

2.6 Acknowledgement

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Chapter 3 Development of an Auto-Driller System Based on Optimal Control Theory

Abstract

Drilling performance optimization, or drilling at the minimum cost and highest productivity, has been sought after since the earliest days of establishing drilling engineering as a science. In recent years, operators have turned to automation to address this problem. This paper provides a review of the history of drilling optimization from 1950 to the present day focusing on the chronological evolution of optimization techniques such as correlation of ROP and MSE with drilling parameters, statistical correlations between drilling parameters and performance, and modelling analysis to characterise disfunction for transferring power from surface equipment to the bit, followed by the design process of an auto driller system that sets optimized drilling parameters based on an optimal control theory. Starting from a numerical optimization problem minimizing an MSE formulation corrected for rotary speed sensitivity, the selection and verification of a drilling model to be used as a constraint for the optimization problem, and finally a simulation validating the auto-driller system, and a discussion of the limitations of the current design and how to improve upon it.

Introduction

As early as the 1950s, studies were conducted to improve bit technology, investigate hydraulic principles, improve drilling fluids, and most importantly optimize performance. The 1970s brought fully automated rig systems, equipped with closed-loop computer systems that could control drilling variables. In the mid-1980s, field personnel could perform optimization by referring to graphical templates and equations. In the 1990s, optimization became part of the well planning process, aiming to obtain the best possible well construction performance[1]. Further studies developed the “Drilling the Limit” optimization techniques [2]. By the 2000s, real-time monitoring techniques became a reality with the help of the rapidly developing communication industry. A few years later, the first real-time operations support centers were established.

These centers acquire drilling parameters in real-time, thanks to the development of electronic data acquisition systems linked to computers [3]. Most recently, the development of smart computer systems enabled drilling penetration rate and bit lives to be optimized through drill-off tests [4]. The literature is rich with drilling optimization methods that are either through direct correlation to rate of penetration, statistical correlation, correlation with amount of energy being used, correlation with the amount of vibration, data-based drilling advisory systems, or a combination of multiple methods. This paper contains a chronological review of the emergence of most methods, grouped in three categories: Performance Improvement and Enhancement, Modeling and Analysis of Drill string Dynamics, and Development of Advisory Systems. The paper then displays the possibility of constructing an auto driller system by combining multiple methods into a nonlinear programming problem aiming to move the bit from one point to a desired target depth with optimum performance through various constraints that include a model of the system. This proposed method happens to be a well-established control method termed Optimal Control.

Review of Performance Optimization Methods

Early Work

Among the earliest publications on optimization, Speer [5] suggested a new comprehensive approach in 1958 to determine optimum drilling techniques. His work showed the empirical interrelationships of Rate of Penetration (ROP), Weight on Bit (WOB), Rotary Speed (RPM), hydraulic horsepower, and drillability of the formation. He integrated five relationships into one chart to define the optimum drilling technique using minimum field test data.

A year later, Graham and Muench [6] published their study combining WOB and RPM to derive an empirical mathematical expression. Their approach used a method of mathematical analysis of the drilling-related costs to find an optimum condition. They derived mathematical formulations for bit life expectancy and drilling rate as functions of depth, RPM, and bit weight. Their work yielded a means for using any set of different drilling conditions to calculate an optimum WOB and RPM that minimizes total drilling costs.

In 1962, Maurer [7] derived his perfect cleaning model to predict ROP for roller-cone bits. The perfect cleaning condition means that all the rock debris is removed between tooth impacts. The model established a relation between ROP, WOB, RPM, formation strength, and bit size. A year later, Galle and Woods [8] investigated applying an optimal WOB and RPM to obtain the lowest drilling cost; developing a mathematical relation, graphs, and a procedure for field applications. The developments were used to determine the best combinations of WOB and RPM. Their approach assumed a bit wear rate value that is a function of time, bit weight, and bit diameter. The given equation was limited to a load application of 10,000 lbf per inch of bit diameter. They also published an equation that related the tooth wear rate of milled tooth bits designed for soft formations to the RPM.

A completely new optimization approach emerged in 1965 [9] using the concept of Mechanical Specific Energy (MSE). He defined it as the mechanical work done to excavate a unit volume of rock. In his conclusions, he stated that there is a remarkable correlation between the MSE and the crushing strength of rocks. This later became a very successful approach for tracking drilling performance.

Improvement in on-site computer systems for bit weight and rotary speed control allowed Young in 1968 [10] to develop a novel optimization system. Young formulated a set of equations describing drilling performance consisting of the following: drilling rate as a function of WOB and bit tooth height, bit wearing rate as a function of bit rotation speed, bit tooth wear rate, and drilling cost. The work showed that the integration of these equations for optimum WOB and RPM constants yields the best solutions for those parameters.

Articles from the 1970's to the 1990's

A statistically driven analysis was developed by Reed in 1972 [11] using a Monte Carlo based model. The method used a WOB and RPM model that was solved with a linear, least-squares technique, and curvilinear smoothing techniques. The method made it very easy to include constraints and proved valuable due to its rigor. In the same year, Wilson and Bentsen [12] investigated various drilling optimization procedures concentrating on optimization of WOB and RPM. In their study, three methods of progressively increasing complexity and increasing data requirements were developed. The first method is a point optimization method to minimize the drilling cost per foot during a bit run. In contrast, the second method is an interval optimization method to minimize the drilling cost of a selected interval. The third and most complex method is a multi-interval optimization method for minimizing the drilling cost over a series of intervals. The authors concluded that their model of equations could be used as a guide toward good drilling procedures with considerable cost savings.

Arguably one of the most significant studies performed regarding drilling optimization was introduced by Bourgoyne and Young in 1974[13]. It was based on a statistical analysis of the drilling parameters from previous wells in a field. A linear ROP model was constructed, and multiple regression analysis of drilling data were obtained from the model. This was done to select the RPM, bit hydraulics, and bit weight. This model is commonly used in the industry due to its robustness. Effects of formation attributes, such as strength, compaction, and depth of the formation in addition to the pressure differential across the hole bottom, as well as drilling features, such as bit diameter, RPM, bit wear, bit weight, and bit hydraulics, were included in model data analysis. It was concluded in the work that about 10% of drilling costs could be saved using uncomplicated drilling optimization equations.

A new approach was later developed by Reza and Alcocer (1986) [14]. They used the Buckingham Pi theorem, a theorem for dimension analysis in creating expressions with dimensionless formats. The theorem is used to improve nonlinear, dynamic, multidimensional mathematical formulations for extended applications in drilling. The model consisted of three equations for ROP, rate of bearing wear, and rate of bit dulling. Their work also showed the effect of drilling parameters such as WOB, RPM, bit radius, bit nozzle radius, bit bearing radius, characteristics of drilling fluid, differential pressure, etc. on the developed model. In the same year, Simmons [15] performed one of the earliest real-time drilling optimization studies. Simmons stated in his conclusions that a combination of current engineering technology, combined with real-time optimization, will improve drilling efficiency. The study concluded that regarding optimization, we must start from the planning stage to the actual field implementation. All available past drilling performance data must be analyzed by the drilling planner, who correlates them to the current well being planned, enabling the prediction of the current bit performance. These predictions are to be utilized by the drilling supervisor as guidelines to be combined with his experience to fine tune for optimal performance.

Moving forward, Warren [16] published his ROP prediction model in 1987. His work includes the bit cleaning “cuttings-removal process”, also termed the “Imperfect Cleaning Model” to differentiate it from the “Perfect Cleaning Model” of Maurer [7]. His model has three terms: one for the WOB effect, one for the tooth penetration into the formation, and the third term is for cuttings removal. The model fits the experimental data for tri-cone bits of both steel tooth and insert types.

The industry started looking into improving performance by reducing the energy wasted in drill string vibrations around 1988. One of the first methods that was presented used torque feedback from the applied string torque and was introduced by Halsey et al [17]. Torque feedback allows the rotary table speed to respond to dynamic torque variations, preventing stick-slip oscillations. The method uses torque as a feedback signal in the control loop, which is needed to maintain the RPM set point while also maintaining constant torque. Stick-slip was only prevented when the speed was adjusted, meaning the torsional waves were dampened at the rotary table preventing their reflection down the drill string. The main drawback of this method is that it needs an accurate measurement of the torque, which was very hard to get at the time.

In 1989 Bourdon et al [18] developed a data acquisition system to analyze drill off test data from laboratory experiments and rig sites. They analyzed more than 50 data sets from field and lab work. Field data was recorded in different lithologies, and inclinations with two different bit sizes (215.9 mm and 152.4 mm). Lab data was recorded for a single bit size (215.9 mm) and was recorded for several different types of rock. The results emphasized the importance of the quality of the sensors used for data logging and concluded that there was no significant transient effect in the ROP response during any of the drill off tests.

In the early 1990’s the industry started to recognize that the performance of rotary drilling systems is often limited by self-excited vibrations. Self-excited vibrations are the main cause of early fatigue of drill pipes and premature failure of bits. Through damage to equipment, and increased downtime, drill-string vibrations were reported to account for 2–10% of well costs [19]. That realization has expanded the concept of drilling optimization to include avoiding these vibrations.

An offshore drilling data set was used by Maidla and Ohara [20] in 1991 to calibrate an ROP prediction model. They compared their results to the Bourgoyne and Young's model [13]. Their work aimed to minimize drilling costs based on selecting bit, bit bearing configuration, WOB, and RPM. Their study concluded that the ROP for consecutive wellbores in the same area could be predicted and optimized using regression coefficients calculated from previous well drilling data. The study found that the predicted performances are dependent on the quality of the data used to produce them, and proposed the use of iso-cost, and iso-ROP graphs for optimizing drilling cost.

The concept of MSE was revisited by Pessier and Fear [21] In 1992. They improved on the MSE technique, created by Teale [9]. The authors implemented a computer simulation and laboratory measurement tests to establish an energy balanced formulation for borehole drilling subject to hydrostatically pressurized conditions. They applied the derivation for the MSE formulation and identified methodologies for drill bit bearing problem identification. The identification methods continuously monitor the specific energy and bit-specific coefficient of sliding friction. These monitored terms were more efficient and reliable than WOB and ROP concentrated evaluation.

Also, in 1992, E. Detournay [22] published a paper that built on the work established by Fairhurst and Lacabanne [23] to produce a phenomenological model for the drilling action of drag bits. The work showed that bit-rock interaction is characterized by rock cutting and frictional contact forces. These forces can be represented by decomposing the torque and WOB into two components associated with these fundamental processes. The model postulated that the cutting component of the torque and WOB is proportional to the Depth of Cut (DOC) and that there is a linear constraint between the frictional component of the WOB, torque, specific energy, and rock strength.

In 1993, Wojtanowicz and Kuru [24] proposed a new technique for the planning and control of the drilling process. The proposed method utilized single-bit control with an optimal multi-bit drilling program for a well. Comparison of the dynamic drilling strategy to conventional drilling optimization and typical field practices showed an estimated potential drilling cost saving of 25% and 60%, respectively. The proposed method was shown to be the most cost-effective for expensive and long-lasting Polycrystalline Diamond Compact (PDC) bits due to their effectiveness, which led to a reduced number of required bits per hole.

A simple method for mitigating stick-slip was presented by Pavone and Desplans [25] in 1994. By thoroughly analyzing the data obtained by a Measurement While Drilling (MWD) system, they found that stick-slip can be avoided by using stability analysis. The studies' main focus was on using the MWD data to derive a model of the drill string that describes stick-slip. They derived parameters for a PID controller that controlled the RPM to attempt to cure stick-slip. The resulting system was underdamped, which led to high vibrations. Their study did not show how exactly they derived the PID-parameters.

Advancements in computer technology coupled with a clearer understanding of the drilling process allowed Cooper et al [26] to develop a simulator program for well drilling in 1995. This program was aimed to be simple to understand and use. The simulator included characteristics in which drilling engineers could experiment with changing effects of the operating parameters to optimize drilling operations. The simulator contained an algorithm that determines drilling ROP, wear rate of the bit, overall drilling cost and time, and cost per foot, during the drilling run. In the same year, Mitchell [27] demonstrated the purpose of selecting optimal WOB and RPM values. One of the essential reasons was defined to be producing the minimum drilling cost per foot. Controlling the direction of the borehole and recognizing over-pressured regions were also among optimum parameters selection. His work also mentioned the contouring method of selecting optimal weight and string speed.

Dubinsky and Baecker [28] developed a simulation system for several drilling conditions in 1998. They examined dynamic behavior of drill bit, simulating key dynamic drilling dysfunctions such as lateral vibrations, bit bounce, torque shocks, bottom hole assembly (BHA) and bit whirl, stick-slip, and torsional oscillations. They concluded that the model for the on-line drilling optimization requires the previous and accumulated practical data in order to be used in tuning parameters in next iterations.

Articles from 2000's to 2010

Akgun [29] investigated the controllable drilling parameters that affect drilling rate, mud weight, RPM, WOB, bit shape, and hydraulics, in 2002. Selection of the controllable parameters properly was concluded to significantly enhance drilling rate, with the introduction of an upper drilling rate limit or "technical limit" concept which cannot be passed without compromising the safety of drilling operations. Values of RPM and WOB variables should be at possible maximum feasible rates taking into consideration the minimum bit operational cost and stability of the drill string. Hole cleaning and bit hydraulics must be considered while selecting flow rate at an optimum value to drill safely at the technical limit.

In 2003 a study by Ursem et al [30] demonstrated the use of a real-time operations center (RTOC). The study showed that an operator and a service company can limit downtimes by enhancing communication. The RTOC communication improvement led to improved interventions and showed that critical decisions are usually multidisciplinary, therefore requiring a common ground for all interested parties. The study concluded that the integrated operations approach used in RTOCs can influence unexpected outcomes in real time in contrast with the costly lesson learned approach in use by the industry.

The Drilltronics project developed by Rommetveit et al [31] in 2004 launched a system that collected all available surface and subsurface data to optimize drilling performance. The project developed a bit loading optimization module that regulated the WOB and RPM at the bit. The module was used in conjunction with a stick slip preventing algorithm that increased the ROP by 15% to 30%.

William and Jeff [32] showed a method for determining Mechanical Specific Energy (MSE) in real time remote monitoring in 2005. The work showed how MSE behavior can be effectively understood from conducting real time MSE tests and how it can be an acceptably beneficial tool for drilling technicians and engineers. A practice of tuning drilling parameters to reduce MSE is shown as a good rule of thumb. During the same year Dupriest and Koederitz[33] also evaluated drilling efficiency using the MSE concept. Their approach added an MSE track to the normal mechanical drilling logs used by drillers. Analysis of the MSE value in real time facilitated the detection of drilling problems such as bit balling.

The year 2005 also witnessed the presentation of an active vibration damper (AVD) introduced by Cobern and Wassell [34]. The AVD is a tool that gets mounted between the drill string and the BHA. It is designed to reduce drill string vibration, and it has a structure similar to that of a shock sub. However, it uses a magnetorheological fluid (MRF); a fluid which has a viscosity that can be changed by the influence of electromagnetic fields instead of the conventional hydraulic damper. This allows the user to control the viscous properties of the fluid by varying the viscosity of the MRF, thus, enabling the manipulation of the damping coefficient of the AVD. The relative motion of the bit is measured in real-time during drilling, and the damping properties are adjusted continuously. Results from drilling tests have been very promising, and has shown that by varying the damping coefficient, vibration, and variation of WOB can be reduced.

Milter et al [35] demonstrated in 2006 that a real-time data link between a support center for drilling, well intervention and production operations, and a rig, that had the data monitored by a highly skilled multidisciplinary team, significantly contributed to the reduction of unforeseen events and well shut ins. This in turn increased the time during which regular operations were performed and thus increasing efficiency. Emphasis was placed on the piped data quality to multidisciplinary relevant personnel that are not essentially at a predetermined remote location, but anywhere with high-speed internet communication. The efficiency of the optimization was based on judgment of the expert involved, which is based on their experience in the process. It was concluded that using real-time data transmission as a means of automatic surveillance caused a reduction in occurrence of unforeseen events and well shut-ins, and improved consistency of operations.

A study by Monden and Chia [36] in 2007 showed that operation support centers can become the decision-making point instead of the rig site. For many operations, real time connectivity between the rig and the support center has become the norm, a data centric approach to drilling optimization can improve drilling performance and having an operations support center has a direct impact on time and cost.

In 2008 Detournay et al [37]. published a complete model of the drilling response of drag bits. The model describes three successive regimes that are present in the drilling response of drag bits. While the bit operates in phase one, the depth of cut per revolution is low. This phase is characterized by the dominance of the frictional contact process and by an increase of the contact forces as the depth of cut increases. During operation in phase two, the contact forces are fully mobilized, and during phase three the actual contact length increases. Experimental evidence was obtained with a small drilling machine and was in support of this model. This model is an expansion of Detournay earlier model [22], and provides a prediction of the down hole reaction forces associated with drilling with a fixed cutter drag bit, as well as the expected ROP.

Armenta, [38] developed Drilling Specific Energy (DSE), which was defined as the work done to excavate and remove a unit volume of rock underneath the bit. The DSE formula modified Teale's original MSE equation to include a bit hydraulic-related term on the specific energy. At a constant WOB, bit hydraulic horsepower per square inch (HIS) is the main driver to move from the inefficient to the efficient drilling condition. Experimental data has shown that there is a power-function correlation between DSE and ROP, with inefficient drilling at high DSE values and low ROP, and efficient drilling with low DSE and high ROP. Experimental and field data have shown that DSE values tend to the rock confined compressive strength (CCS) when the system is drilling at optimum conditions, and that DSE has a better correlation than MSE, with the CCS. The data also showed that DSE can be used to identify specific inefficient drilling situations such as bit balling.

Iversen et al [39] developed a system that connected to a rig control mechanism in the North Sea. The system transmitted real time signals from surface and downhole sensors. The system analyzed drill string mechanics, fluid hydraulics, cuttings transport, wellbore torque and drag. The study showed that the system can monitor parameter trends that would help guard against issues such as wellbore instability, poor hole cleaning, high torque or drag. The study concluded that the system may alleviate some of the challenges like loss of circulation, mechanical and differential sticking, and hole pack-off tendencies. The system would also suggest changes to be made to assist in avoiding the predicted issues. The study also mentioned that the calculation functionality of the system is dependent on the quality of the data as well as the correct setup of the system.

Iqbal [40] demonstrated a computer algorithm in order to calculate and optimize drilling optimization procedures using real-time parameters for roller cutter insert type of bits. This method consists of some steps including calculating the weight exponent given in drilling ROP, finding the optimum revolution speed of the string and parameters of WOB using plots or correlation. The relation of lease cost per foot is used to select the optimum parameter. The study concluded that the efficiency of exploratory wells could be enhanced using the same technique where no proven information would be available.

Rashidi et al [41] put forward a novel approach to compute real-time bit wear from a combination of MSE and ROP models. The stated approach, unlike ROP models, takes the major differences between those two models into consideration. Particularly interesting results that were obtained from the work show a linear relationship between rock drillability and MSE.

A modelling error compensation control approach to suppress stick-slip was developed by Puebla et al [42]. The method relied on a drill string that was modelled as a simple torsional pendulum driven by an electric motor. The model consisted of damped inertias that were mechanically coupled by an elastic shaft. Using a modelling error function, two different controllers were developed: A cascade controller and a decentralized controller. The cascade controller used the electrical properties of the motor, and full state feedback. The utilized states are the relative position between coupled inertias and their angular velocities. The decentralized controller used the electrical properties of the motor and the WOB. Drive system oscillations are regulated with the motor, while BHA oscillations are regulated by adjusting the WOB. The same state feedback system is used in this controller. Successful suppression of stick-slip was achieved in numerical simulations, but no actual system has been tested.

National Oilwell Varco presented their own stick-slip prevention system which they named SoftSpeed, [43]. SoftSpeed was basically an acceleration feedback PI-controller, which controlled the speed of the drive. The controller was tuned to dampen torsional oscillations in the drill string. The system's main innovation was the online tuning of the PI-controller.

Eren [44], published a study in 2010 that proposed the use of a multiple regression model to optimize drilling performance in real time as a function of available data. He optimized Bourgoyne's model for effective functions at each data point. His approach for field parameter optimization required the use of a computer network that transmitted all relevant field data to an operations support center where a database at a central computer continuously calculates the model parameters and transmits the recommended parameters back to the field team. The study concluded that data quality plays a pivotal role in optimizing performance using regression methods. It was suggested that using a reduced number of data points that represent the existing data trend could give acceptable results, and that the use of normalized down hole parameters instead of surface parameters provided better results specially for inclined wells.

Hareland and Rashidi, [45] presented a new ROP model. The model was derived directly based on rock craters fractured by a single insert. The model reflects the interaction between tri cone bits and the rock, with good field verification results. In addition to ROP prediction, simulations were successfully carried out to predict the unconfined rock strength of formations using the same model. The predicted rock strength was compared to offset well logs and was found to be matching in both trends and values

Recent Work

Alum and Egbon [46] used real-time bit data acquired from wells in Niger Delta reservoirs to develop semi-analytical models for ROP in 2011. These models were obtained by carrying out regression analysis of the parameters that contain differential pressure in the equations of the Bourgoyne and Young Model in order to obtain regression constants. Mathematical expressions connecting ROP and drilling fluid properties were then generated using the obtained regression constants.

Also, in 2011 Koederitz and Johnson[47] showed the improvement and field testing of an autonomous drilling system that uses a test process to assess the drilling performance of a specified set of targeted set points. The set points are identified by a research method whose development was based on earlier work in the application of real-time MSE display. Field testing results that were presented are generally favorable and indicate a practical and flexible potential for autonomous drilling optimization without drilling knowledge which is promising in a range of cost-effective applications.

Elshafei, Khamis and Al-Majed[48] presented a unified approach for real-time drilling optimization of the drilling parameters and directional steering in 2015. The approach combined the conventional drilling parameters as well as the directional steering control. The proposed objective function compromised between trajectory tracking accuracy, drilling effort, and drilling time. The optimization problem was solved subject to operations limits and constraints using constraint optimization techniques.

In 2016 Yashodhan et al [49] launched an Artificial Neural Network drilling parameter optimization system to provide the rig-site operator real time data analysis to help in decision making to increase the operating efficiency, increase the ROP, maximize the bit lifetime, and decrease the total cost. The operating parameters such as WOB, and RPM can be selected depending on the provided data. The proposed system saves much more money via reducing the drilling days.

Also, in 2016 Jiang and Samuel [50] presented a combination of two optimization techniques, the Artificial Neural Network and the Ant Colony optimization, to simultaneously predict the ROP. The inputs to the Neural Network are the depth, WOB, RPM, the mud flow rate, and the gamma ray reading from Logging While Drilling (LWD), where the ROP is considered as the output. The Ant Colony algorithm is used to optimize the ROP. The results showed how the Neural Network succeeded to calculate the ROP without prescribed models.

A team at Baker Hughes[51] published a study on a self-adjusting PDC bit that can dynamically adapt its depth of cut (DOC) to the constantly changing drilling environment. This dynamic change allowed for delivering improved ROP while mitigating vibrations. The bit which was later given the commercial name TerrAdapt employs replaceable, compact, and self-adjusting cartridges enclosing a passive hydro-mechanical feedback mechanism. When the bit is engaged the cartridges resist unintended fluctuations in depth-of-cut at the fast time scale and mitigate vibrations, while allowing for gradual changes in DOC which facilitates fast and efficient drilling. The concept for this technology was validated through full scale laboratory testing and in research wells.

In 2018 Eren [52] published another study that examined the data from 40 wells drilled in the Middle East to develop an ROP indexing methodology for drilling performance data. The study showed that the drillability performance comparisons currently in use by the industry are not feasible for benchmarking performance and that the drilling industry needs a new methodology that utilizes the available rig data and the advanced computing power both in the field and in operation control centers. The study introduced methodology that is based on rate of penetration data; eliminating flat time events in which the depth of the well is not increasing. It takes advantage of daily drilling report (DDR) data as an input and produces benchmarking data that identify the rate of penetration performance of an ongoing well. This methodology eliminates non-productive time (NPT) events which masks performance of a relatively efficient wells.

In 2021 De Moura et al [53], [54] ran a set of laboratory drill off tests. When the data was fitted to Maurer's model [7] it was noticed that the bit calibration constant in the model was dependent on the WOB. The relationship between the calibration constant and the WOB was linear, which meant that the quadratic relationship between ROP and the drilling parameters represented in the model was actually a cubic relationship. Moreover, the cubic relation is arranged in a way that can be used to estimate a founder point, making this the first model to be able to estimate the technical limit for drilling for a specific drill bit.

Conclusion Drawn from Review

Regardless of the optimization method being used, be it correlation to ROP, correlation to MSE, a basic statistical method, an advanced AI technique, or a model for drill string dynamics, an estimate of rock strength being drilled is required to optimized performance. Conventionally, all rock strength estimates are acquired through geophysical logging, or to a lesser extent, through core sample analysis after drilling is completed. Every operator has a massive amount of data that has been collected from their fields through geophysical logs and seismic surveys. Geophysical logs are considered the absolute gold standard of downhole data accuracy, as they are a direct measurement. Seismic surveys come with a great deal of uncertainty due to being limited in resolution to the wavelength of the seismic waves which may not be able to identify smaller geological features. A certain level of uncertainty is present with regards to the tops of geological formations extracted from seismic data. Prior to drilling a new well, the operator usually uses the available data, mainly seismic data, and logs of some offset wells, to construct a geological prognosis of the new well. These prognoses are usually good for well planning purposes but are not sufficiently accurate for real-time drilling optimization. The recent development of look ahead of the bit technologies [55]–[57] in combination with the application of machine learning techniques to estimate rock strength [58] [59] have greatly improved the data quality available for real time drilling optimization. The removal of the geological uncertainty reduces all the previously discussed optimization methods to bit characterization, and drilling parameter selection.

Theoretical Analysis and Development of the Auto-Driller System

Since optimization for minimum MSE is a widely accepted industry practice, analyzing MSE will be the starting point for the development of the auto-driller system. The mathematical formula for MSE is:

$$\mathrm{MSE} = \frac{W}{A} + \frac{120\,\pi\,N\,T}{A\,ROP} \qquad \textit{Eq. 3-1}$$

where W is the downhole weight on bit, A is the area of the bit, N is the downhole rotary speed of the bit, T is the torque on the bit, and ROP is the rate of penetration.

The relation contains two control variables, [W and N] which are related to the surface applied parameters through a model of the drill string, a single constant [bit area], and two observed values [T and ROP] which can be related to the control variables.

According to [21][38] Torque on bit can be approximated as a function of weight on bit through the relation

$$T = 1/3\ \mu\ D\ W \qquad \textit{Eq. 3-2}$$

Where μ is the friction factor, D is the bit diameter, and W is the downhole WOB.

Finally, an accurate prediction of the ROP and the founder point relating them to the control variables is required. The empirical method for finding the founder point developed by De Moura et al [53], [54] was found to be in agreement with field drill off data published by Dupriest et al [33] shown in Figure 3-1.

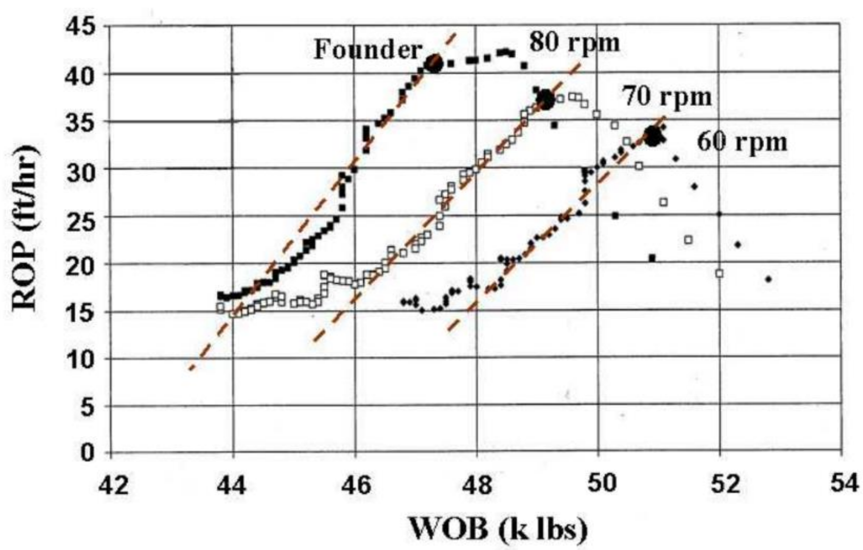

Figure 3-1 Drill off test data [33]

The same data was captured and used to calculate MSE values as shown in Figure 3-2, showing correlation between max ROP and min MSE which coincides with the compressive strength of the rock as per Teale [9].

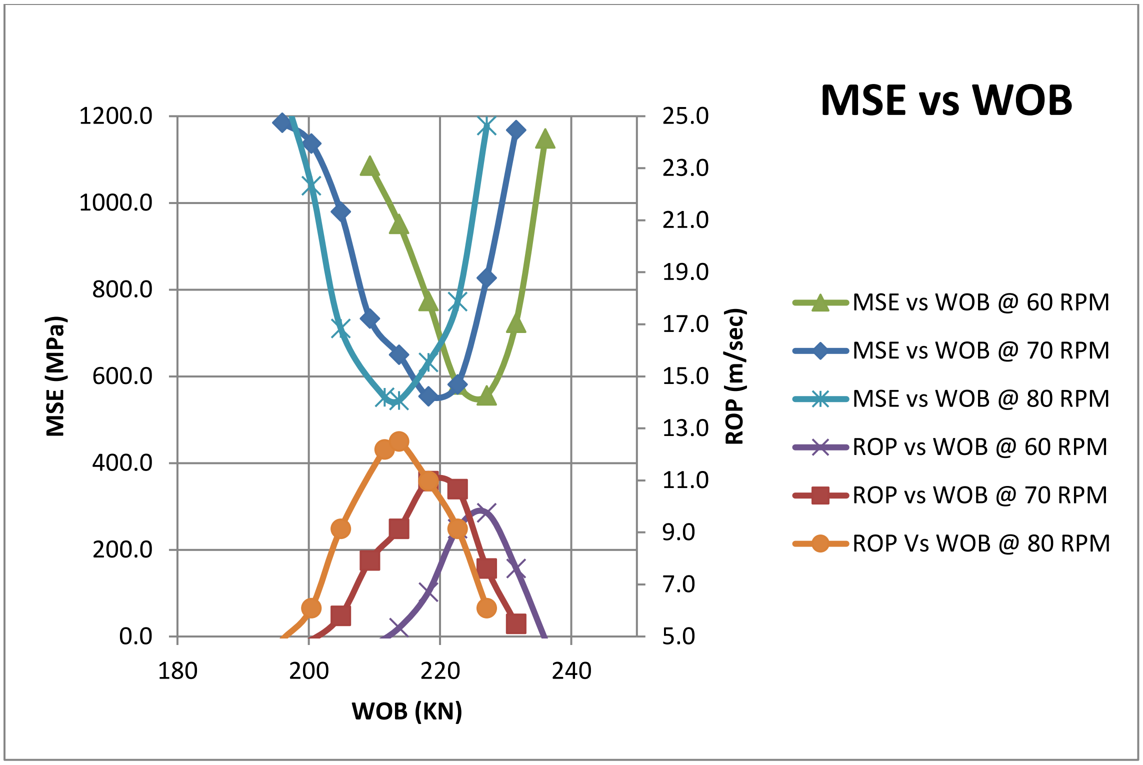

Figure 3-2 MSE and ROP against WOB at different rotary speeds

The formula for MSE can be rewritten as shown in Eq. 3-5 by substituting for the ROP term with the modified formula developed by De Moura et al [53], [54]

$$\text{ROP} = \frac{K\,(W - W_0)^2\,N}{S^2 D^2} \qquad \textit{Eq. 3-3}$$

and

$$K = a\ \ W + b \qquad \textit{Eq. 3-4}$$

where: a and b are bit constants, W is the downhole weight on bit, W_0 is the threshold weight on bit, N is the downhole rotary speed of the bit, S is the formation strength, K is the bit constant, and D is the bit diameter.

Substituting for ROP in the MSE relation, and to simplify the equation, W_0 will be considered negligible compared to the weight on bit and the bit area will be replaced by $\frac{\pi * D^2}{4}$ then the MSE relation becomes

$$\mathrm{MSE} = \frac{4\,W}{\pi\ \mathrm{D}^2} + \frac{160\,\mu\,\mathrm{S}^2\,\mathrm{D}}{K\,W} \qquad \textit{Eq. 3-5}$$

The resulting equation does not have a rotary speed term, which means that MSE is only a function of WOB. The experimental work by Hamrick [60] and the data plotted in Figure 3-2 verify that varying the bit rotary speed has a minimal effect at best on MSE and that the main driver behind it is the WOB.

Here we can choose to optimize performance through MSE and thus producing an optimal value for WOB alone by minimizing the mathematical expression. MSE can then be constrained with a soft inequality constraint limiting it below the formation strength. Then we will need to use another means of optimization for rotary speed. Alternatively, we can produce an artificial construct that is sensitive to both WOB and RPM that can be used in a more complex nonlinear program. Scaling the MSE value using the ROP produces this construct. Mathematically, dividing the MSE by the ROP will introduce the rotary speed in the denominator of the formula.

Physically, MSE is measured in Joule/ m^3, and ROP is measured in m/hour which is m/sec in SI units. This scaling will result in a quantity with the unit N.sec/m^3. The unit N.sec is the unit used to measure impulse. Impulse signifies a change in momentum, and the unit for the quantity is the change in momentum for unit volume of rock drilled. Based on the physical interpretation of the unit, the quantity is named mechanical specific impulse or MSI

$$\mathrm{MSI} = \frac{4\,S^2}{\pi\ \mathrm{K\,W\,N}} + \frac{160\,\mu\,\mathrm{S}^4\,\mathrm{D}^3}{K^2\,W^3\,N} \qquad \textit{Eq. 3-6}$$

Mechanical specific impulse is sensitive to both changes in weight on bit and bit rotary speed. The drill off test data from Figure 3-1 was used once again to construct MSI/WOB graphs in Figure 3-3.

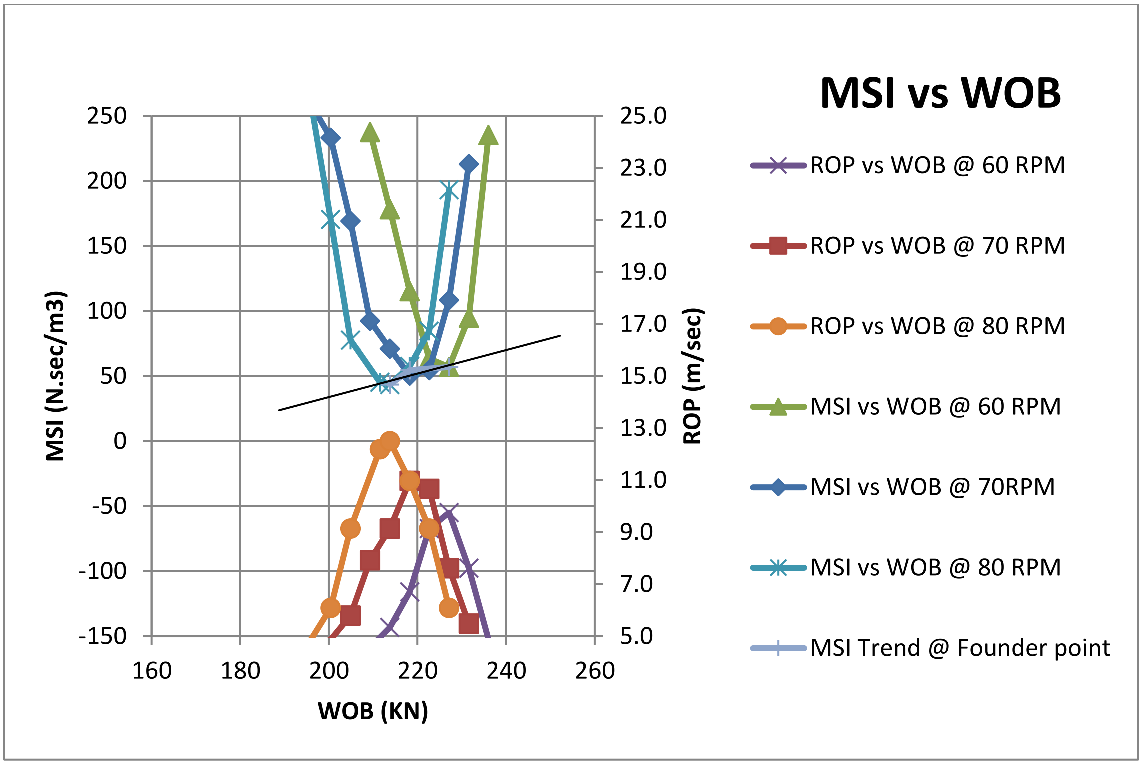

Figure 3-3 MSI and ROP against WOB at different rotary speeds

The figure shows that MSI and MSE follow a similar behavior when WOB is varied. Both quantities decrease as weight on bit is increased up to the founder point, then a sharp increase is observed. The main difference is that MSI is much more sensitive to changes in rotary speed as shown by the trend line value at the founder point.

A nonlinear programming problem minimizing either MSE or MSI can produce optimal drilling parameters. Constraints representing the technical limits, estimated rock strength values, and a simple model of the drill string, must be incorporated in the problem to accurately describe the system's behaviour. This proposed nonlinear programming problem is an optimal control theory-based controller.

Optimal Control and Model Predictive Control

According to Liberzon [61] optimal control problems are optimization problems centred around control systems and cost functions. Control systems are modeled as ordinary differential equations (ODEs) of the form shown in Eq. 3-7.

$$\dot{x} = f(t, x, u), \qquad x(t_0) = x_0 \tag{Eq. 3-7}$$

Where x is a vector of states whose values lie in $\mathbb{R}^n$, u is a vector of control inputs in a control set $U \subset \mathbb{R}^m$, t is time, t_0 is the initial time, and x_0 is the vector of initial states.

Cost functions associate a cost with each possible behaviour. For a certain initial condition (t_0 & x_0) the behaviour is parametrized by the control function u. Therefore, the cost function assigns a cost value to each possible control. A basic cost function is presented in Eq. 3-8.

$$\mathrm{J(u)} \coloneqq \int_{t_0}^{t_f} L(t.x(t), u(t))dt + K\ (t_f, x_f) \tag{Eq. 3-8}$$

Where L and K are the running cost function and the terminal cost function respectively, t_f is the final time, and x_f is the final state.

The optimal control problem is defined as shown in Eq. 3-9:

$$\text{Minimize } \mathrm{J(u)} \coloneqq \int_{t_0}^{t_f} L(t.x(t), u(t))dt + K\ (t_f, x_f) \tag{Eq. 3-9}$$

$$\text{Subject to } \dot{x} = f(t, x, u),\ x(t_0) = x_0$$

In layman terms, the most basic optimal control problem can be described as: attempt to find the control action u that minimizes J(u) over all possible control actions (or a predefined set of control actions as mandated by defined constraints). When this is applied in a digital control setting, a discrete time version of the same quantities is used in place of the continuous counterparts, replacing "∫" with "∑" and the time notation with time step etc. It is immediately noticed that the cost function is only a function of the control actions, which makes this effectively an open loop controller. Since the drilling environment is already full of uncertainties such as the geological uncertainty discussed earlier, it may not be the best approach to utilize an open loop controller to try to achieve optimum performance. Luckily a solution has already been developed for this problem, and is known as a receding horizon control, or model predictive control (MPC).

The foundations of MPC are deeply rooted in optimal control theory, with the exception that MPC is almost exclusively implemented in a discrete time fashion. Basically, MPC uses a dynamic model to forecast the system behaviour and through optimizing the forecast, produces a set of the best control actions over a prediction horizon, then applies the best control at the current time step. Additionally, MPC can use a record of past measurements to predict the most likely values of future states by reconciling the measurements with the system model. This is called state estimation [62][63]. Figure 3-4 illustrates how the MPC controller works.

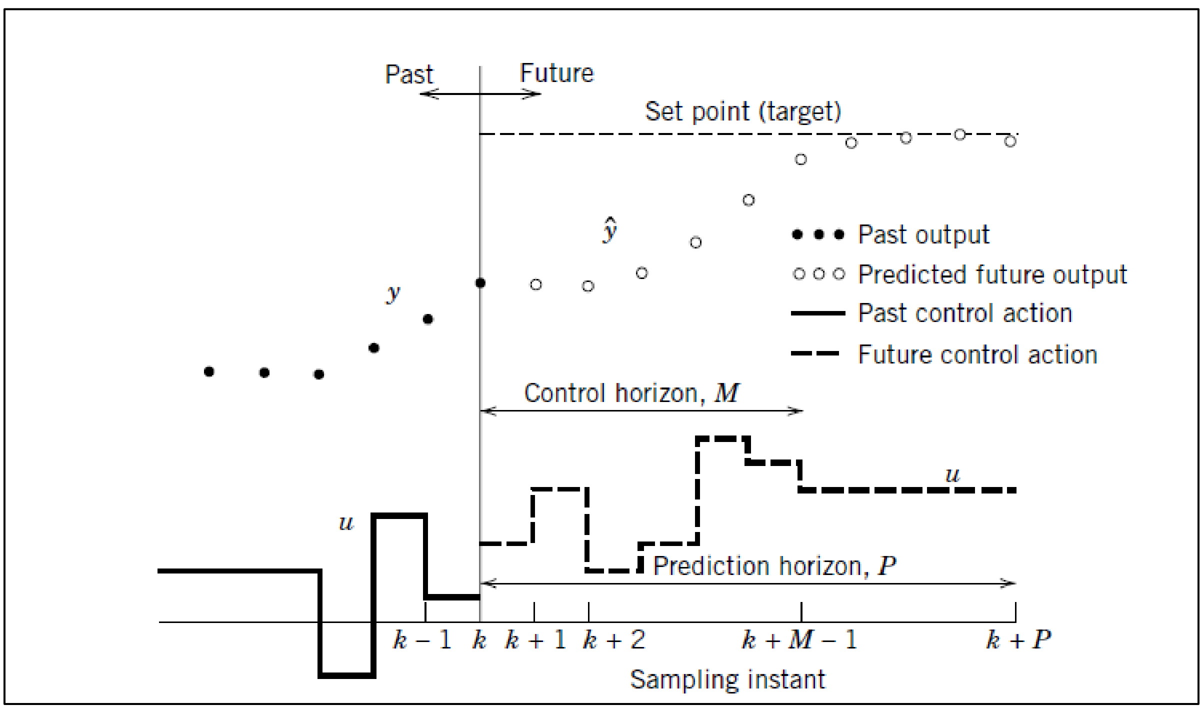

Figure 3-4 MPC Concept Illustration [63]

As illustrated in Figure 3-5, the dynamic model of the system is used to forecast the output values, which are compared to the actual outputs of the system and serves as feedback to the prediction block.

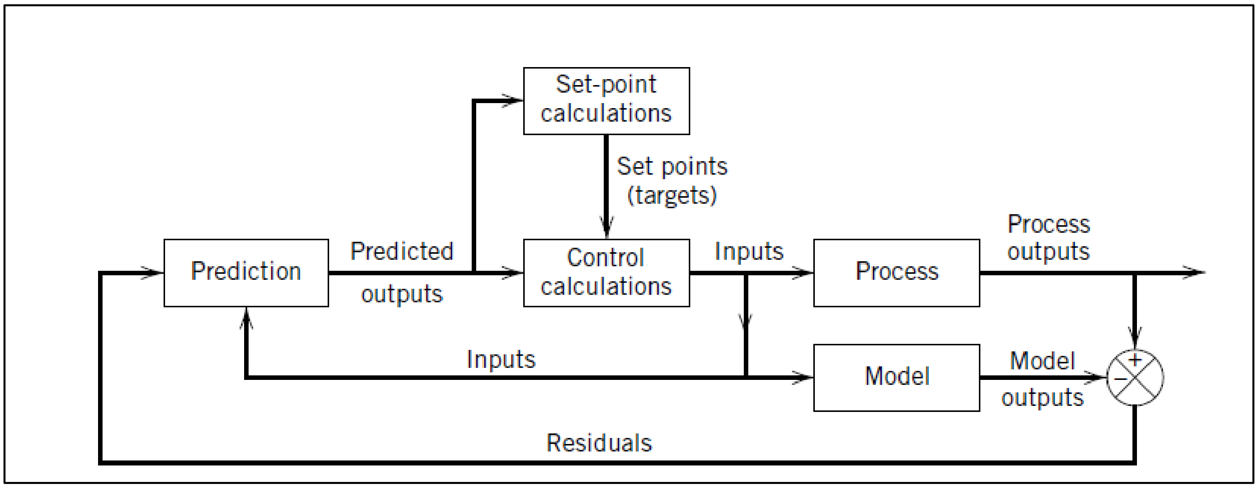

Figure 3-5 MPC Block Diagram [63]

An MPC controller produces its control actions based on current measurements from the system and the forecasted values of the outputs. The controller determines the required sequence of control moves to move the predicted output to the set point in an optimal manner [63]. In this paper we will be focusing on MPC of the quadratic regulator type where a quadratic objective function J, is to be minimized while satisfying a set of constraints. One of the most commonly used cost functions, which is the one used in this paper, is the general standard quadratic function implemented in the MATLAB MPC toolbox [64] defined in Eq. 3-10.

$$J(Z_k) = J_y(Z_k) + J_u(Z_k) + J_{\Delta u}(Z_k) + J_\varepsilon(Z_k) \qquad \textit{Eq. 3-10}$$

Where $J(z_k)$ is the quadratic problem decision, $J_y(z_k)$ is the output reference tracking term, responsible for keeping the selected outputs at or near a specified reference. $J_u(z_k)$ is the manipulated variable tracking, responsible for keeping selected manipulated variables at or near specified targets. $J_{\Delta u}(z_k)$ is the manipulated variable move suppression term responsible for adjusting manipulated variables rate of change. and $J_\varepsilon(z_k)$ is the constraint violation term, to be used when constraint violations are unavoidable, by setting soft constraints that allow a feasible solution for minimizing the cost function. More details on these terms can be accessed in the MATLAB documentation [64]. Cost functions, or as they are sometimes called objective functions, are in no way limited to this form, and can be customized to fit any scenario as needed, especially in the cases where terms can be exchangeable with the problem constraints, to help formulate a more solver friendly problem[62].

Control Problem formulation

The Drilling System Model

The first step of formulating the control problem is selecting a high-fidelity dynamic model of the drilling process to be used as a constraint. Modeling drill string dynamics is a complex process that can be achieved using a multitude of different methods. A comprehensive review of these methods was covered by Ghasemloonia [65]. An area of particular interest in modeling drill string dynamics is the modeling of high frequency torsional vibrations, commonly referred to as stick slip. Research has shown that axial vibrations, commonly referred to as bit bounce, are the precursor to other vibration modes [66]. Figure 3-6 shows the typical drilling stability diagram, the required high-fidelity model would be able to simulate this behaviour.

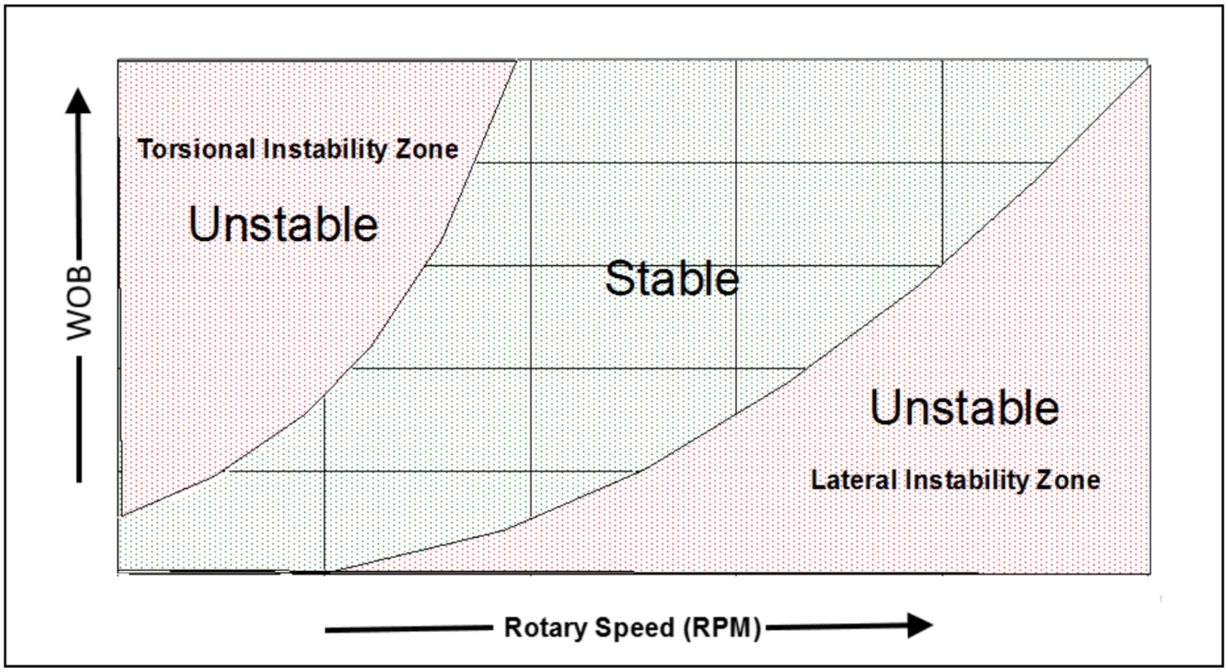

Figure 3-6 RPM-WOB Satbility Diagram [67]

The simplest method to simulate stick slip behaviour is with lumped mass models. A two degrees of freedom lumped parameter model consisting of an axial model of the drill string coupled to a torsional one through a valid bit-rock interaction model provides the desired behaviour [66], [68]–[70]. Conventionally, axial and rotary behaviour are modeled using the general laws of motion or Bond Graphs, and the coupling is usually done using the Detournay [37] or a quasi static model bit-rock interaction model [69], [71]. The models based on Detournay's work are usually referred to as RGD models after the names of the authors who developed them (Richard, Germay, and Detournay).

A modified RGD model developed by Nandakumar et al [68], which accounted for structural damping of the drill string, was selected as the basis for the model for this study. The model is illustrated in Figure 3-7.

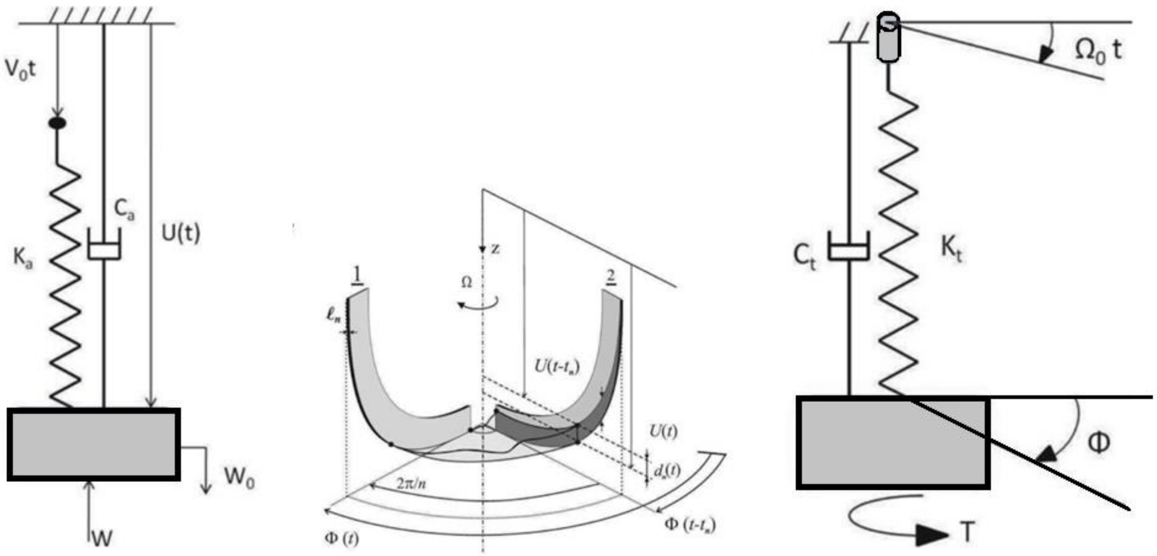

Figure 3-7 Lumped mass FBD of Axial Component of Drill string, Rotary Component of Drill string and Drill Bit (modified from[68]*)*

The equations of motion for this system are:

$$M\ddot{U} + C_a\dot{U} + K_a(U - V_0t) = W_0 - W \qquad \textit{Eq. 3-11}$$

$$I\ddot{\Phi} + C_t\dot{\Phi} + K_t(\Phi - \Omega_0 t) = -T \qquad \textit{Eq. 3-12}$$

where W_0 and Ω_0 are the applied WOB and rotary speed respectively as control inputs or manipulated variables, and W and T are the observed WOB as a reaction force at the bit, and the observed reaction torque at the bit respectively, and V_0 is the steady state ROP. The system has four states, namely bit position "depth" U, bit velocity $\dot{U}$ which can be referred to as ROP, bit angular position Φ, and bit rotary speed $\dot{\Phi}$. Detournay's bit-rock interaction model defines the observed weight on bit W and the observed torque on bit T as follows

$$W = W_c + W_f \qquad \textit{Eq. 3-13}$$

$$T = T_c + T_f \qquad \textit{Eq. 3-14}$$

$$W_c = \xi \epsilon \mathrm{ad} \qquad \textit{Eq. 3-15}$$

$$W_F = \sigma a l \qquad \textit{Eq. 3-16}$$

$$T_c = \frac{a^2 \epsilon d}{2} \qquad \textit{Eq. 3-17}$$

$$T_f = \frac{\mu \gamma \mathrm{a} W_f}{2} \qquad \textit{Eq. 3-18}$$

where σ is the maximum contact pressure at the bit rock interface, ϵ is the intrinsic specific energy of the rock, ξ characterizes the inclination of the cutting forces on the cutting face, γ is a coefficient related to the orientation of the cutters, μ is the coefficient of friction, l is the length of the wear flats on all cutters, a is the bit radius, and d is the depth of cut.

The depth of cut per revolution for a bit with n blades is calculated as

$$d = n\,(U(t) - U(t - t_n)) \qquad \textit{Eq. 3-19}$$

where t_n is a state dependent time delay caused by the presence of torsional oscillations and is calculated through the relation

$$\Phi(t) - \Phi(t - t_n) = \frac{2\pi}{n} \quad \textit{Eq. 3-20}$$

Substituting for W_c, W_f, T_c, and T_f we get the following set of equations that represent our dynamic system.

$$M\ddot{U} + C_a\dot{U} + K_a(U - V_0 t) = W_0 - \xi\epsilon ad - \sigma al \quad \textit{Eq. 3-21}$$

$$I\ddot{\Phi} + C_t\dot{\Phi} + K_t(\Phi - \Omega_0 t) = -\frac{a^2\epsilon d}{2} - \frac{\mu\gamma a W_f}{2}$$

$$d = n\,(U(t) - U(t - t_n))$$

$$\Phi(t) - \Phi(t - t_n) = \frac{2\pi}{n}$$

Since these equations contain a state dependent time delay, they are not classified as ordinary differential equations (ODEs) but are a special class of differential equations named delay differential equations (DDEs). DDEs are differential equations which have the future state as a function not only in the current state but a past state depending on some time delay. Unlike ODEs whose solution may oscillate when the system has two components and may behave chaotically if there are at least three components, DDEs may already have oscillatory, or chaotic behavior in a scalar case. Several approaches are available to solve such a set of equations, some approaches rely on transforming the problem into another simpler equivalent one such as a Volterra integral equation, a system of ODEs for which a robust method of solution is available, a set of partial differential equations (PDEs) with a particular set of initial and boundary conditions, or by combining discrete ODE methods with interpolation [72].

Model Simulation Parameters

After selecting the modeling method, a drill string design was required for running the simulations. An 8.5-inch (203.2 mm) bit drilling a 2000 m deep well was to be modeled. These bits are usually run at a WOB range from 5 to 30 metric tons, at a rotary speed between 100 and 180 rpm, without the assistance of downhole motors. The simplest drill string configuration for an 8.5-inch bit run would consist of drill collars for providing WOB, and drill pipe to transfer the bit and BHA to the bottom of the hole. The drill string is designed so that the drill pipe section is always under tension, with a neutral transition zone in the drill collars, which are the main source of WOB, to prevent buckling of the drill pipe. Bit parameters suggested by Nandakumar et al [68] were selected to drill a medium strength rock formation. Suitable lengths of NC 50 6.5-inch drill collars and 5-inch S-135 drill pipe were selected based on the WOB required for the bit. Dimensions and weight per unit length from standard tubulars tables were used to calculate string mass, inertia, axial stiffness, torsional stiffness, and structural damping. The model parameters shown in Table 3-1 were used to solve Eq. 3-21 using the forward Euler integration method in combination with an interpolation scheme to account for the state dependent delay. Equations 3-22, 3-23, and 3-24 were used to estimate the initial conditions based on a selected set point.

$$V_0 = \frac{\Omega_0 d_0}{2\pi} \qquad \textit{Eq. 3-22}$$

$$d_0 = \frac{W_0 - \sigma a l}{\xi a \epsilon + \frac{C_a \Omega_0}{2\pi}} \qquad \textit{Eq. 3-23}$$

$$\Phi_s = -\left(\frac{a^2 \epsilon d_0 + \mu \gamma a^2 \sigma l + 2 C_t \Omega_0}{2K_t}\right) \qquad \textit{Eq. 3-24}$$

Table 3-1 Simulation Parameters

Bit parameters	Number of blades [n]	6
	Bit radius [a] in meters	0.1
	Wear flat length [l] in meters	0.001
	Inclination of cutting forces on cutting face coefficient [ξ]	0.4
	Orientation of cutters coefficient [γ]	1.3
	Friction coefficient [μ]	0.4
Rock parameters	Intrinsic specific energy of the rock [ϵ] in MPa	170
	Max contact pressure at bit rock interface [σ] in MPa	170
Tubulars	Length of NC 50 collars in meters	250
	Youngs modulus of tubulars [E] in GPa	209
	Modulus of rigidity of tubulars [G] in GPa	79.3
	Structural damping coefficient	0.05

The initial conditions were calculated for 150 KN and 15 Rad/sec as the set point. The results shown in Figure 3-8 were obtained. It is immediately obvious that the results are unrealistic since the depth of cut per revolution, shown in the bottom left graph in the figure, is quite excessive. it is also noticeable that the intensity of the axial and torsional vibration shown in the simulation is growing with time, a sure sign that the system is underdamped.

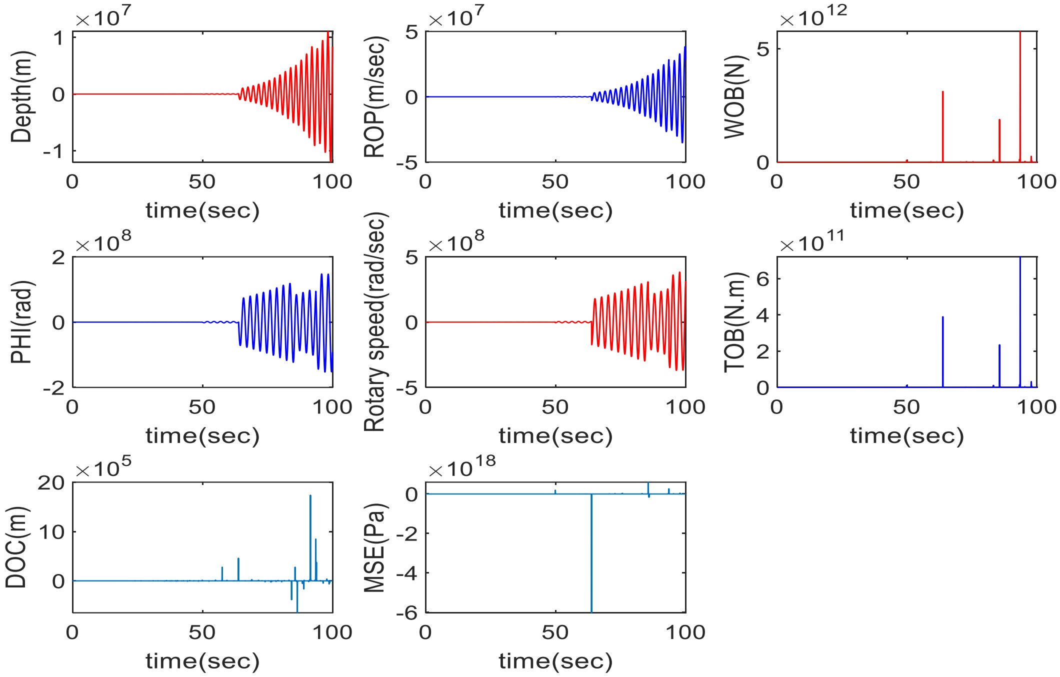

Figure 3-8 initial simulation result at 150 KN and 15 Rad/sec

To overcome these problems additional damping was added to the model to account for the effects of drilling fluid and rock contact based on the studies of Sarker et al and Kamel et al [69], [70]. The depth of cut formula was also modified to limit the value to a reasonable figure by multiplying it by a sigmoidal function. The bit selected for this simulation as mentioned earlier is an 8.5-inch bit which typically has 13 mm cutters, the sigmoid was selected to effectively limit the depth of cut to 10 mm to allow for cuttings generated by the bit to be evacuated, this has built into the model a physical limit for depth of cut which counts as a founder point, that would cause drilling dysfunction when the limit is reached and would make the model more in line with the lab observations by De Moura et al [53], [54]. The simulation was repeated, and the result is shown in Simulation Result with Limited DOC (Figure 3-9).

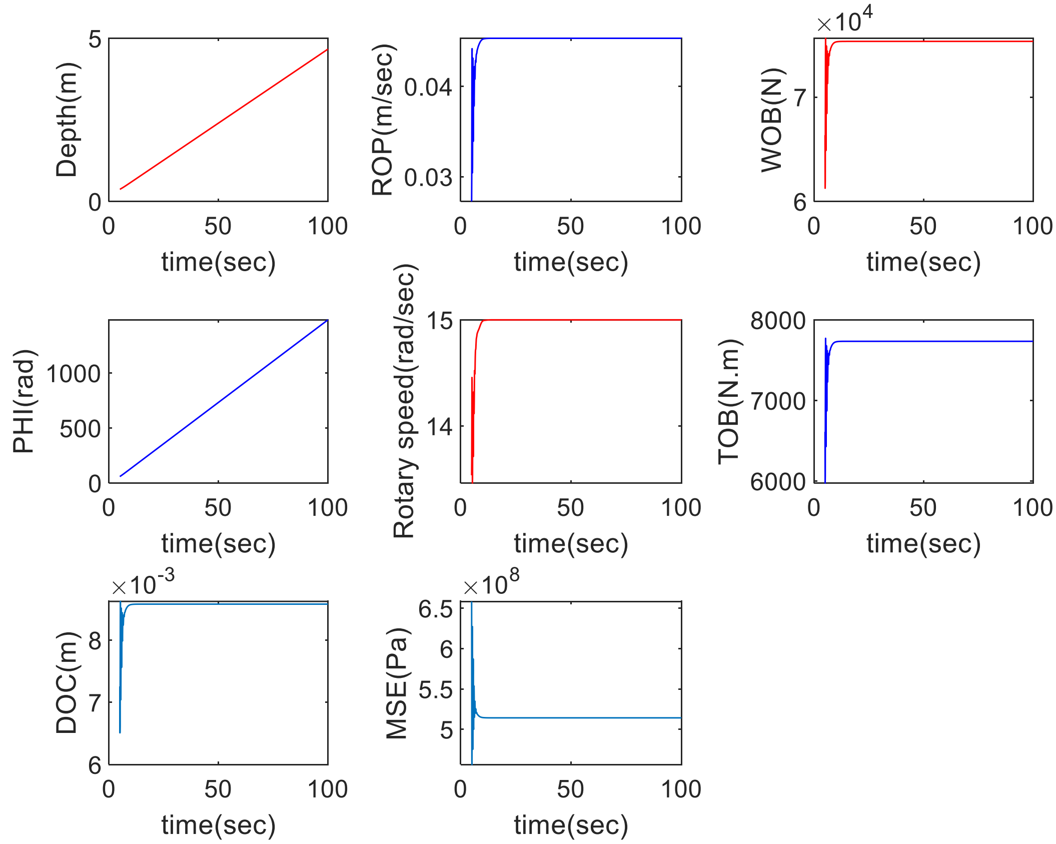

Figure 3-9 Simulation Result with Limited DOC at 150 KN and 15 Rad/sec

After making sure that the model is producing reasonable results, it was time to verify that it produces results consistent with the RPM-WOB stability diagram. The simulation result in Figure 3-9 shows a stable drilling condition except for a transient response in the first few seconds (Figure 3-10), this stable behaviour should be driven into the torsional instability zone by reducing the rotary speed, and into the lateral instability zone by reducing the WOB. Two more simulations were run at 150 KN and 10 Rad/sec (Figure 3-11), and 100 KN and 15 Rad/sec (Figure 3-12).

The results were projected on the stability diagram as illustrated in Figure 3-13, the stable operating point is labeled “1” on the stability diagram and represents drilling at 150 KN and 15 Rad/sec, the point labeled “2” represents an operating point with the same WOB (150 KN) but with lower rotary speed, and the point labeled “3” represents an operating point with the same rotary speed (15 Rad/sec) but lower WOB.

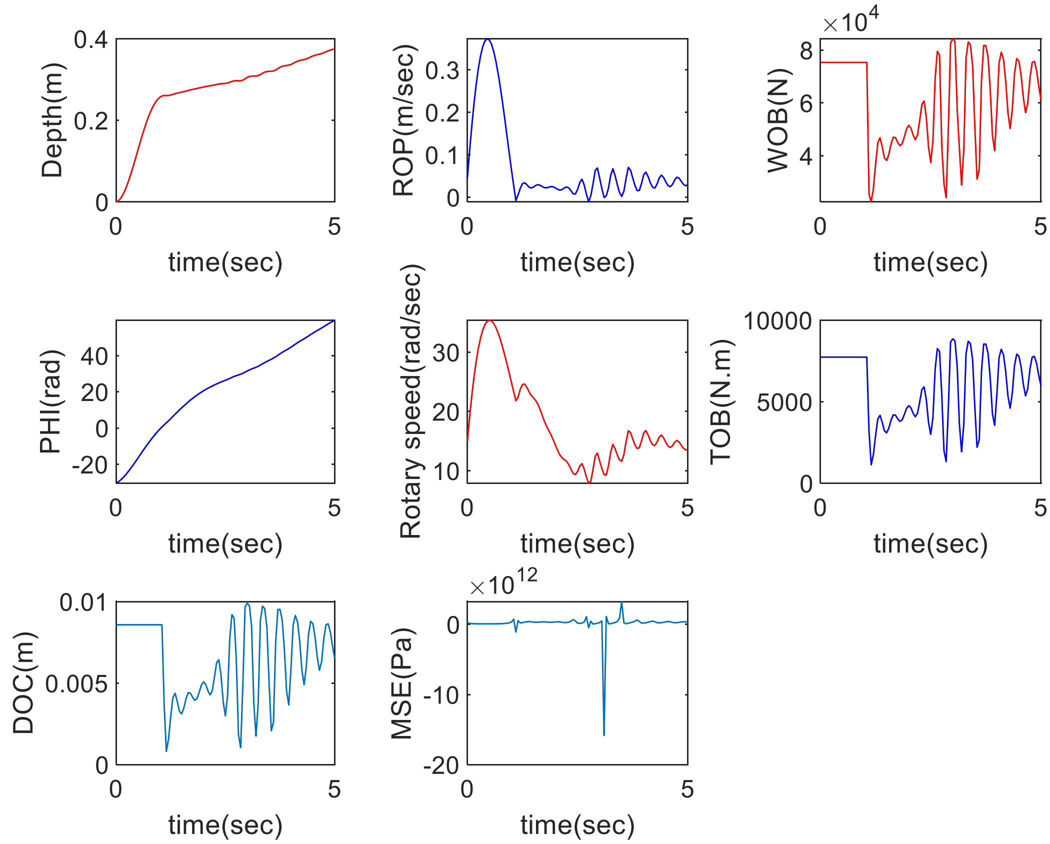

Figure 3-10 Five seconds of Simulation Result with Limited DOC at 150 KN and 15 Rad/sec

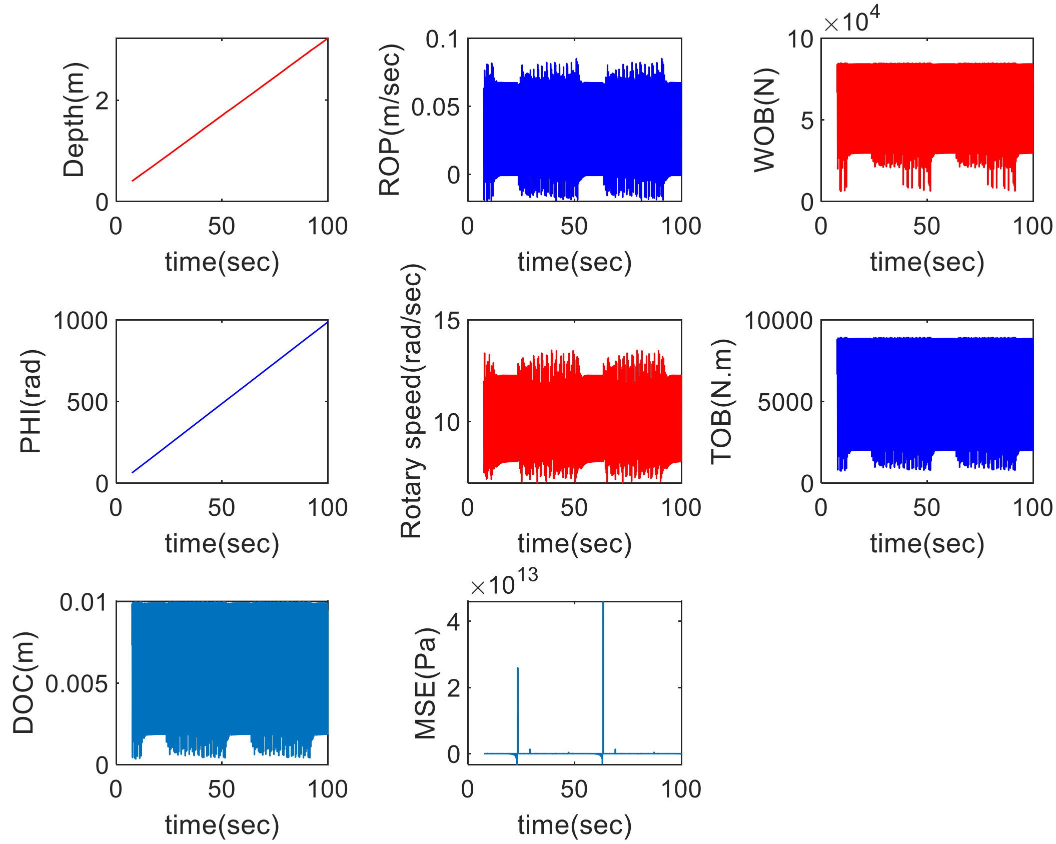

Figure 3-11 Simulation Result with Limited DOC at 150 KN and 10 Rad/sec

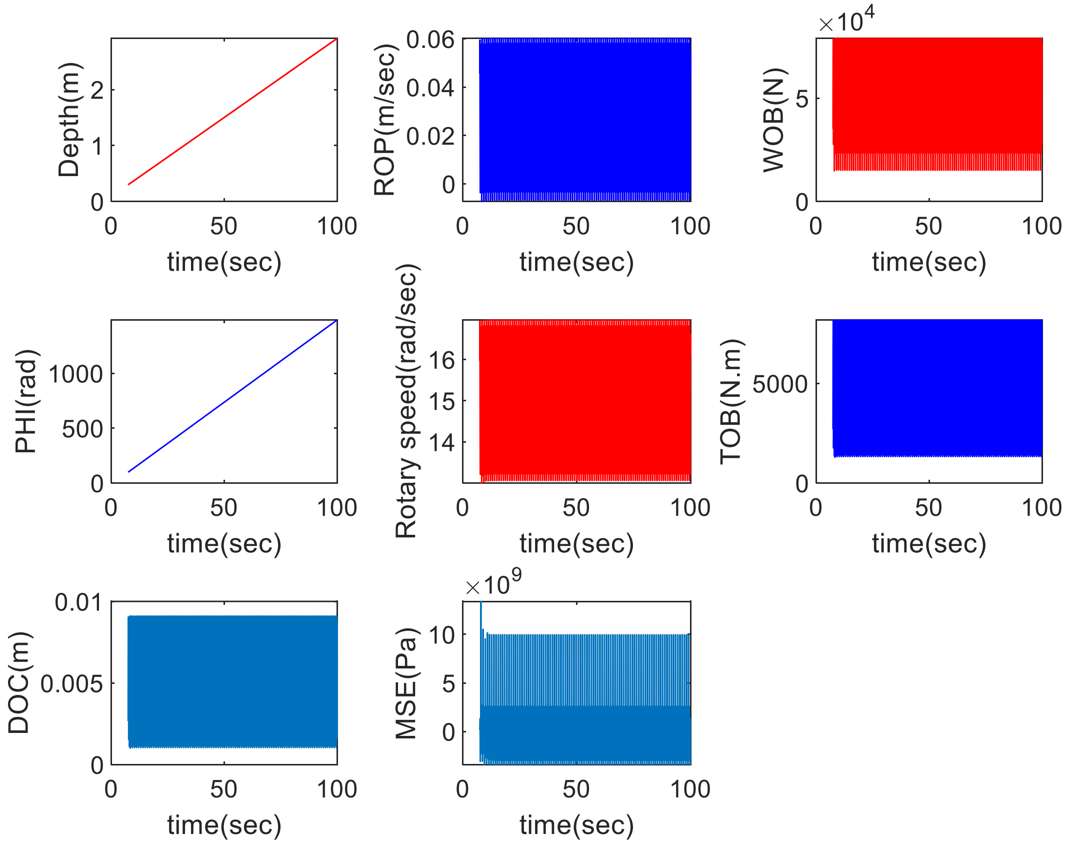

Figure 3-12 Simulation Result with Limited DOC at 100 KN and 15 Rad/sec

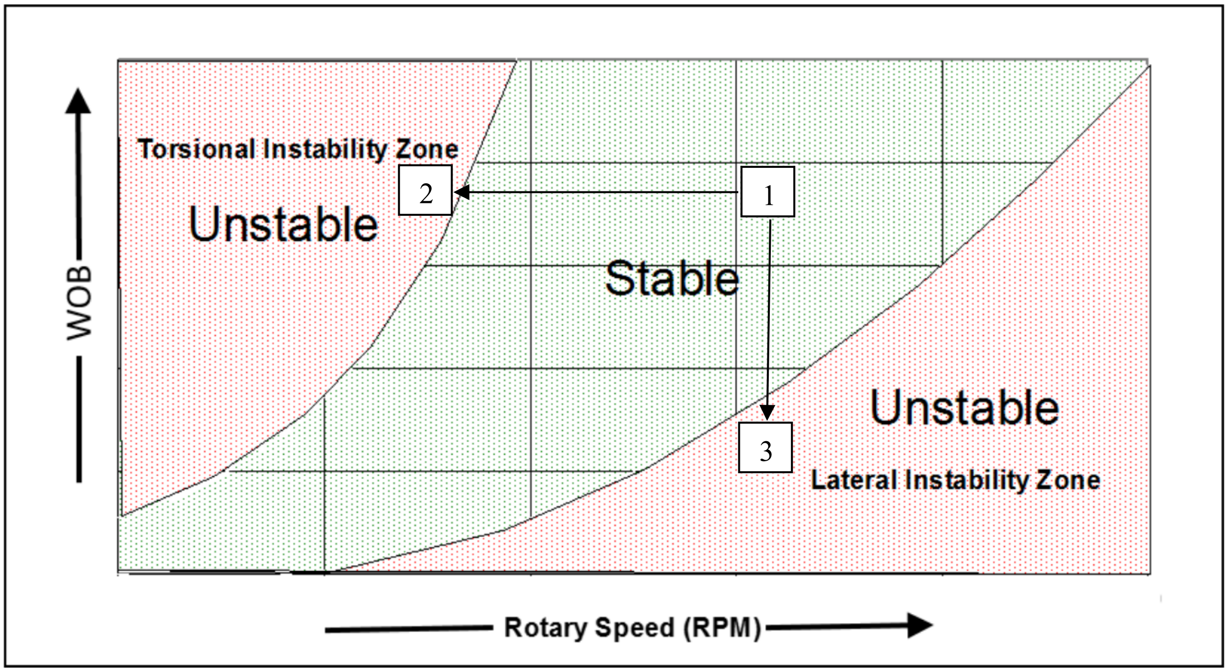

Figure 3-13 operating point projection on stability diagram

The results have shown a reasonable correlation with the expected behavior, and development of the MPC optimization problem was started based on the selected model.

MATLAB MPC Simulation and Results

Formulation of the proposed nonlinear model predictive control (NMPC) based auto-driller using the MATLAB Optimization toolbox was developed following the example in [73]. The controller concept was to have the bit drill to a specified depth. The system output was defined as bit depth, thus allowing all states and inputs to be free for optimization within the set constraints. The cost function consisted of three terms that tracked the depth relative to a given reference, minimized sudden changes in the manipulated variables and minimized the value of MSI. The problem was formulated as shown in Table 3-2.

Table 3-2 problem formulation

Main MPC Problem	Minimize $$J_y(Z_k) = \sum_{j=1}^{n_y}\sum_{i=1}^{p}\left\{\frac{w_{i,j}^{y}}{s_j^{y}}[r_j(k+i\|k) - y_j(k+i\|k)]\right\}^2 + \sum_{j=1}^{n_u}\sum_{i=0}^{p-1}\left\{\frac{w_{i,j}^{\Delta u}}{s_j^{u}}[u_j(k+i\|k) - u_j(k+i-1\|k)]\right\}^2 + \sum_{j=1}^{n_y}\sum_{i=1}^{p}\{MSI(k+i\ \|k)\}$$ With respect to $\dot{X}(1) = X(2)$ $$\dot{X}(2) = \frac{(U(1) - WOB - Ca\ X(2) - Ka\ X(1) + Ka\ V0\ t)}{M}$$ $\dot{X}(3) = X(4)$ $$\dot{X}(4) = \frac{(-TOB - Ct\ X(4) - Kt\ X(3) - Kt\ U(2)\ t)}{I}$$
Input Constraints	$U(2) <$ 20 rad/sec $$U(1) < \text{minimize}\ \frac{4S^2}{\pi\ KWN} + \frac{160\mu S^4 D^3}{K^2 W^3 N}$$ With respect to $$\text{MSE} = \frac{4W}{\pi\ D^2} + \frac{160\mu S^2 D}{KW} < \varepsilon$$
State Constraints	$U\ (1)\ < 0.3\ m/sec$ $U\ (2) < 20\ rad/sec$

Where: $X(1)$ is the bit depth, $X(2)$ is the bit velocity, $X(3)$ is the bit angular position, $X(4)$ is the bit rotary speed, $U(1)$ is the applied weight on bit, $U(2)$ is the applied rotary speed, y is the desired output depth or the first state $X(1)$, u is the manipulated variable, r is the desired reference depth to drill towards, MSI $(k + i\,|k)$ is a representation of MSI expressed in $U\,(1), U\,(2)\ and\ X\,(2)$. Setting the optimization problem as illustrated optimizes the MSI for the whole drill string in the objective function and for the bit alone in the constraints.

The prediction horizon was initially set for the equivalent of five seconds, and the control horizon for half a second. The initial conditions were set to drilling at 100 KN and 10 Rad/sec which is an unstable condition, and the reference point was set to drill 30 meters, equivalent to the length of one stand of drill pipe. MATLAB encountered an error related to high level of nonlinearity and the solver "fmincon" was unable to converge to a solution. Further investigation of the problem showed that NMPC controller from the utilized toolbox uses direct numerical solutions, a technique similar to the single shooting techniques described in [62], whose main drawback was the propagation of non linearity throughout the model making it difficult for the solver to converge on a solution. The simulation parameters were revised to try to reduce nonlinearity. The objective function was simplified to use MSE instead of MSI and the term limiting the rate of change of control variables was removed, the prediction horizon and control horizon were revised to smaller values, and the optimization problem for MSI in the constraints was replaced with static limits. The results are shown in Figure 3-14.

The controller successfully managed to drill as per the given instruction, but the results seem to be counter intuitive considering the formulated problem. As soon as the simulation started the controller raised the WOB to the maximum allowable limit, and decreased the rotary speed, which slows down the ROP, and induces drilling dysfunction. The simulation ran slower than real time, and the MATLAB diagnostics tools showed that most of the processing time was spent on the interpolation function used to adjust the time delay component of the model. Several other simulations, with modifications to the cost function and constraints, were run to try to improve the simulation time and explain the strange behavior leading to the controller's decision to reduce the rotary speed.

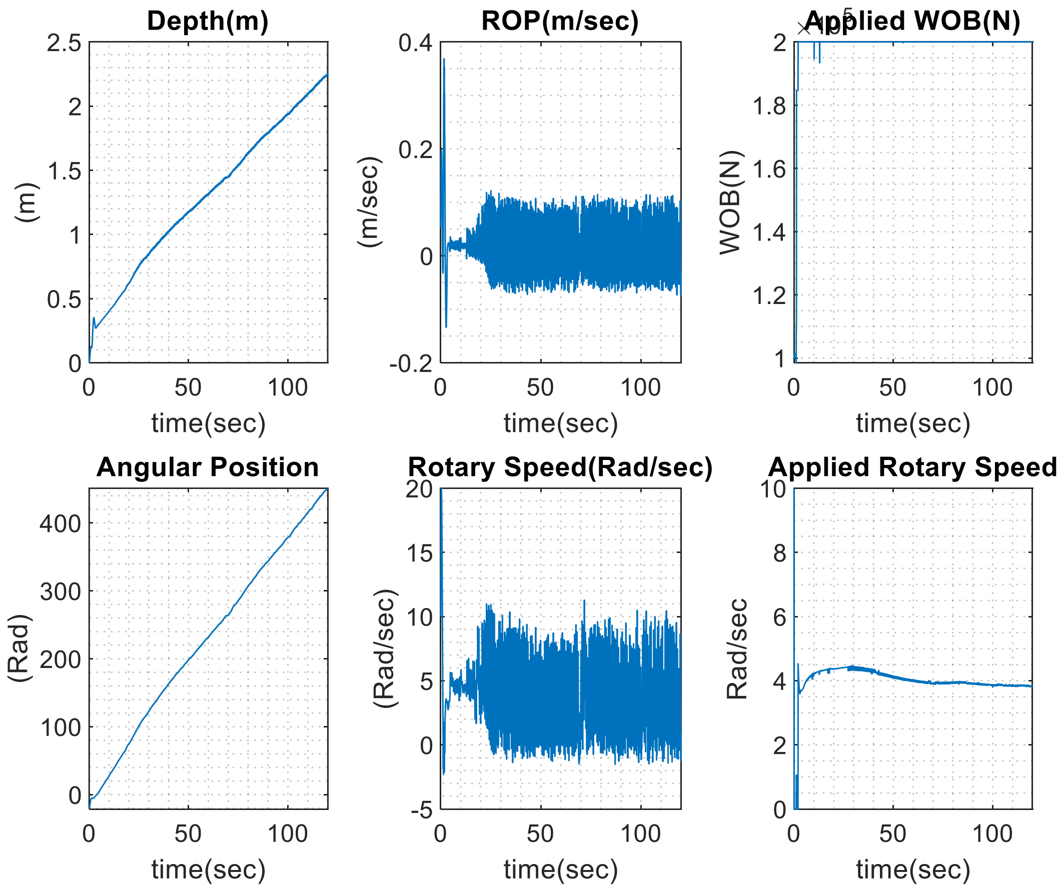

Figure 3-14 MPC simulation result

It was eventually found out that the transient response shown earlier in Figure 3-10 is violating the state constraints in the problem formulation and is causing the controller to reduce the rotary speed to try to uphold the constraint. It was also deduced that the reduced prediction and control horizons are the reason why the controller remains at the reduced rotary speed instead of optimizing for improved performance.

The simulation was repeated without the constraint on the values of the states (Figure 3-15). In this new simulation the same transient response from earlier is still observed but the controller behavior is radically changed. The controller immediately increases both WOB and rotary speed, moving the operating point into the stable zone, and maximizing ROP. There was also a significant improvement of the processing time of the simulation. The simulation ran faster than real time as the number of iterations for solving the optimization problem decreased significantly with the elimination of the drilling dysfunction.

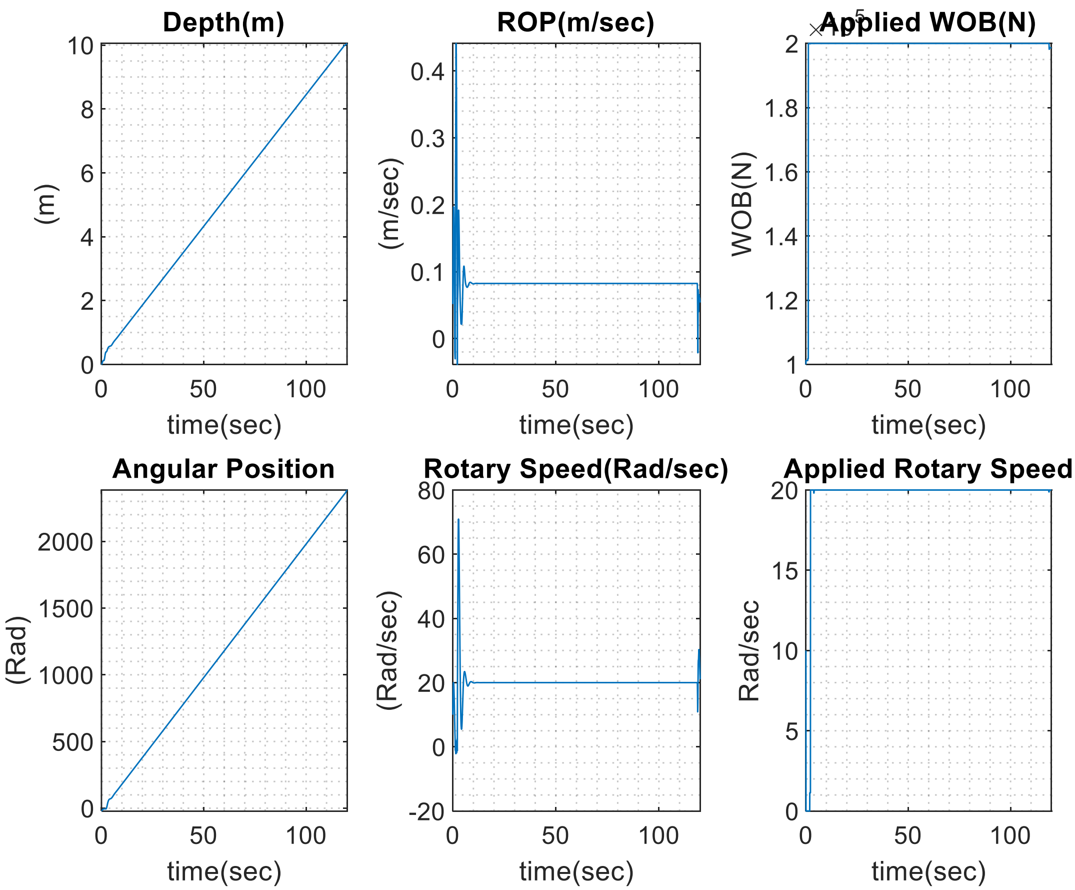

Figure 3-15 MPC Simulation Result

The system was successfully able to drill ahead in a simulation, but there are some limitations due to propagation of nonlinearity through the system. A prediction horizon covering the dynamic response of the system was not used, causing the controller to settle in undesired operating points due to its inability to converge on an optimal solution. This will, under certain conditions, reduce the ability of the auto driller to mitigate undesired vibrations and adapt to changes in the drilling environment. These problems can be overcome by reducing the complexity of the drill string model by converting the model from a DDE, whose solution requires interpolation, and consumed most of the processing time while encountering drilling dysfunction, into ODEs. The Galerkin projections method for converting DDEs to ODE's was recently applied to convert the RGD model into low dimensional approximation ODE model [74]. Combining this low dimensional approximation model with an algorithmic differentiation solver such as "IPOPT" [75], instead of the numerical solver used in the MATLAB Optimization toolbox, and using a different problem formulation method such as multi-shooting or the colocation method [62], compared to the single shooting method will speed up the simulation significantly, and allow for the use of longer prediction and control horizons as well as the use of more complex cost functions and constraints. The conversion into ODE will have the added benefit of turning the time delay terms, and the depth of cut into state variables. This enables the development of more versatile cost functions that can relate directly to down hole reaction forces and depth of cut. A cost function aiming to move the bit ahead while minimizing MSI and its rate of change related to down hole forces, while minimizing the rate of change of the inputs should provide a good drilling response once the nonlinearity problems have been addressed, and a prediction horizon covering the dynamic response of the system is attained.

Conclusions and Future Work

The development of drilling optimization methods has started since drilling for oil started, but the efforts to achieve the goal seem fractured and disorganized. Researchers have worked in different directions: direct correlation, statistical methods, energy monitoring, drill string dynamics analysis, control systems for vibration suppression, remote operations support centers, and drilling advisory and automation systems, but none of these systems takes a holistic approach to the problem. Optimization at the bit rock interface may generate the best set of parameters for the best ROP but that may not necessarily be the best set of parameters for sequestering drill string vibrations and vice versa. The optimal control approach allows for combining most of the optimization methods in a single nonlinear programing problem. The clear advantage of the optimal control approach is its ability to tackle competing objectives using a single optimizable objective function, and a set of constraints that goes with it, thus eliminating the controller tuning problems associated with classical controllers. A model predictive controller-based auto driller was proposed and tested, with the results showing that it can maximize ROP, and mitigate undesirable vibrations simultaneously. However, the system as it stands now suffers from limitations caused by the highly nonlinear nature of the model describing the drilling process. Although the system was able to select an optimal operating point, it is operating with a very limited prediction horizon which is less than the dynamic response time of the drilling system. This would make the MPC unable to converge on an optimal solution for some unstable conditions. This problem can be overcome by simplifying the bit rock interaction term of the model, and using a more efficient numerical technique for solving the optimization problrm.

Once a suitable formulation is established and tested for stability and optimality, experimental trials in a controlled lab setting would take place to further verify the suitability of this technique for field applications. Field applications of this technique will require the development of machine learning applications that can estimate the rock strength ahead of the bit, as well as estimate the friction factors, damping coefficients, and bit wear from real time data. The values predicted by machine learning can be substituted in the model as functions of depth, time, or both depth and time. Once the MPC is perfected it can be deployed to the field. The system should be provided by the required data from rig sensors and historical offset wells to properly tune the model. The MPC will act as a supervisory controller that collects the data and produce an optimum operating point from minimizing the objective function. The optimum operating point can then be fed into rig systems. The formulation can also be used as a planning tool for well engineers to simulate drilling the well based on available geological models and evaluate real time performance by using this simulation as a digital twin.

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Chapter 4 Development and Implementation of a Hardware in the Loop Drilling Simulator

Abstract

Research in drilling optimization has shown that unmitigated vibrations are the root cause of many drilling inefficiency problems. Modeling and simulation of the drilling process has therefore become an essential part of understanding drilling dynamics and optimizing performance. Multiple simulation-based methods have been used to better understand drilling vibrations, and to develop mitigation methods. Most of the models used are simple models that fail to capture bit-rock-fluid interaction accurately enough. Researchers at the Drilling Technology Laboratory at Memorial University have designed and built a hardware-in-the-loop (HIL) drilling simulator aimed to simulate drilling in Deepwater environments. The simulator includes real-time bit-rock-fluid interactions as a physical component of the simulator, thus eliminating the complexity of their modeling from any verification simulation. This paper shows how the novel design of this simulator utilizes a compliant pneumatic system in combination with a stiff high frequency hydraulic actuator, to provide weight on bit to drill a rock sample using the motion profile of a long and flexible drill string, with the added complexity of environmental interaction of a floating drilling rig in a Deepwater environment. The software of the simulator enables the use of any type of model to describe the motion of the drill string, giving it a great deal of flexibility. A description of this simulator hardware, its control system, and operating software are discussed and an overview of the capabilities of the system is demonstrated through simulations and laboratory drilling experiments. Results of the simulations and experiments confirm that the HIL system can simulate the corresponding Drilling Stability Diagram for a long and flexible drill string on a floating drilling unit.

Introduction

Hardware in the loop (HIL) simulators have been a part of the marine, automotive, aerospace, and defense industries for a long time. They have been used to validate systems such as controllers for safety systems and unmanned vehicles when modeling of the process being evaluated becomes overly complicated. A HIL simulator isolates hard-to-model components of a system as physical systems or prototypes. These physical components are then connected with a software model representing the remaining components of the system, rather than having a small-scale physical model of the entire system, which could be very costly, or a complete software model, which could be impractical. This type of simulator maintains a bidirectional or closed-loop information flow between the physical and virtual sub-systems, thus giving a more accurate and cost-effective complete model of the desired process[1].

Damage to downhole equipment and poor performance cost the oil and gas drilling industry millions of dollars every year. Rising costs are even more critical when considering the recent move towards exploring deeper water and environmentally sensitive areas characterized by a small window of time for operations. An average Deepwater mobile offshore drilling unit (MODU) daily operating cost is upwards of one million US dollars. When operations in remote environmentally sensitive areas are considered, the cost per minute for non-productive time (NPT) can quickly add up.

Unmitigated vibrations in bottom hole assemblies (BHA) have been identified as the primary culprit for both tool failure and inefficient drilling. The industry strives to minimize the damage and mitigate vibration by compromising drilling parameters, resulting in lower Rates of Penetration (ROP). A reconciliation that balances both where we get the best of both worlds is required. ROP optimization and vibration control have been recognized as the largest contributors to improving operational efficiencies, reducing NPT, and improving the overall quality of the wells drilled [2].

Having identified unmitigated vibrations as the primary cause of inefficiency, a massive amount of effort has been dedicated to understanding and analyzing drill string dynamics and bit rock interaction. Methods such as the use of Mechanical Specific Energy and its many variants to optimize performance, identify lithology, estimate pore pressure have emerged and met wide acceptance[3]–[6]. Digital-twin based systems for mitigation measures have also been developed [7]–[10]. These systems require further verification prior to evolving them from forecasting simulations to being deployed as control systems that input control actions to rig systems directly. Most of these systems at their core are high fidelity models of drilling systems that have been simplified to run faster than real time to be able to produce predictions of drilling performance. Unfortunately, drill string vibrations are coupled with a very sophisticated boundary condition at the bit-rock interface, with axial, lateral, and torsional vibrations being excited by the cutting, frictional and hydraulic forces present at the bit [11].

Rock penetration cannot be captured using a single model. It requires many models to capture bit-rock-fluid interactions that occur during initial frictional, bit-rock contact, cutter engagement, crack formation and propagation, chip formation, and removal by the circulated drilling fluid. These processes are subject to rock anisotropy, causing behaviors that vary between brittle and visco-plastic deformation, based on the bottom hole pressure and stress state of the rock. It is also subject to the rate at which the generated chips, also called cuttings, are removed from the cutting process. In the field, this occurs by circulating drilling mud, a non-Newtonian fluid that cools, lubricates, and cleans the bit from the drilled cuttings.

This complex coupling has made producing accurate computational models of the process quite problematic. The industry has tried to overcome this modeling difficulty using several approaches: transfer functions, finite element analysis, wave propagation formulations, and normal mode analysis. Meanwhile, simulating the non-Newtonian drilling mud requires the use of computational fluid dynamics (CFD) simulations to be carried out simultaneously with the rock cutting and the drill string dynamics models to produce accurate results [12]–[15].

Extensive effort has therefore been put into modeling these processes and capturing all their aspects. The most reliable methods usually are the numerical methods, such as the Finite Element Method (FEM), Finite Difference Method (FDM), Discrete Element Method (DEM), verified and calibrated with experimental and field data (e.g.[16]–[22]). The most common feature of these methods is their computational intensiveness and difficulty of parameterization.

In an effort to facilitate more complex studies into ROP optimization, vibration mitigation, and automation of the drilling process, the industry has produced a multitude of full-scale drilling simulators. These simulators investigate specific issues that are difficult to produce using numerical simulations, such as the well completion test facility developed in the early 1980's [23]; which is an outstanding example of the initial simulators of this class of simulators. Its design was aimed to gain insight into the factors involved in the downhole equipment failure and its modes. It was capable of investigating thermal loading, internal pressurization, and axial tensioning, and featured a helium leak detection system. Another example of physical simulators is the development of a system that was used to investigate the effect of chip formation and loading patterns using single PDC cutters under atmospheric and hydrostatic pressures [24].

In 2011, the National Energy Technology Laboratory reported the development and use of an Ultra-deep Drilling Simulator. The system was designed to investigate the effects of High Pressure, High Temperature (HPHT) conditions on drilling performance, creating a simulated bottom hole condition. It was equipped with a high-pressure drilling cell that had an x-ray imager and tri-axial load transducers to study the complex non-linear PDC cutter penetration mechanism [18]..

Shortly thereafter, a full-scale laboratory setup capable of recreating downhole conditions for testing of full-size bits was developed. In a published study, the simulator was used to investigate how penetration rates were affected by the composition and properties of drilling fluid [25]. Afterwards in 2022 a drilling simulator was developed to evaluate the steering response of PDC bits. This new simulator utilized an actual size bit to drill directed holes in large limestone blocks. The results were compared to a quasi-static finite element model that utilized a simplified bit-rock interaction model formulated by a single bit steerability parameter [26].

As mentioned earlier, a HIL simulator is a setup that models a process by virtually emulating parts of it in software, and prototypes the remaining parts physically in hardware, while maintaining a bidirectional or closed-loop information flow between these physical and virtual components. This approach constitutes a simulator that captures the best of both worlds, the high fidelity and speed of physical systems minus the prohibitive cost associated with them, and high computational complexity for fully numerical models. These advantages did not go unnoticed by the drilling industry. In 2010 a HIL simulator was used to validate and tune a robust controller that was designed to eliminate stick-slip vibrations by compensating for the effect of drill string compliance and the wellbore contact and geometry [27][28]. Contemporary research into the development of rotary steerable system's trajectory control systems has also made extensive use of physical and HIL simulators, to simulate the complex conditions under which these systems operate [29][30]

Several other studies in the following years have reports of various HIL systems. Those systems were developed to provide genuine training experience, verify that automation systems will perform properly in the field, and develop and test control systems for rotary steerable systems [30]–[36].

Following multiple lines of research that are closely related to optimizing ROP and minimizing the impact of harmful vibration on drilling tools, the team at the Drilling Technology Laboratory at Memorial University of Newfoundland has started working on the conceptual development of an in-house HIL simulator since 2014 [37]. The scope of its development was centered around the capability of accurately reproducing field conditions for validating control and automation systems in the lab environment at a low cost, compared to field trials. In the subsequent sections, the design of the simulator's hardware, and control system is demonstrated. Several verification tests were performed to demonstrate the ability of simulator to reproduce the behaviour of field observed drilling stability diagrams. An example of how the HIL simulation component of the control system works is provided through a distributed systems model of a drill string, implemented using bond graph theory.

The HIL simulator implements a numerical model for the drill string dynamics while relying on a physical drilling rig for the bit-rock-fluid interaction part of the simulation. A wide range of different models with different approaches to drill string geometries and configurations can be used to generate command signals to the physical system based on desired inputs. The physical system has a unique feature that facilitates this HIL simulation, namely the interaction between two sources of axial force (weight on bit), one being a compliant pneumatic system, and the other being a stiff light weight high frequency hydraulic actuator. The response of the bit as measured from the physical system is then fed back into the numerical model, forming the closed loop of information flow shown in Figure 4-1 and Figure 4-2.

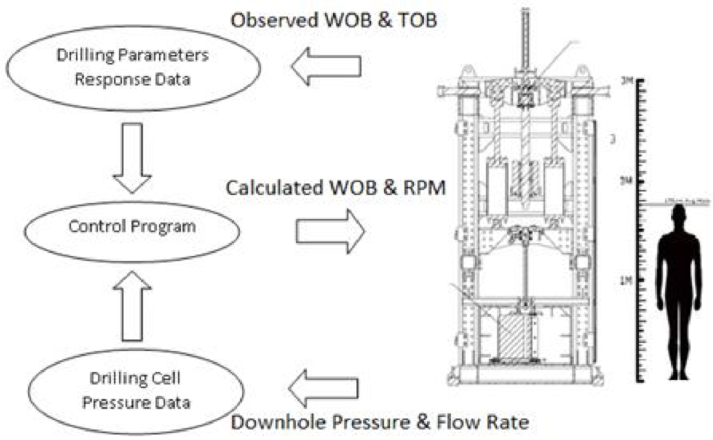

Figure 4-1 Conceptual Development of The Simulator at Memorial University

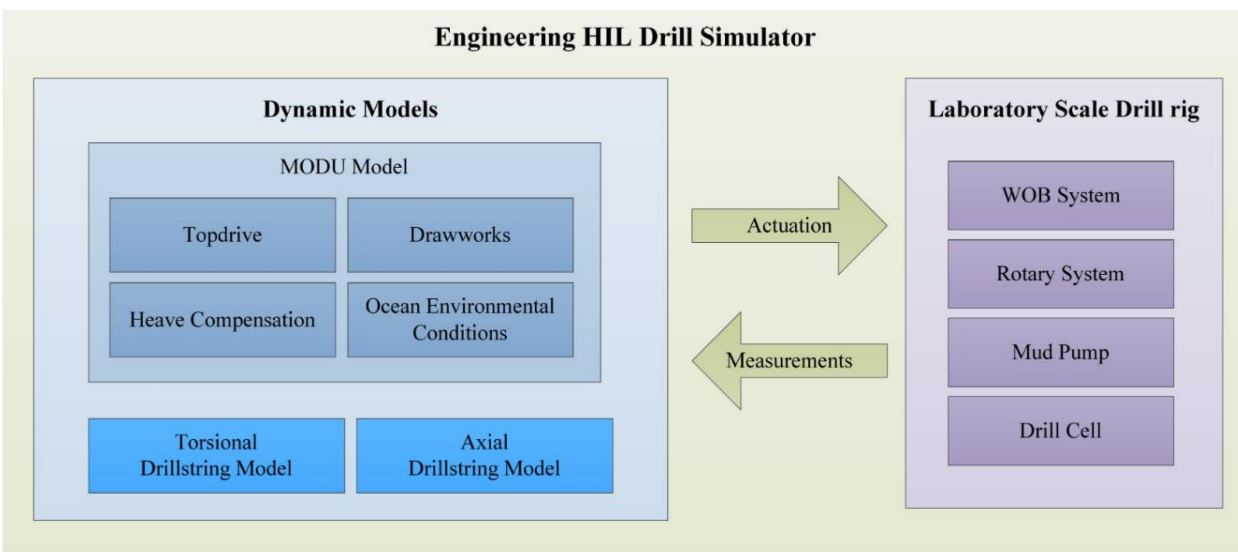

Figure 4-2 Conceptual Development of The Simulator at Memorial University [37]

Mechanical Conception and Design

Drilling Simulator Frame

The physical rig was designed with the intent to study the effects of vibration on drill string stability, drilling efficiency in terms of ROP, bit wear, well control, and the development of control systems for optimizing performance. The range of operating conditions produced by the system was selected to scale with operating conditions encountered in the field. The system is capable of producing axial vibrations up to 100 Hz and torsional vibrations up to 50 Hz. It can accommodate any type of bit up to 4.5 inches in diameter. The basic design, as shown in Figure 4-3 and Figure 4-4, consists of four sub-systems: the axial motion component, rotary motion component, the fluid circulation component, and the high-pressure drill cell.

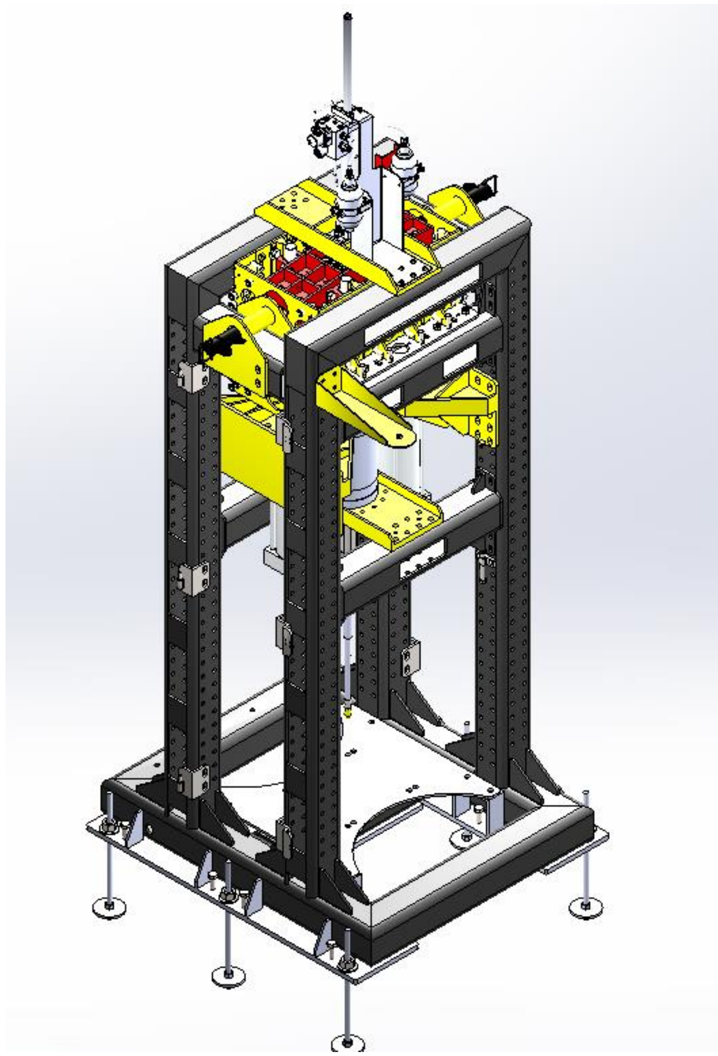

Figure 4-3 Isometric view of the HIL [37]

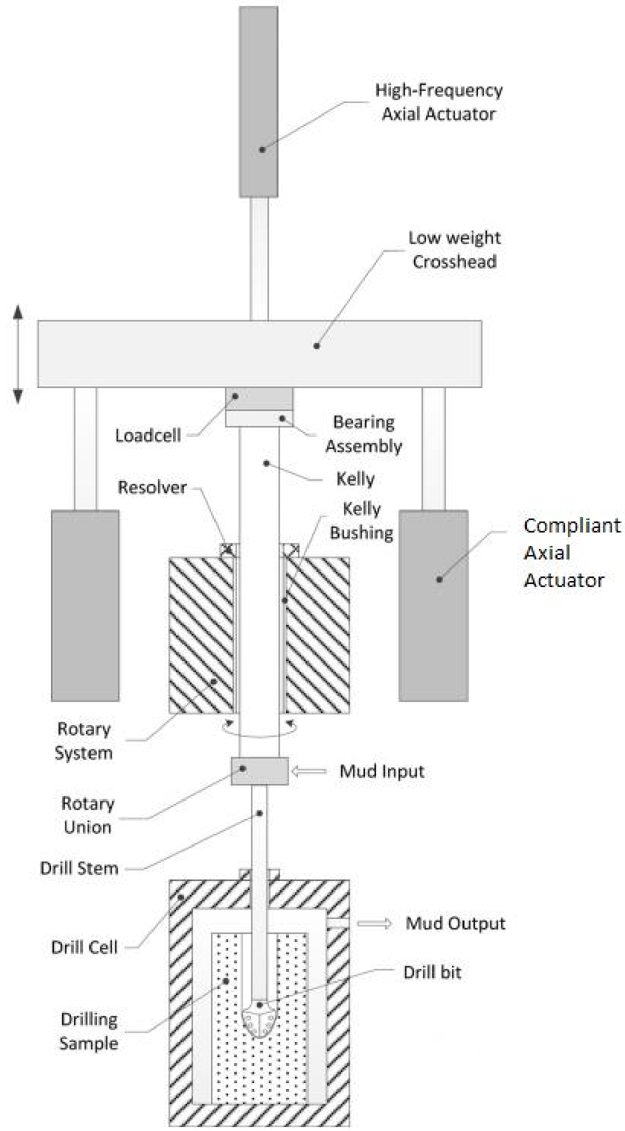

Figure 4-4: Detailed Section of the HIL [37]

The Axial Motion Component

The axial motion system of the rig is responsible for applying Weight on Bit (WOB) and axial vibrations on the bit. The system uses pneumatic and hydraulic cylinders in tandem to produce axial forces. The WOB has two components, a static component produced by the pneumatics, and a high-frequency axial load of up to five hundred kgf at up to 100 Hz supplied by a hydraulic servo actuator. The high-frequency component simulates the action of an actual rig's hoisting system, the dynamics of a long flexible drill string, and the wave interaction with the rig in the case of a floating offshore drilling unit. Both the hydraulics and pneumatics operate in parallel resulting in the hydraulic axial vibration being superimposed on the static WOB applied by the pneumatics. It is also possible to have the pneumatic cylinders pressurized and sealed at a predetermined pressure to function as an air spring that would resist the movement of the hydraulics. The moving bridge connecting pneumatics and hydraulics was specially designed to be strong enough to transmit the required loads yet sufficiently light in order not to impede the high-frequency component provided by the hydraulics. The system employs several sensory systems to provide active feedback. A dual bridge load cell mounted at the top of the drill string, in the junction between the hydraulics and pneumatics, records the exerted force, a magnetostrictive displacement transducer records the bit position, and various pressure transducers are in place to record the applied forces. The system also has the spare capacity to expand its sensors loadout with accelerometers to measure accelerations at specific points of interest and give a more comprehensive data set from experiments.

The Rotary System

The rotary system is intended to mimic a top drive system, which is the most common type found on modern drilling rigs. A 33 KW hollow shaft, high torque, synchronous servo motor, capable of starting with approximately 1200 Nm, and sustaining 560 Nm at 550 RPM, is mounted between the two pneumatic cylinders just below the moving bridge that axially moves the drill string. The drill string is rotated via a spline assembly that goes through the hollow shaft motor (labeled Kelly and Kelly bushing in Figure 4-4). The whole rotary system is controlled using a Variable Frequency Drive (VFD) that can control the rotary speed at one RPM increments up to 1000 RPM, with the ability to impose a torque limiter on the drilling process. The system is equipped with a high-resolution optical encoder that provides an accurate readout of the rotary speed, and the onboard controller on the VFD provides a torque readout based on the electric current driving the motor.

Fluid Circulation System

At the heart of the fluid circulation system is a positive displacement triplex pump with a drive speed controller enabling the user to select a flow rate between 0.5 to 50 USGPM with an increment step of 0.5 USGPM. The pumped fluid goes through a custom-made rotary swivel shown in Figure 4-5. The swivel consists of a rotating inner shaft that serves as the connection between the spline assembly driving the drill string and the drill string itself. The rotating shaft is supported by two sets of bearings and high-pressure rotary seals that seal against a non-rotating housing. The non-rotating housing is held in place by a torque reaction fixture on the body of the drill rig. The torque reaction fixture allows the whole swivel assembly to move axially with the drill string while preventing it from rotating, thus allowing the string to rotate and move axially while the fluid injection port moves axially only.

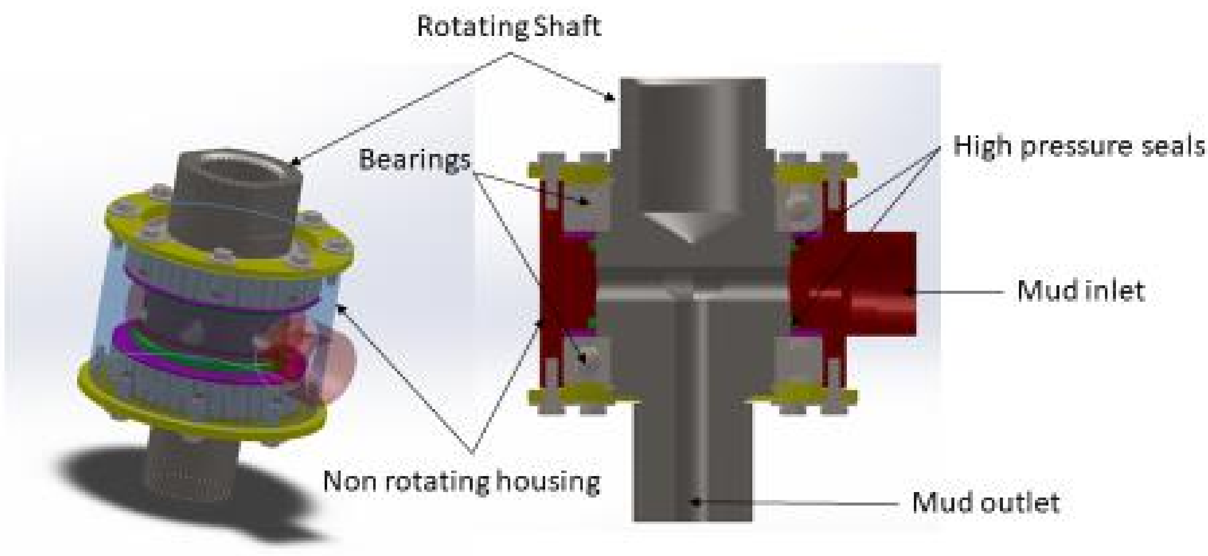

Figure 4-5 Isometric View and Section of the Custom Swivel

High Pressure Drill Cell

The cell is meant to simulate bottom hole differential pressure conditions including the simulation of a gas kick. This is achieved by having a rock sample that has a permeable bottom part and a non-permeable top part held in place in the cell with air pressure being injected from the bottom. As drilling progresses through the sample at the right pressure conditions, the bit will transition from the non-permeable part into the pressurized permeable part, thus inducing a gas kick.

The cell is designed with a rated working pressure of 1000 psi of internal pressure and tested to 1500 psi. The cell consists of a cylindrical container held in place between two caps equipped with high-pressure seals and are held against the cylinder by four struts, as shown in Figure 4-6. The lower cap sealing assembly has an air injection port that is used to simulate gas kicks. A power screw is used to move the caps to position before they are locked in place by tightening the nuts on top of the four struts. Above the top cap assembly, there is a bit housing sealing assembly consisting of a housing and a high-pressure rotary seal. This assembly seals against the drill string while allowing it to freely rotate and move axially. The top part of this assembly is capped by a brass bushing that serves as a wear bushing to prevent damage to the bit housing assembly and the drill string. The assembly also serves as the outlet for drilling fluid and drilled cuttings, with a mud outlet present just below the high-pressure rotary seals. The drill cell is designed to accommodate six-inch diameter, one-foot-long rock samples. The bit housing accommodates any two-inch diameter bit as long as it can fit in the space available between the top of the rock sample and the bottom of the rotary seal assembly.

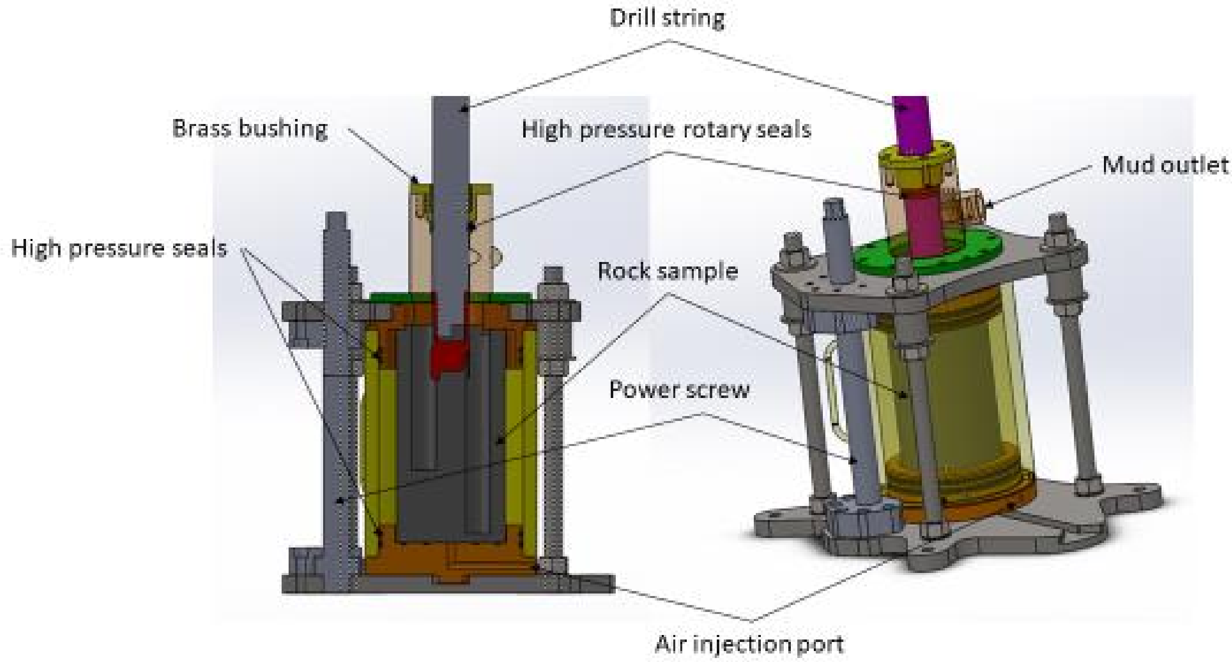

Figure 4-6 Isometric View and Section of the Drill Cell

The outlet of the drill cell delivers the drilling fluid and cuttings to a managed pressure drilling (MPD) style sensor package and control valve manifold as shown in Figure 4-7. The manifold has a pressure sensor to record the outlet pressure, a Coriolis flowmeter to record the mass flow rate and density of return fluid and cuttings mixture, and a conductivity meter to detect the gas percentage. The return flow is throttled by a choke valve that maintains the back pressure and has a pressure relief valve that would bypass the choke valve in case of an overpressure incident. The sensor package runs in parallel with a sensor bypass flow path. The alternate path allows for the return flow to pass through the choke valve only without going through the sensor package so that the sensors can be taken out of the loop if they are not in use to prevent excessive wear by the continuous flow of cuttings.

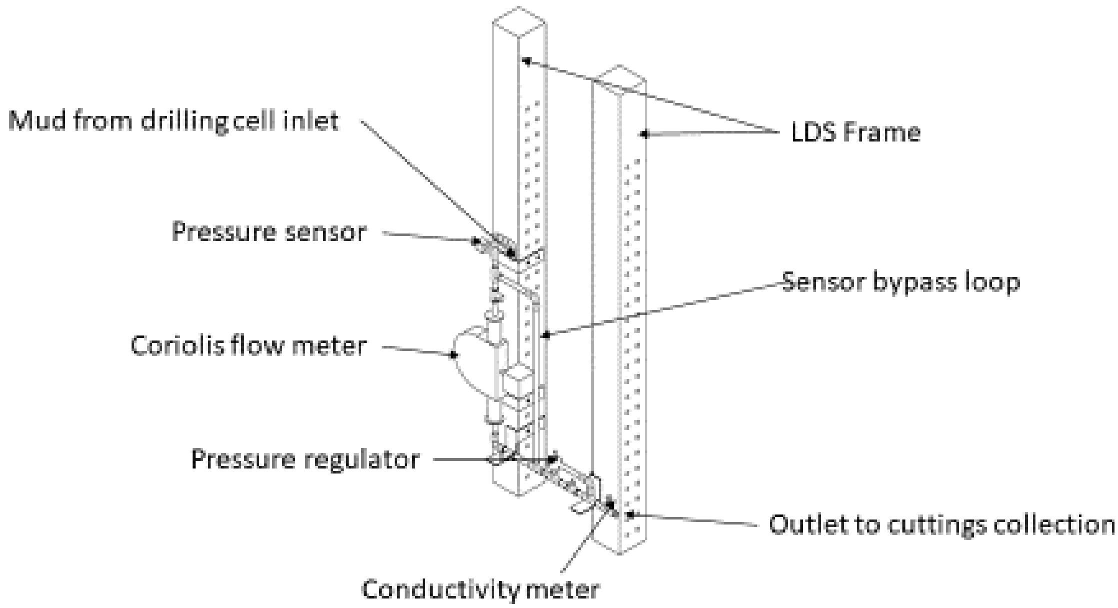

Figure 4-7 MPD Manifold and Sensor Package

Instrumentation and Control

The control system is the heart of the HIL simulator. It controls the rig, runs dynamic models, logs data, serves as the user interface, and most importantly has built-in safety features to prevent harm to the user and equipment from the field scale forces present in the simulations and experiments. The key components of the control system for the HIL simulator are described in Figure 4-8. The control software is distributed between a Real-Time Operating System (RTOS), Field-Programmable Gate Array (FPGA), and a Safety Shutdown System. The control hardware available consisted of a safety PLC unit and a data acquisition system incorporated into the real-time controller/FPGA platform.

The safety shutdown system is designed, to PL_d, ISO-13849 standards. In case of an emergency situations, it is programmed to shut down all facilities to a safe state, thus protecting personnel and the equipment. This system manages all Emergency-Shut-Down (ESD) functions, and it runs in parallel with and overrides the primary real-time operating system.

The control system is designed to provide bidirectional communication and control between a virtual numerical model component and the physical drilling rig. The communication greatly depends on the fidelity, bandwidth, and unobtrusiveness of the simulator's actuators and sensors. The system's sensors were selected to have low inertia and high bandwidth to ensure capturing the system's dynamics without invading them. Real-time deterministic processing of the models for exact time frame matching was also required to maintain the fidelity of the control system. The constraints set stringent requirements on the signal conditioning, digital signal processing, integration routine, and operating system. The control system and user interface were implemented using an NI cRIO control platform with an integrated FGPA backplane dedicated for low-level signal processing and communication with the physical components, running at 10 kHz. The control platform runs on an RTOS to ensure the completion of every integration step within the real-time step, set by the interrupt clock at 5 kHz.

The system is also outfitted with a manual control pendant that allows the user to operate the entire system manually. The pendant is fitted with axial motion controls, rotation controls, and selector switches that would toggle between pneumatic and hydraulic actuation and manual and automatic drilling. The pendant has an emergency stop button as well as a master reset switch that clears all faults. The manual mode is intended to facilitate moving the bit while setting up samples for experiments and to soft start drilling to make sure that the bit is seated correctly in the rock before full drilling parameters are applied.

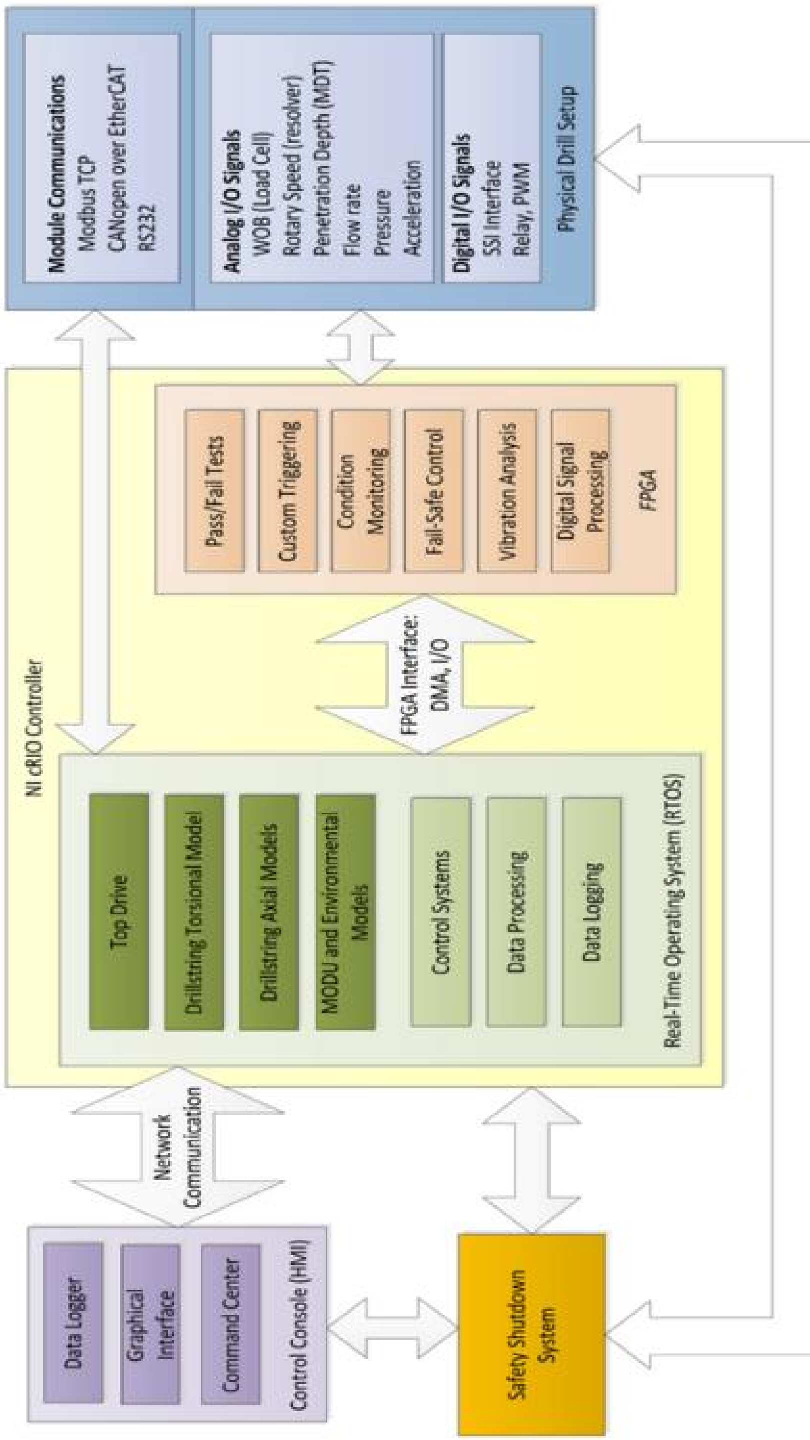

Figure 4-8 Control System Architecture of the HIL[37]

Operating System

The RTOS is implemented in the NI LabView development environment. Two distinct operating systems were developed for the system: i) a real-time user interface, control system and data logger, and ii) a diagnostic tool for troubleshooting and debugging. The diagnostics program was created to confirm that all electrical connections to the various systems were functioning correctly. It consists of a simple data acquisition loop that reads and displays all digital and analog inputs as raw signals (true/ false indicators and voltage readouts). It produces signals for all digital and analog outputs to be measured at the connection ports. The purpose of this program is to ensure that all components have been installed successfully.

Based on the system configuration and the scope of experiments proposed to be performed using the HIL Simulator now named the Large Drilling Simulator (LDS), it was decided to develop the operating system software as a finite state machine. This software configuration enables the user to select a mode of operation that will fit the desired experiment through the control pendant attached to the system. The organization of the state machine, and the control pendant are shown in Figure 4-9. Every state is a dedicated control program that activates the needed sub-systems, logs required sensor data, and maintains the required safety features. The simulation-driven module of the software is a unique component of the system. The simulation-driven module performs simulations on the native LabView environment or a linked MATLAB/Simulink simulation using feedback signals from the sensors. The module then runs the sensor feedback signals with various models to produce a desired motion profile for the drill bit.

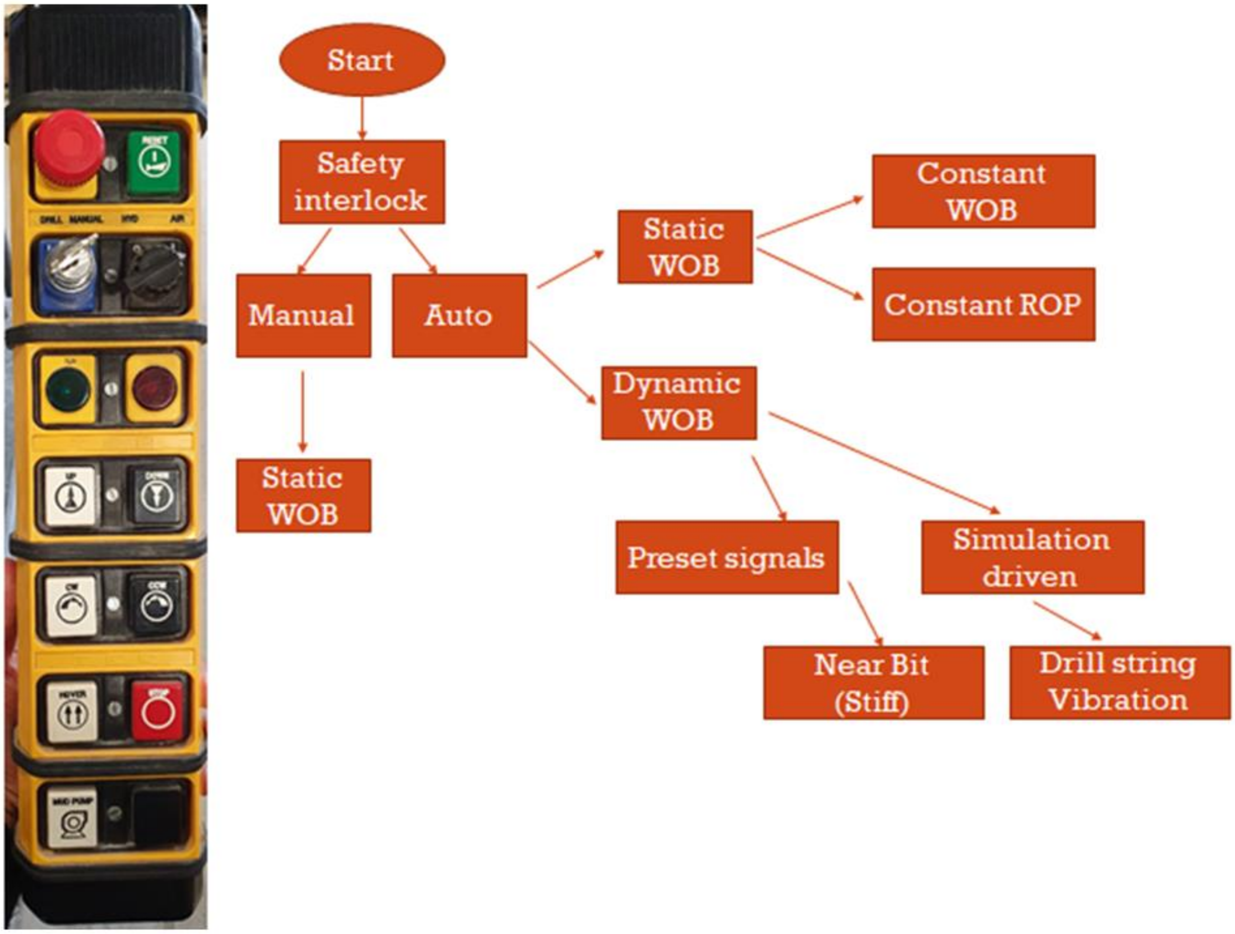

Figure 4-9 Control Pendant (left) and Structure of the Finite State Machine used to develop the RTOS (right)

The operating system is split onto three platforms that run together in synergy to carry out the required functions (Figure 4-10). There is the safety program running on the safety PLC, the main control program running on the c-RIO system, and the user interface, data logging, and communication program running on the computer console. All the systems are connected to a control pendant that serves as the primary control point for the user in the manual operating mode, and for resetting the safety systems in case of a fault. Both the PLC and the cRIO communicate their state to the computer console. The console then passes the required information for each system to operate to its designated recipient.

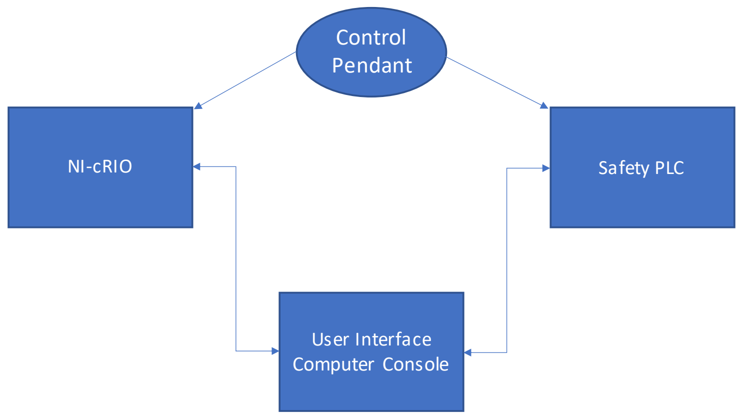

Figure 4-10 The Three Platforms constituting the Operating System

The Safety PLC program

The PLC program is the primary safety control measure. It is a simple Boolean algebra function that validates that the system is safe to operate. It checks that all emergency-stop buttons are in the safe position and that the user has activated the cRIO control system. Once all the inputs are valid, and the user presses the fault reset button on the control pendant for two seconds, the output of the PLC program is then transformed to a set of digital enable signals to the energy sources for the LDS. Since all the emergency control signals are hard-wired in the PLC, as soon as an emergency stop is pressed or the cRIO standby signal is interrupted, the PLC will disconnect power to the LDS, causing the system to shut down in place.

The NI cRIO program

The cRIO program includes the state machine, the user interface, and the data acquisition. The state machine has eleven states, not all of which are operating states. The first state is an initialization state and a secondary safety control measure. It retrieves data from the safety PLC, the manual control pendant, and the control interface, and decides if the system is in a safe state or not. Once the controller and the safety PLC agree that the system is safe to operate, according to the sensor readouts, the program reads the signals from the control pendent and enables the proper state as described in the flowchart depicted in Figure 4-11.

The user interface, as shown in Figure 4-12, was designed to mimic the interface found on a cyber rig. The gauge on the left displays the observed WOB as measured by the load cell. The pneumatically applied WOB and hydraulically applied WOB are as calculated from the pressure readings and cylinder geometry. The gauge on the right displays the torque on bit, while the central gauge shows the block position. Below the gauges are numerical displays showing the same values, in addition to the rotary RPM, and the input fields for desired WOB, RPM, and torque limit. The top row has a readout of the operating state in the state machine and a “Stop All” button that moves the program into the shutdown state. The shutdown state puts the rig in a safe state, vents all pressures, and shuts the system down.

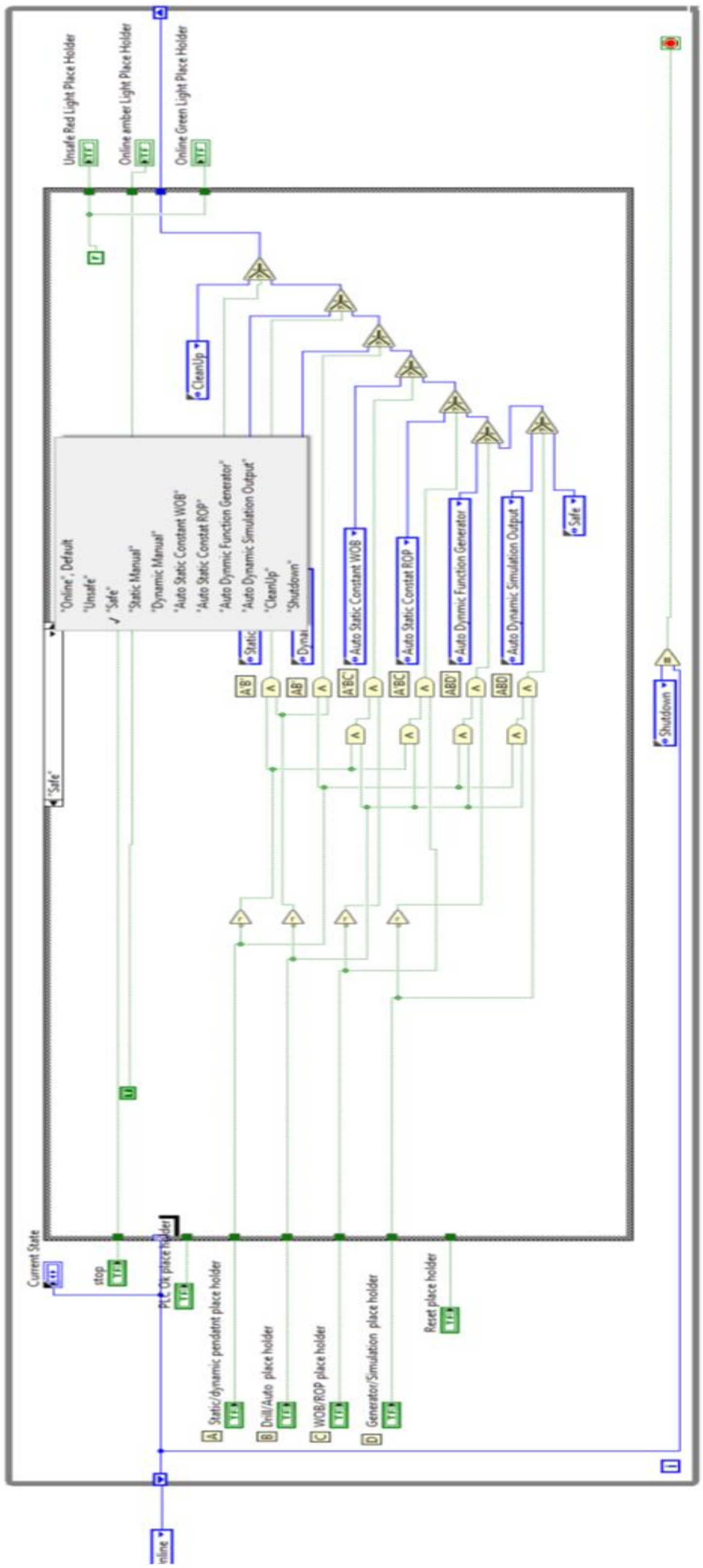

Figure 4-11 Implementation of the State Machine Safety Interlock Logic

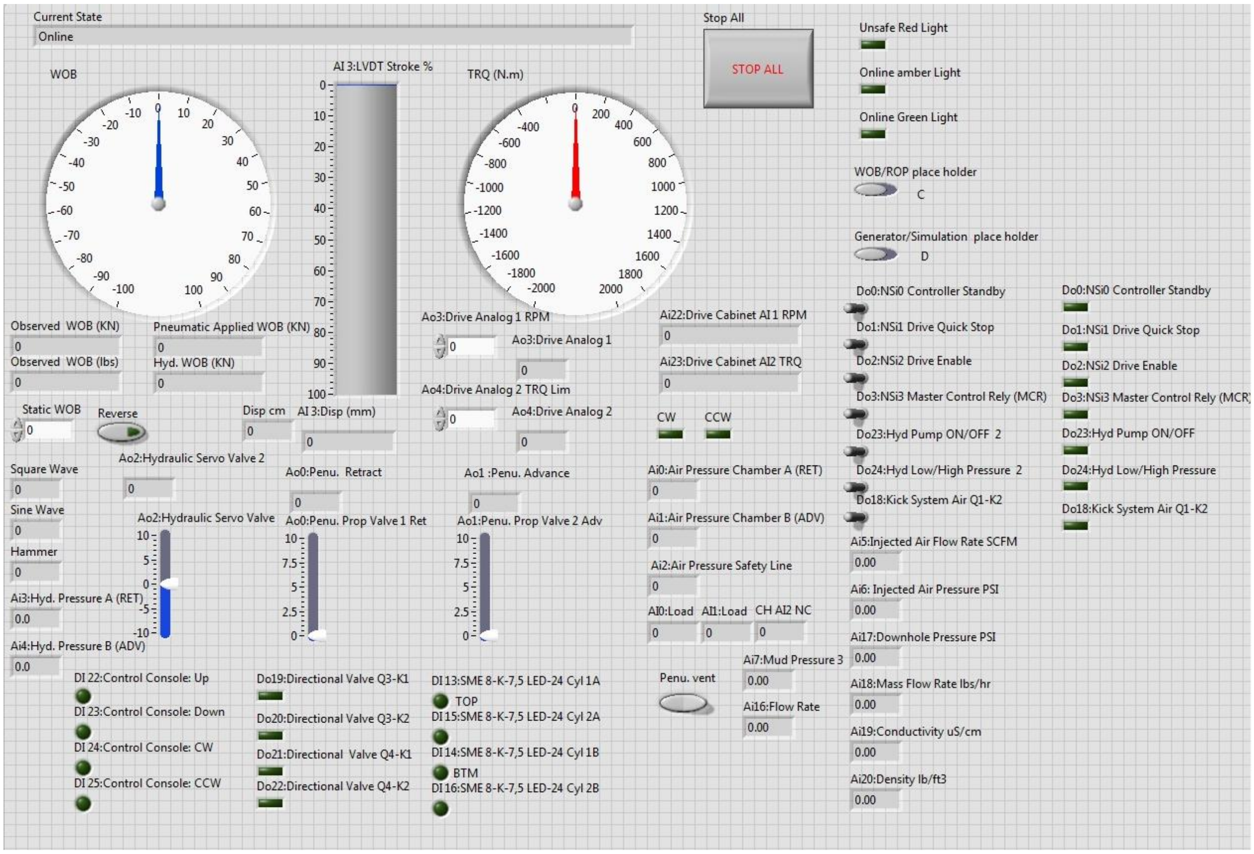

Figure 4-12 LDS user interface

The Computer Console Program

The final component of the operating system is run on the computer console, and it communicates with the safety PLC and cRIO through an ethernet network connection. The program has a signal generator that can create a sine wave, a square wave, and a hammer blow (a very narrow high amplitude positive cycle square wave) at a wide range of frequencies. These signals are intended to be used as driver signals for the hydraulic axial and rotary systems, to generate a predetermined motion profile. This program also contains a data-logger that records all sensor readouts on demand. A FINS/UDP routine that reads all the PLC readouts and communicates them to the cRIO program. It can also send instructions to the PLC to shut off the power to the system in case of a secondary safety incident or a shutdown.

System Components Verification

Multiple experiments were conducted to ensure the functionality of the system. The first round of experiments consisted mainly of active drill off tests (DOT), where at a constant rotary speed, a fixed WOB is applied for a fixed time, and the ROP is recorded. The test was repeated with two different materials to ensure that the produced data would be consistent with the Maurer model [38]. The materials used were, Concrete blocks that were specially designed by the group to be a rock-like material for drilling experiments, and locally sourced granite blocks that were used as an ultra-hard and abrasive material for wear studies, each drill off test was repeated twice to ensure data repeatability. The results are shown in Figure 4-13 indicating that the drilling behavior is consistent with Maurer's model, showing a close resemblance to a quadratic increase in ROP with the increase in WOB, and that more complex experiments can proceed.

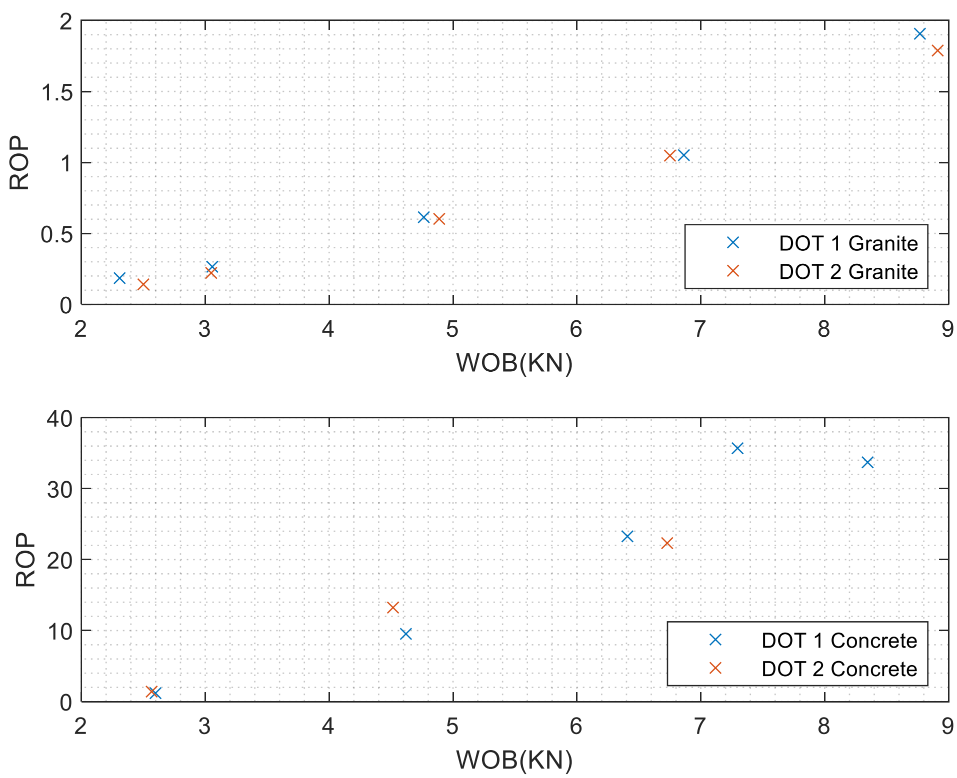

Figure 4-13 Drill Off Test in Concrete

The second round of testing aimed to produce unstable drilling conditions to show drilling dysfunction. A 50 mm bit was rotated at 300 RPM and used to drill through a granite block with a WOB of 4 KN. These conditions created an unstable drilling condition, as observed in the measured WOB shown in Figure 4-14. The measured WOB varied between 1 and 6 KN signifying significant bit bounce compared to the reference value of 4 KN, with a dip in WOB values into the negative region near the end of the test while unloading. The unstable condition is also observed in the highly erratic torque observed while drilling. It is worth noting that no variation is observed in the bit rotary speed since this configuration uses a short, stiff drill string without an input of a simulated long drill string to produce such a variation. Considerable damage was also observed on the bit at the conclusion of the test further confirming the existence of bit bounce (Figure 4-15). The bit was given a dull grading of (1-1-CC-A-X-I-WT-TD) which is consistent with bit bounce damage.

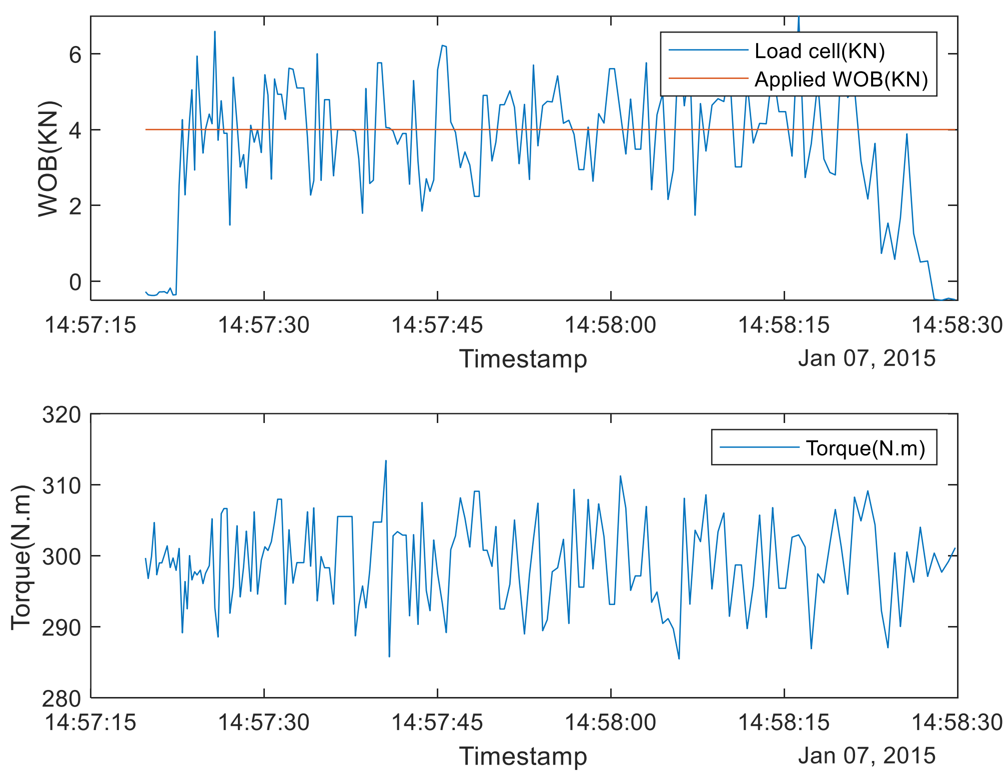

Figure 4-14 Unstable Drilling Condition Testing

Figure 4-15 Bit Damage

The third round of testing was designed to see how well the hydraulic and pneumatic system interacted to simulate rig heave generated by the ocean waves. The pneumatic cylinders were pre-charged to an equilibrium position, and then the hydraulic system was given a command signal to oscillate in a sinusoidal pattern. The hydraulic system successfully compressed the pre-charged gas in the pneumatic cylinders chambers and moved the bit with a sinusoidal pattern as shown in Figure 4-16, thus proving the system capable of superimposing rig heave on any drilling experiment.

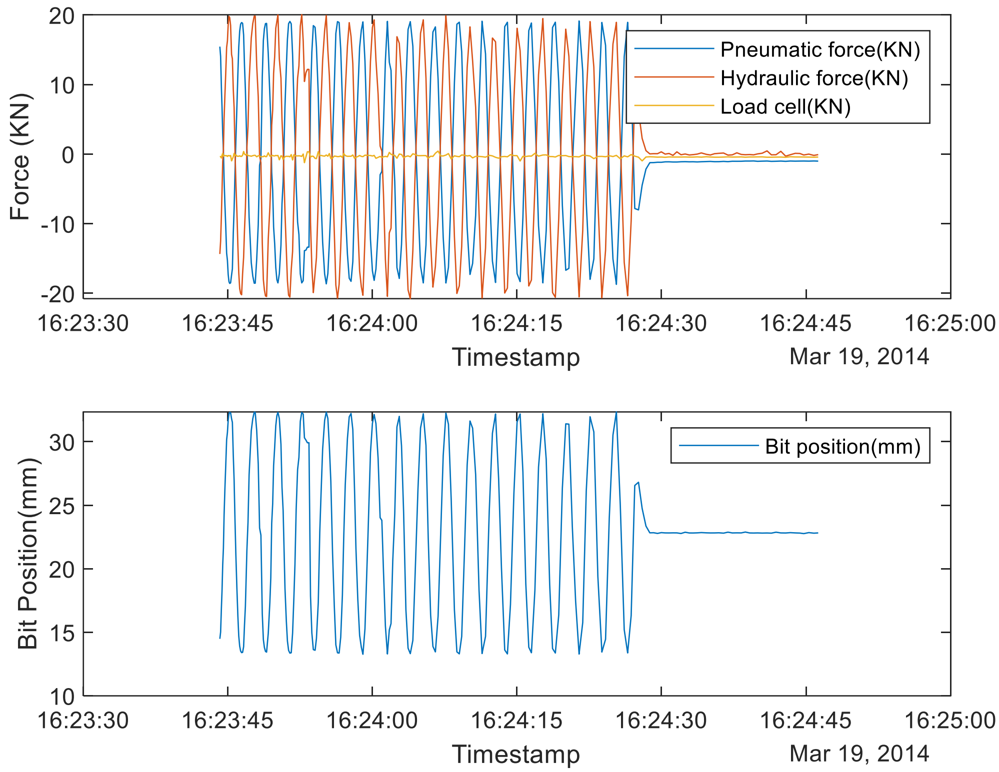

Figure 4-16 Pneumatic Hydraulic Interaction

The fourth round of experiments was to evaluate the MPD system and high-pressure drill cell. The results of these experiments were used to verify enhanced kick detection methods [39], [40].

In this experiment, a concrete cylinder (6-inch diameter by 12-inch height) with a pre-drilled and pressurized air pocket at its bottom is held inside the pressured drilling cell (Figure 4-17). Drilling progressed through the top part of the cylinder until it reached the pressurized zone. The signs of a kick occurring were observed on the user interface and recorded for later analysis. The recorded kick indicators include an increase in downhole pressure, sudden increase, then decrease in mud flow-out rate, drop in the density of the fluid coming out of the cell, decrease in mud conductivity Figure 4-18.

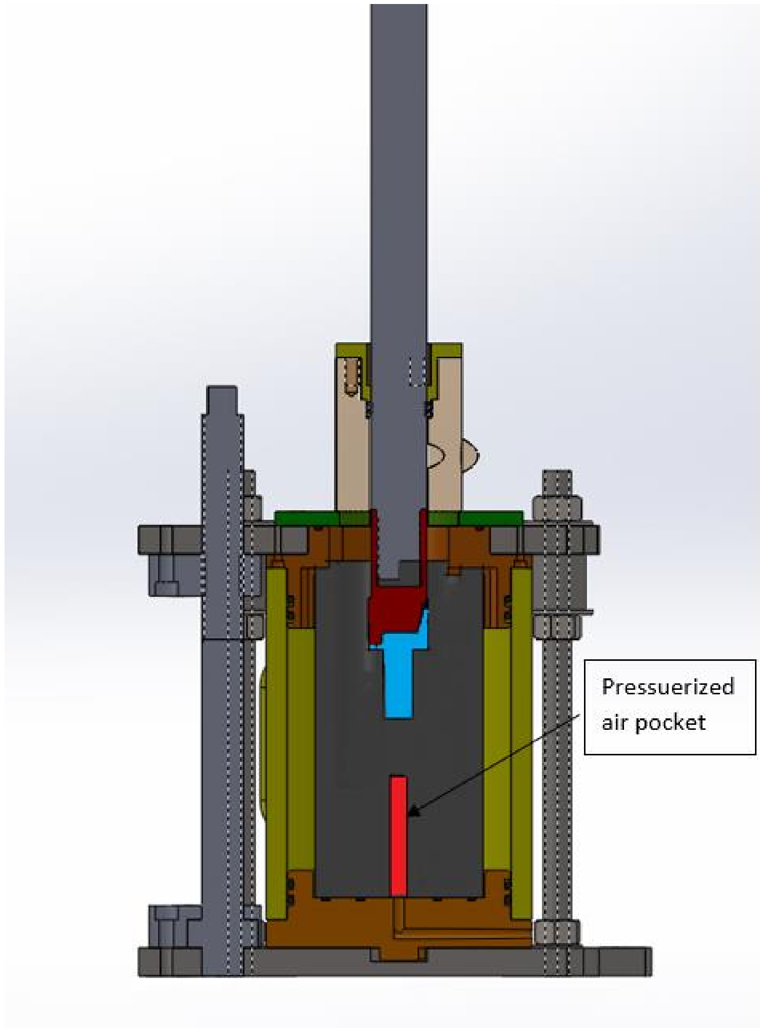

Figure 4-17 Kick Experiment Illustration

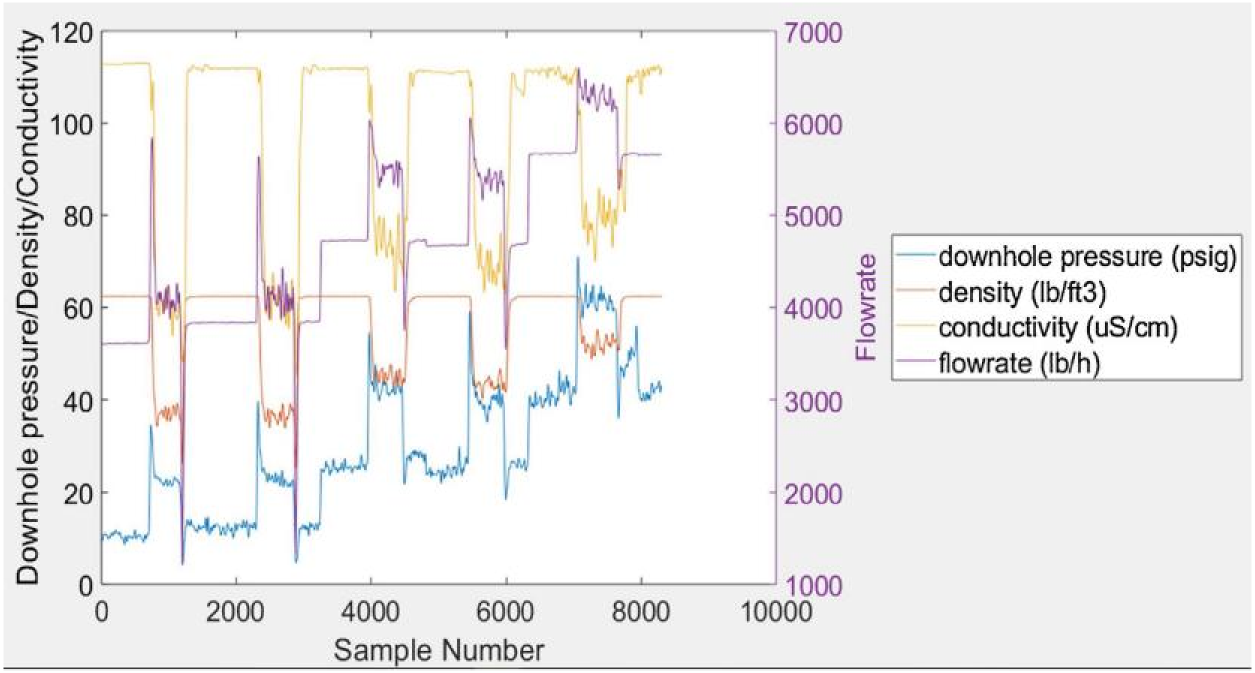

Figure 4-18 Pressure cell recorded data [39]

Dynamic Models and Simulating a Long and Flexible Drill String

The dynamic model is a vital component of the HIL simulator framework. It calculates the response of a long and flexible drill string when it is subjected to the applied drilling parameters and the reaction forces recorded by the simulator's sensors, and then gives the controller inputs that forces the bit behave as if it was connected to the end of the modeled drill string. A bit connected to a long and flexible drill string behaves according to the stability diagram shown in Figure 4-19. The HIL simulation is expected to produce similar behaviour.

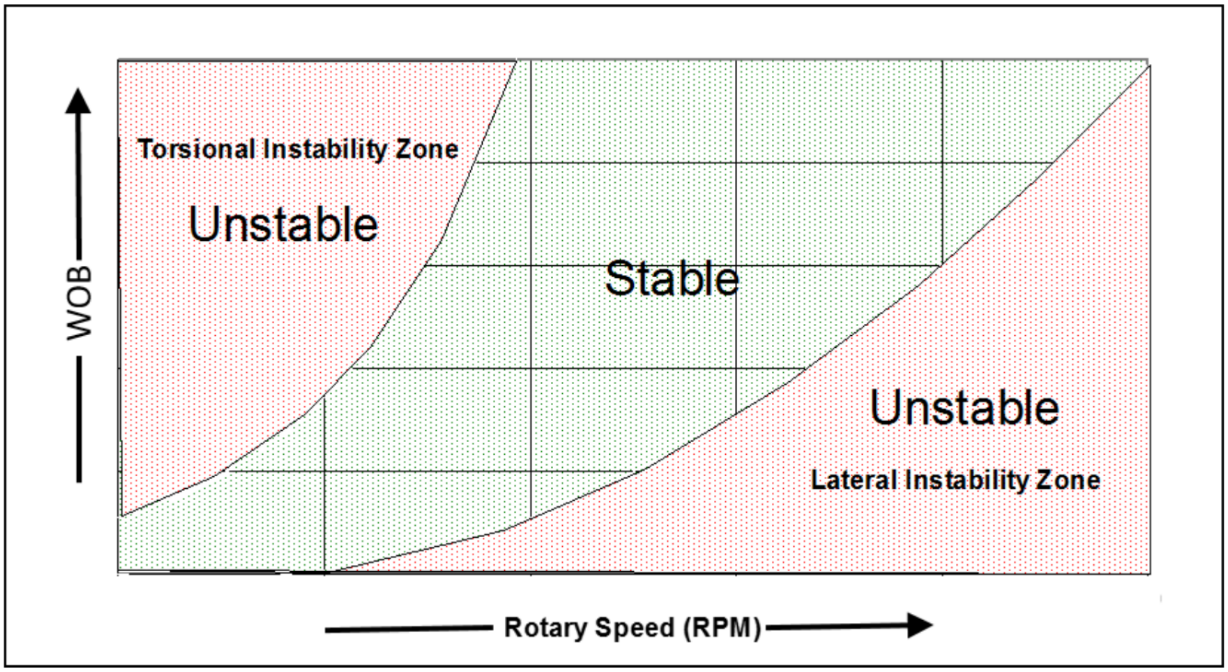

Figure 4-19 RPM-WOB Stability Diagram [41]

Bond graph modeling

Bond graphs are a graphical method of modeling a physical system, which allows for simple derivation of state-space representations of the modeled system. It is considered as a natural progression of a block diagram, except that in a bond graph the arrow linking elements, referred to as bonds, represents the bi-directional flow of power, the flow of power is represented by two variables, flow and effort, and their product is the instantaneous power. The bonds link together bond graph elements which represent, power sources, power storage elements (Inertia & Compliance elements), power dissipation elements (R elements) or power conversion (Transformer, & Gyrator elements) Table 4-1 shows the common elements and their mathematical representation. The relationship between elements is set using the (1) or (0) junctions which can be described as the sum of flows or sum of efforts at a point respectively similar to Kirchhoff's current and voltage laws in electrical systems modeling. Each bond is denoted by two marks, a half arrow to describe the positive direction of flow, and a vertical bar that describes causality which describes the mathematical relationship between the two power variables. The elements can be single ported or multi ported elements to accommodate any level of complexity. Bond graphs were created by Professor Henry

Paynter in the 1950's. He theorized that all physical interactions could be described by energy and power. He developed the first representations of power interaction during his attempt to establish a generalized concept that graphically captured electric circuit diagrams. [42]. Dean Karnopp further developed the bond graph notation in the 1960s by incorporating the operating rules of power direction and causality that are known nowadays [43]. A simple mass spring damper system is modeled into a bond graph as an illustration in Figure 4-20.

Table 4-1 Bond graph elements [44]

Element	Symbol	Constitutive relation (linear relation)	Mechanical example
Resistor	$\vdash\!\rightharpoonup R$ $\rightharpoonup\!\mid R$	$e = Rf$	Damper
Capacitor	$\vdash\!\rightharpoonup C$ $\rightharpoonup\!\mid C$	$e = \frac{q}{C}$	Spring
Inertia	$\rightharpoonup\!\mid I$ $\vdash\!\rightharpoonup I$	$f = \frac{p}{I}$	Mass
Source of Flow	$S_f \vdash\!\rightharpoonup$	$f = f(t)$, given $e(t)$, arbitrary	Prescribed velocity source
Source of Effort	$S_e \rightharpoonup\!\mid$	$e = e(t)$, given $f(t)$, arbitrary	Imposed Force
Transformer	$\vdash\!\overset{1}{\rightharpoonup} TF \vdash\!\overset{2}{\rightharpoonup}$ $\overset{1}{\rightharpoonup}\!\mid TF \overset{2}{\rightharpoonup}\!\mid$	$e_1 = me_2$ $f_2 = mf_1$ $e_2 = e_1/m$ $f_1 = f_2/m$	Rigid lever
Gyrator	$\vdash\!\overset{1}{\rightharpoonup} GY \overset{2}{\rightharpoonup}\!\mid$ $\overset{1}{\rightharpoonup}\!\mid GY \vdash\!\overset{2}{\rightharpoonup}$	$e_1 = rf_2$ $e_2 = rf_1$ $f_2 = e_1/r$ $f_1 = e_2/r$	Gyroscope
1-junction	$e_2 \mid f_2$ $\underset{f_1}{\overset{e_1}{\rightharpoonup\!\mid}}\ \mathbf{1}\ \underset{f_3}{\overset{e_3}{\rightharpoonup\!\mid}}$	$e_1 - e_2 - e_3 = 0$ $f_1 = f_2 = f_3$	Geometric compatibility
0-junction	$e_2 \mid f_2$ $\underset{f_1}{\overset{e_1}{\vdash\!\rightharpoonup}}\ \mathbf{0}\ \underset{f_3}{\overset{e_3}{\rightharpoonup\!\mid}}$	$e_1 = e_2 = e_3$ $f_1 - f_2 - f_3 = 0$	Dynamic equilibrium of forces (Newton's Law)

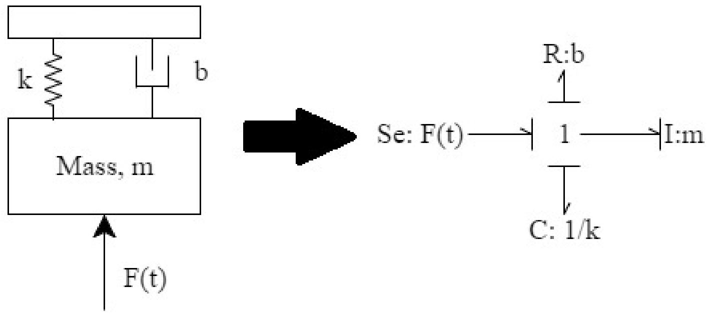

Figure 4-20 Simple mechanical system bond graph model

Bond Graph Modeling of the Drill String

Following the modelling method proposed in the original HIL simulator proof of concept paper [37], which planned the use of a simple coupled drill string model to drive the simulation, based on the bond graph models developed by Sarker et al [45], [46]. These models were constructed following the conventions for distributed parameter systems, and state space equations formulation and reduction described by Dean Karnopp et al [44], and had the ability to expand or reduce model complexity as desired.

The drill string consists of drill pipes, heavyweight pipes, drill collars, and several other accessories such as jars and stabilizers. Drilling fluid, usually a non-Newtonian shear-thinning fluid, is being circulated through the pipe and up the annular space between the pipe and the walls of the well. The majority of the drill string is under tension, except for a small segment of drill collars above the bit. This section is usually referred to as the bottom hole assembly (BHA). The point of transition from tension to compression is called the neutral point. The position of this neutral point in the BHA, and consequently, the weight on bit (WOB), is determined by the driller, by controlling the movement speed of the traveling block from which the drill string is suspended. The string is also rotated usually by a top drive system and swivel suspended from the traveling block just above the drill string. The drill string can be modeled as a set of axial mass, spring, and dampers, and a set of rotary inertias, springs, and dampers, coupled together by a bit rock interaction model as seen in Figure 4-21.

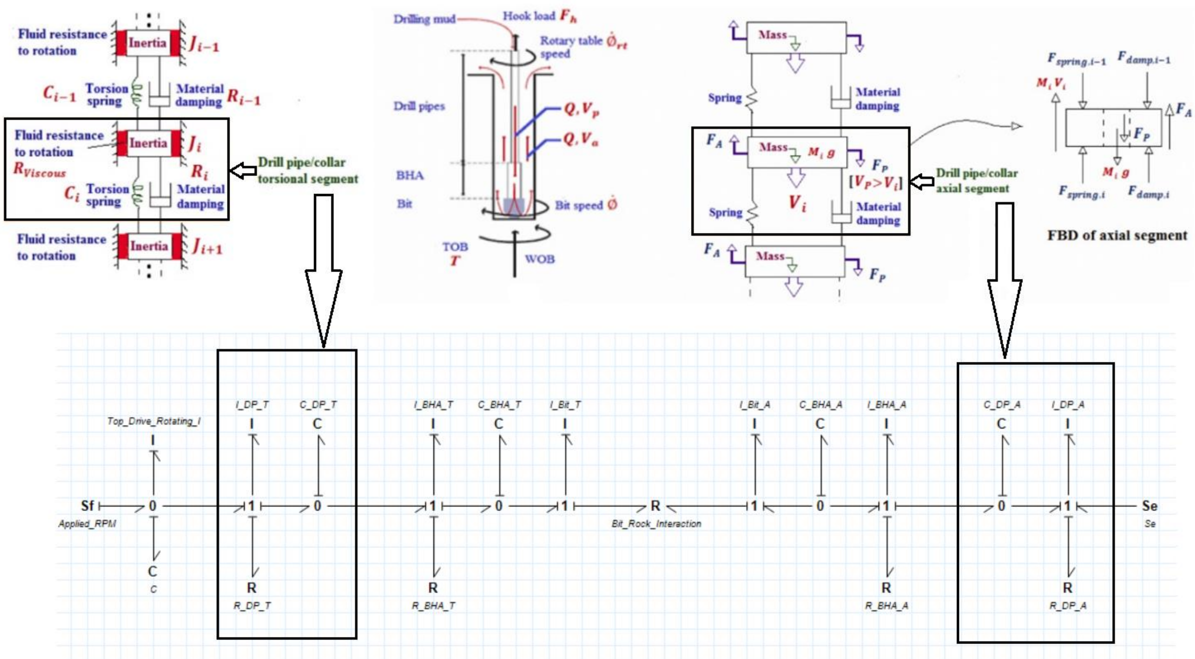

Figure 4-21 Simple Drill String Bond Graph Model

The model consists of two branches connected by a bit-rock interaction model. The right branch is the axial model consisting of linear masses dampers and stiffnesses, and a model of the traveling block as a source of effort. The left branch represents a model of the top drive as a source of flow along with a torsional model of the drill string consisting of rotary inertias, damping, and stiffnesses. The bit-rock interaction model is the complex, computationally demanding, part that would be replaced in this case with the HIL simulator. The replacement of the coupling term with the Hardware effectively splits the model into two separate models that process the inputs (desired WOB and bit rotary speed) provided to the simulator and produce an axial speed set point for the hydraulics component of the axial system, and rotary speed set point for the rotary system as shown in Figure 4-22.

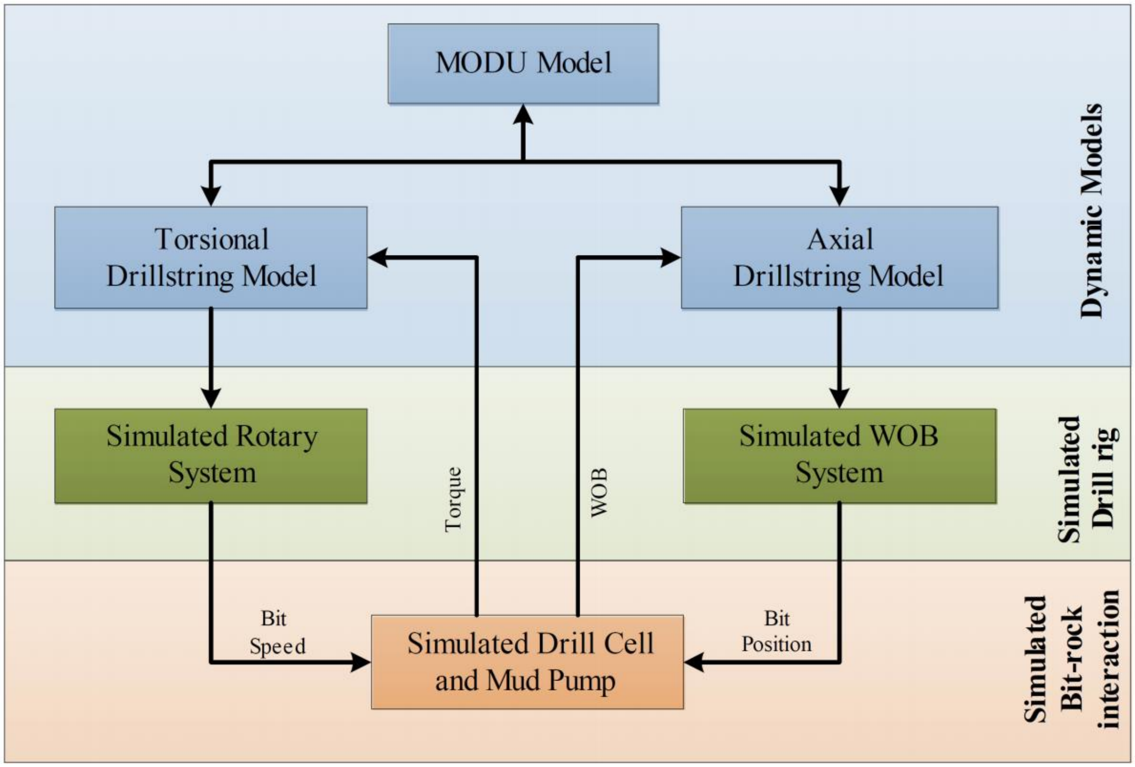

Figure 4-22 HIL Drill String Model [37]

Design of Bond Graph Models for use with the HIL Simulator

Since the axial and torsional models are quite similar, an example axial model will be illustrated here. The HIL simulator utilizes a set of drill rods to turn the drill bits connected to it. The smallest sized rod reserved for 2-inch drill bits is 50 mm in diameter, with an internal diameter of 10 mm. This drill rod will be used as the foundation of a basic template model for the simulation driven drill string vibration mode discussed in Figure 4-9, which can be later edited to fit any desired experiment.

Since the self weight of drilling tubulars is the main source of WOB in drilling, buckling is a major concern while designing the model. The maximum WOB to be applied in any experiment running this model must not exceed the WOB generated from the self weight of pipe that would cause buckling. Following the method in [47] a 50 mm steel rod with an inner diameter of 10 mm would buckle under its own weight at a length of 15 meters, limiting the effective WOB to 2.2 KN. The other failure mode of concern that would limit the dimensions of the model is tensile failure due to self weight. For the same dimensions and material, a length of up to twenty kilometers can be reached prior to failure with a safety factor of two.

The number of segments used in the model directly correlates to the accuracy of higher order harmonics of the system's vibrations [44], as well as the run time of the model, since each segment added adds two state variables to the state space of the model. There is a point where we start to get diminishing returns from dividing the model into more segments as we get into higher frequency components that have very little effect on the experimental setup.

For the current example, a five-segment model, with each segment measuring 100 m in length, was generated using 20-Sim as shown in Figure 4-23. Each segment of the model consists of a combination of I, C, and R elements connected by 1 and 0 junctions as illustrated earlier in Figure 4-20 and Figure 4-21. The use of five segments should accurately capture the first two vibration modes which are expected to dominate the motion of the bit. The state space model and Eigen frequencies analysis generated by 20 Sim shown in Figure 4-24 and Figure 4-25. The frequency response of the model shows that the first two frequencies are within the range available by the hydraulic system of the HIL simulator.

The input (u) is the expected hook load, which is a representation of the applied WOB, and the (Bit_Energy_Loss) term represents the WOB observed by the load cell. On the HIL control system's side, the required inputs are provided to the model, the output of this model is the desired axial motion of the bit due to the reaction of a drill string of the modeled length. The controller subtracts the resulting motion produced by the model from the actual motion of the bit, recorded from the MDT sensor, and applies the difference through the hydraulic component of the simulator.

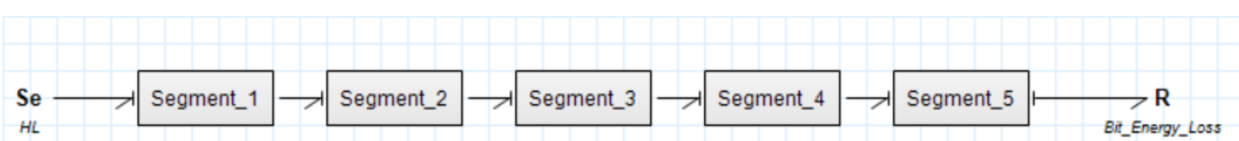

Figure 4-23 Five Segment Axial Model For HIL

```
ẋ = A x + B u
y = C x + D u

Symbolic linear description :
A =
  0.0   1.0 / (rhosteel * Segment_1\I\v)   0.0   -(1.0 / (rhosteel * Segment_2\I\v))   0.0   0.0   0.0   0.0   0.0   0.0
  -(1.0 / Segment_1\C\c)   -(R / (rhosteel * Segment_1\I\v))   0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0
  0.0   0.0   0.0   1.0 / (rhosteel * Segment_2\I\v)   0.0   -(1.0 / (rhosteel * Segment_3\I\v))   0.0   0.0   0.0   0.0
  1.0 / Segment_1\C\c   0.0   -(1.0 / Segment_2\C\c)   -(R / (rhosteel * Segment_2\I\v))   0.0   0.0   0.0   0.0   0.0   0.0
  0.0   0.0   0.0   0.0   0.0   1.0 / (rhosteel * Segment_3\I\v)   0.0   -(1.0 / (rhosteel * Segment_4\I\v))   0.0   0.0
  0.0   0.0   1.0 / Segment_2\C\c   0.0   -(1.0 / Segment_3\C\c)   -(R / (rhosteel * Segment_3\I\v))   0.0   0.0   0.0   0.0
  0.0   0.0   0.0   0.0   0.0   0.0   0.0   1.0 / (rhosteel * Segment_4\I\v)   0.0   -(1.0 / (rhosteel * Segment_5\I\v))
  0.0   0.0   0.0   0.0   1.0 / Segment_3\C\c   0.0   -(1.0 / Segment_4\C\c)   -(R / (rhosteel * Segment_4\I\v))   0.0   0.0
  0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   -((1.0 / Segment_5\C\c) / Bit_Energy_Loss\r)   1.0 / (rhosteel * Segment_5\I\v)
  0.0   0.0   0.0   0.0   0.0   0.0   1.0 / Segment_4\C\c   0.0   -(1.0 / Segment_5\C\c)   -(R / (rhosteel * Segment_5\I\v))

B =
  0.0
  1.0
  0.0
  0.0
  0.0
  0.0
  0.0
  0.0
  0.0
  0.0

C =
  0.0   0.0   0.0   0.0   0.0   0.0   0.0   0.0   (1.0 / Segment_5\C\c) / Bit_Energy_Loss\r   0.0

D =
  0.0

x [1]  =          Segment_1\C\state
x [2]  =          Segment_1\I\state
x [3]  =          Segment_2\C\state
x [4]  =          Segment_2\I\state
x [5]  =          Segment_3\C\state
x [6]  =          Segment_3\I\state
x [7]  =          Segment_4\C\state
x [8]  =          Segment_4\I\state
x [9]  =          Segment_5\C\state
x [10]  =         Segment_5\I\state
ẋ [1]  =          Segment_1\C\p.f
ẋ [2]  =          Segment_1\I\p.e
ẋ [3]  =          Segment_2\C\p.f
ẋ [4]  =          Segment_2\I\p.e
ẋ [5]  =          Segment_3\C\p.f
ẋ [6]  =          Segment_3\I\p.e
ẋ [7]  =          Segment_4\C\p.f
ẋ [8]  =          Segment_4\I\p.e
ẋ [9]  =          Segment_5\C\p.f
ẋ [10]  =         Segment_5\I\p.e
```

Figure 4-24 Symbolic Representation of the Model Generated from 20Sim

frequency {rad/s}	rel.damping	type	kind	Δ gain {dB/dec}	Δ phase {deg}
2.359	1	lag	stable	-20	-90
31.85	0.03704	resonance	stable	-40	-180
60.58	0.01947	resonance	stable	-40	-180
83.38	0.01415	resonance	stable	-40	-180
98.02	0.01203	resonance	stable	-40	-180
3.94e+006	1	lag	stable	-20	-90

system K =	5.714e-005
root-locus K' =	1.321e+017
u =	HL\effort
y =	Bit_Energy_Loss\p.f

Figure 4-25 Eigen Frequencies Analysis Generated From 20 Sim

In order to verify this approach, a rock sample was drilled using the simulator in manual drilling mode, and the observed WOB and bit position were logged. The bit axial velocity was calculated by numerically differentiating the bit position, and the results are shown in Figure 4-26. A synthetic observed WOB signal similar in magnitude and frequency was then applied to the model in 20 Sim to generate axial motion of the modelled bit as shown in Figure 4-27.

Even though both the calculated bit position from the system and the produced by the simulation are noisy, the model successfully generated a motion profile that can be used to drive the hydraulic system and simulate a long and compliant drill string. A similar model is used by the controller to determine the rotary speed of the bit by using the required rotary speed and the measured reaction torque.

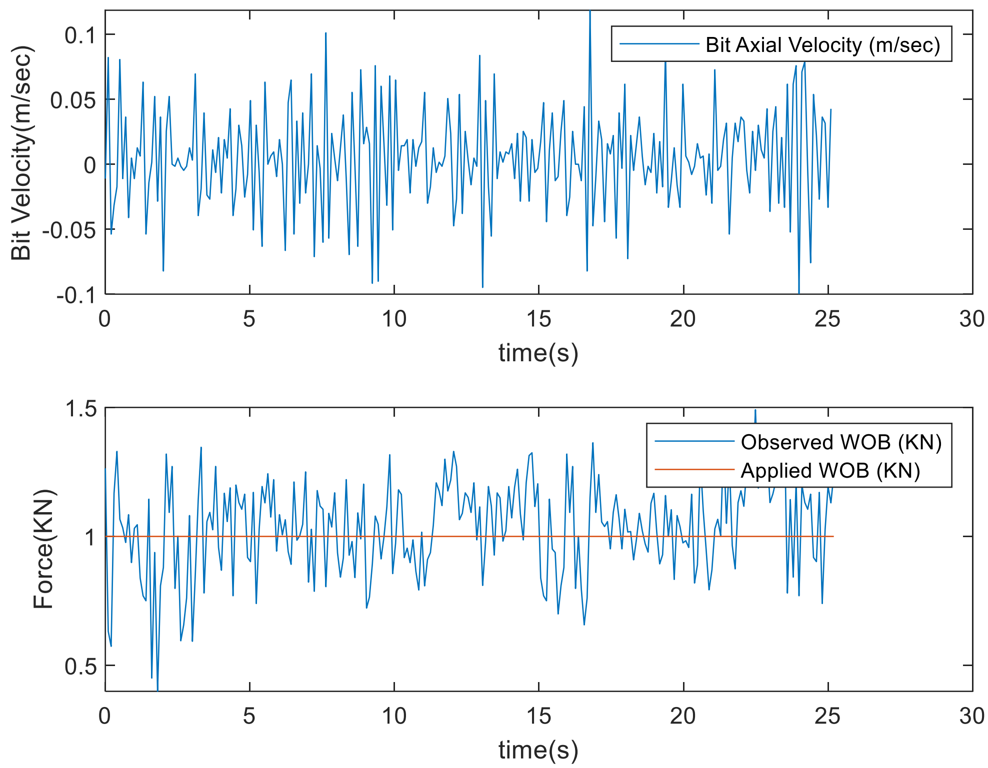

Figure 4-26 LDS Drilling Data

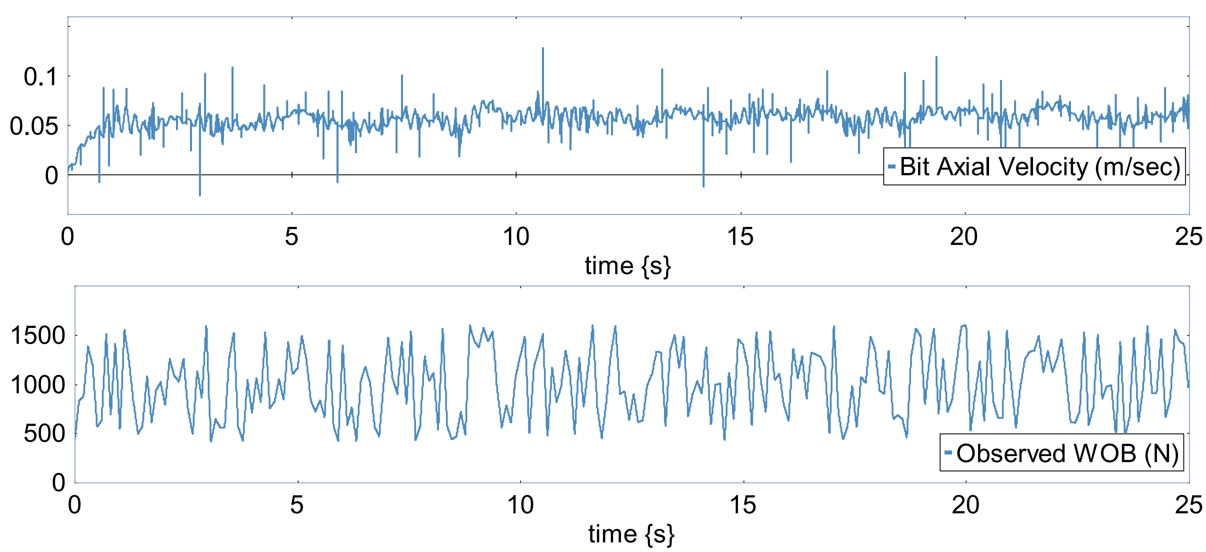

Figure 4-27 Simulation Result with 500 m Long String

A significant amount of noise is observed when differentiating the bit position signal to produce bit axial velocity. This can have a negative impact on the quality of produced bit behaviour. A possible solution is to add an accelerometer to the system and produce bit axial velocity by integrating the produced acceleration signal, which should produce a more stable signal, and both calculated axial velocity signals can be denoised and averaged to get a cleaner axial velocity measurement. The addition of an accelerometer will give the added benefit of a more accurate force measurement. The main method of recording the observed WOB is the dual bridge load cell on the moving carriage between the hydraulic and pneumatic actuators. Recent research suggested that the response of load cells under-predicts the assumed behaviour of the measured phenomenon compared to accelerometers due to their larger inertial mass [48]. The installation of accelerometers before the system can be used for more complex drilling dynamics experiments, will ensure that all the applied forces are being recorded properly from two independent sources.

Conclusions and Future work

A demonstration of the mechanical design and control software of the HIL simulator was presented. The system has a unique design that utilizes two independent sources of weight on bit, a compliant pneumatic system, and a stiff light weight high frequency hydraulic actuator. The two systems work in tandem to enable the simulating a wide range of conditions found on a floating MODU by combining a physical experiment and a high-fidelity model in a single framework. The system is equipped for use as an experimentation platform capable of investigating, drilling efficiency, bit wear, penetration mechanisms, and managed pressure drilling. It also enables the study of the effects of various vibration sources unique to the offshore drilling industry, such as heave-induced vibrations originated from the influence of ocean currents and waves on floating drilling rigs, and bit stability due to the influence of long and flexible drill strings by utilizing a high-fidelity model to produce the desired motion profile. In this paper the capabilities of the system were confirmed by simple experiments, and a distributed parameter systems model implemented using Bond Graph modeling approach was used to demonstrate how the simulator can reproduce the drilling stability diagram of a long and flexible drill string. The system performed as intended during all verification tests. The ability to reproduce the behaviour of drilling stability diagrams in a laboratory environment enables the study and development of drilling optimization and vibration mitigation methods in a cost-effective manner prior to expensive field testing. The staff at the Drilling Technology Laboratory are currently developing a digital twin based automation system [10]. Multiple experiments are currently in development to validate the proposed digital twin approach. The HIL simulations able to reproduce the drilling stability diagram will be used to verify a nouvelle auto driller system that is based on optimal control theory as part of those experiments, and. A wireless accelerometer sensor package designed to be embedded in the drill string above the drill bit is currently being developed as well. This sensor package, coupled with an accelerometer mounted on the moving carriage moved by the hydraulic system, will improve the performance of the HIL simulations performed with the system.

Acknowledgment

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Chapter 5 Bond Graph Modeling of the Hybrid Pneumatic/Hydraulic Axial Motion Component of a Physical Drilling Simulator

Abstract

This paper presents a pseudo-bond graph simulation model of the pneumatic and hydraulic actuating components of an experimental apparatus designed to impose realistic axial inputs to a rock drilling bit for oil and gas exploration or mining. There is a pneumatic actuator, for which air compressibility and heat transfer are included, to generate static weight-on-bit (WOB). Superimposed on the WOB is a dynamic force, generated by a hydraulic actuator, to allow the study of the beneficial effects of vibration-assisted drilling, and/or to capture the effect of the axial vibrations that naturally occur during drilling. The sub-models of hydraulic and pneumatic components are then combined to form a model of the apparatus (the drilling simulator at Memorial University's Drilling Technology Lab). Simulations are then run using the 20 Sim® software, and the results are compared to pressure and displacement sensor readouts from the actual setup. The models, once validated, will be used to design an algorithm to optimize drilling performance.

5.1 Introduction

Millions of dollars are lost annually due to the improper selection of drilling parameters which results in unmitigated vibrations and inefficient drilling. The excessive vibrations cause bits to become dull, resulting in slower drilling rates. They damage down hole tools requiring tripping the string out to replace and repair them. In their effort to improve drilling efficiency, reduce non-productive time, and improve the quality of wells drilled, the industry recognized that vibration control is essential [1]. The industry started producing models that describe rate of penetration as early as 1965 with the introduction of the Maurer perfect cleaning model [2]. To this day it is still very hard to produce a model that describes the drilling process accurately enough to mitigate vibrations. The process is very complex with a collection of nonlinear relations that describe the rock penetration process. Many attempts to model bit rock fluid interaction have been made, with the more reliable approaches usually based on numerical methods calibrated by experimental data. Methods such as the Finite Element analysis method, finite difference method, and discrete element method are the most noted among those [3]. The use of a physical simulator provides the complex nonlinear components in a controlled environment, removing the challenge of modeling or simplifying them. Raymond et al [4] have demonstrated that a laboratory setup can realistically simulate dynamic drill bit behavior. His setup simulated the axial compliance of drill strings with a servo hydraulic actuator that generates bit displacements using a transfer function representing a normal drill string. Different interaction models and vibration modes can be used to recreate any field situation in the lab for further study. The drilling technology lab group at Memorial has developed several bond graph models that represent drill string dynamics in various configurations [5], and bit- rock interaction models [6]. These models are to be used to drive the physical simulator for further studies in drilling dynamics and ROP optimization. This paper describes modeling the axial component of the Memorial University drilling simulator (Figure 5-1) using the bond graph method. This component utilizes both hydraulic and pneumatic components that work in tandem to produce actual bit conditions. The ultimate goal to be reached by further work is to produce a performance optimization algorithm that will minimize energy lost due to undesired vibrations and predict pore pressure in the drilled rock to act as an early kick detection system.

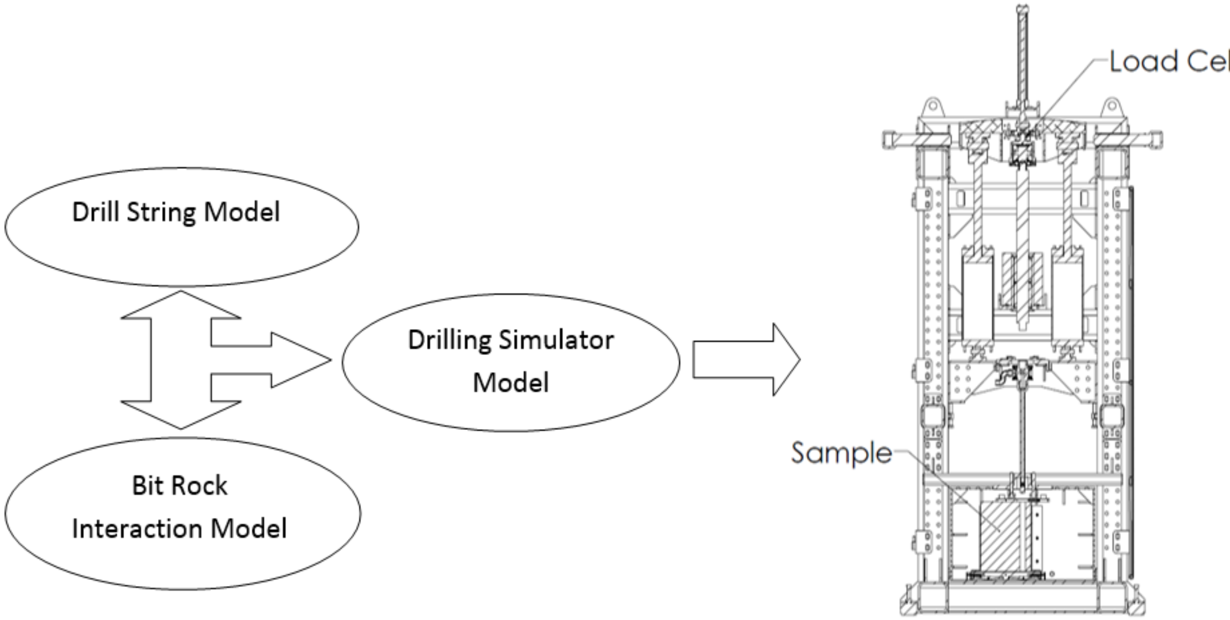

Figure 5-1 Data Flow between Models and Physical Simulator

5.2 The Simulator Setup

The physical simulator system can be divided into two main subsystems (axial and rotary) that are responsible for applying the drilling forces. The rotary system is a 32KW synchronous induction motor controlled by a variable frequency drive that allows for bidirectional speed control with a bidirectional torque limit. The axial motion system, which is the focus of this paper consists of two components. The static component of weight on bit is delivered by two pneumatic double acting cylinders that are supplied with compressed air through two proportional regulators. The weight on bit is determined through the differential pressure between the two proportional regulators outlets. The axial vibrations are supplied through a double acting double rodded hydraulic cylinder. The cylinder direction of motion and travel speed/applied force are controlled through a servo electric 4-way directional control valve. The system contains a mobile bridge connection with the two pneumatic cylinders connected in parallel on one side, and the hydraulic system on the other side. The drill-string is located below the hydraulic cylinder, halfway between the two pneumatic cylinders as shown below in Figure 5-2.

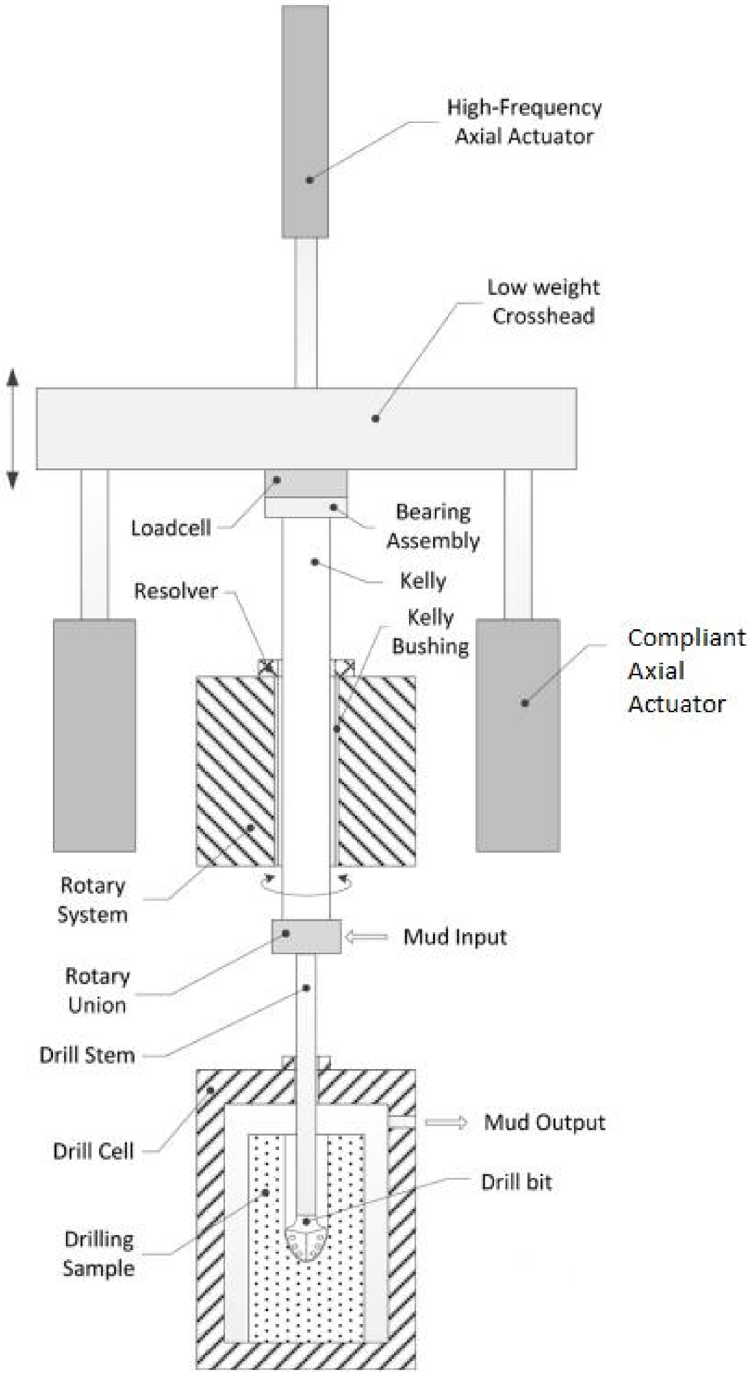

Figure 5-2 Drilling Simulator Cross-Section

Hydraulic Component

The hydraulic circuit consists of a double rodded double acting hydraulic cylinder, a closed–center four-way directional valve, safety valve, and connecting hoses. The components are represented with true bond graphs following Arvani et al [7]. The servo valve is modeled as actuating torque motor block, a servo mechanism, and a nonlinear flow behavior. The nonlinear pressure-flow relation is modeled with modulated R-elements for each valve land, utilizing the equations provided by the manufacturer in the valve's data sheet. The hydraulic cylinder consists of C-elements for each chamber. These capacitors model the oil compressibility in the chambers. R elements are included for friction pressure drop through the hydraulic hoses and the seal friction inside the cylinder. The hydraulic system model shown in Figure 5-3 will be connected in series with the pneumatic model to study the whole system dynamics.

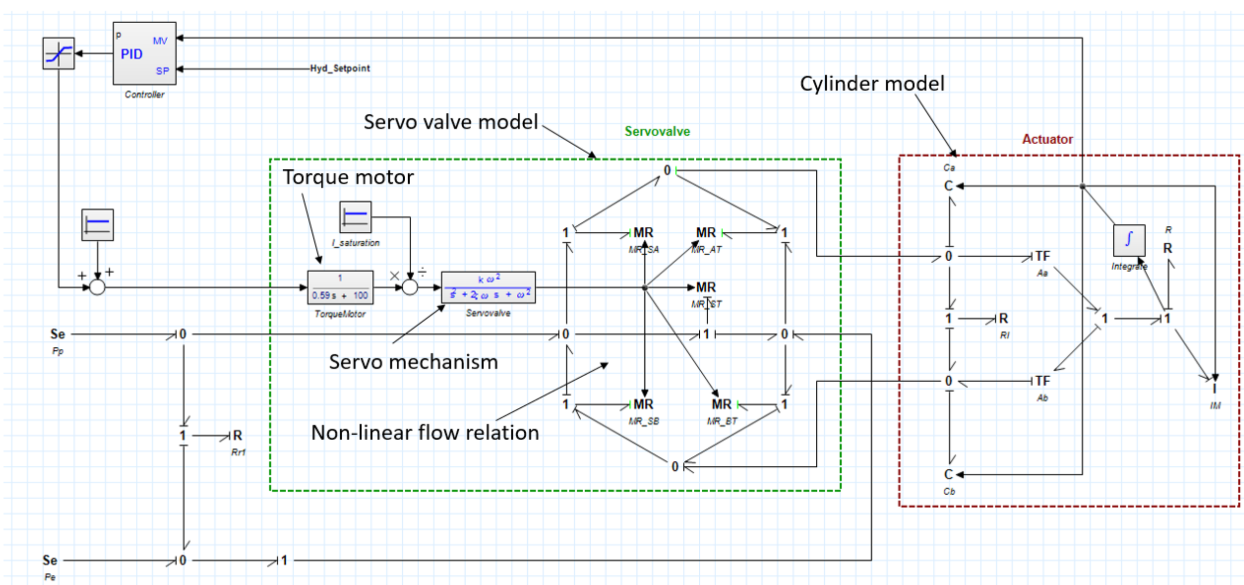

Figure 5-3 Hydraulic system model

Pneumatic Component

Unlike hydraulic fluid systems where the static pressure multiplied by the volume flow rate represented most of the transmitted power, pneumatic systems' operating fluids are compressible and require the use of variable mass control volumes to be accurately modeled. Rochdi et al [8] developed a true bond graph model to describe the process. The true bond graph method models the behavior of the compressible fluids in the actuator chambers by accounting for the change in internal energy as the change in pressure, temperature and chemical potential. The method guarantees energy conservation at the cost of adding more state variables than modeling the process using the pseudo bond graph method.

Rochdi et al [8] and Karnopp [9],[10] et al illustrated that these conditions can be modelled using pseudo bond graphs which differ from the conventional true bond graphs in that the effort variable multiplied by the flow variable does not equal the power flow associated with the bond. Since pseudo bond graphs do not represent power flow, they cannot be attached to true bond graphs. Special ad-hoc elements that satisfy the relations between the new variables on the pseudo bond graph side, with the variables on the true bond graph side of the model. The two pseudo elements that were developed to model pneumatic systems are the thermodynamic accumulator and the thermodynamic restrictor.

The Thermodynamic Accumulator

For a control volume such as the one shown in Figure 5-4where the system contains a mass m and energy E. A stream of gas goes in the system at pressure P_i, absolute temperature T_i, density ρ_i, and volume V_i, and another stream exits the system at pressure P_o, absolute temperature T_o, density ρ_o, and volume V_o.

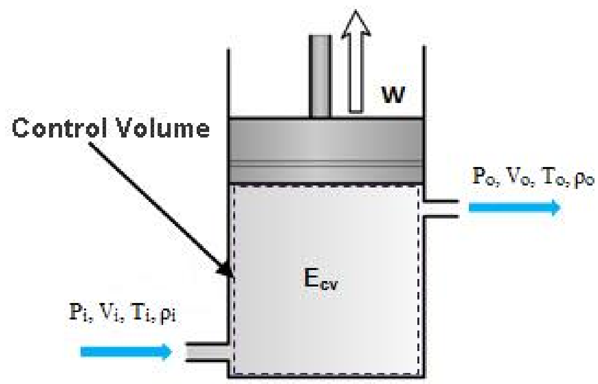

Figure 5-4 Control volume

At any instance in time, mass can be flowing in or out of the system at either port, work done by the gas is indicated by the volume expansion as shown in Figure 5-4. Assuming that the control volume can be represented by a single pressure and temperature and applying the first law of thermodynamics we get the following set of equations.

$$\frac{d}{dt}E = \left(h_i + \frac{v_i^2}{2}\right)\dot{m}_i - \left(h_0 + \frac{v_o^2}{2}\right)\dot{m}_o - p\frac{dV}{dt} \qquad \textit{Eq.1}$$

Where:

E is the internal energy

h is the enthalpy

$\dot{m}$ is the mass flow rate

v is the velocity of the flow

p is the pressure

This relation can be further simplified into the following relations

$$\frac{d}{dt}E = h_i\dot{m}_i - h_o\dot{m}_o - p\frac{dV}{dt}, \quad Eq.2$$

$$\frac{d}{dt}m = \dot{m}_i - \dot{m}_o, \quad Eq.3$$

$$\frac{d}{dt}V = \dot{V}, \quad Eq.4$$

$$E = mc_vT, \quad Eq.5$$

$$pV = mRT. \quad Eq.6$$

Where:

R is the universal gas constant

C_v is the specific heat at constant volume

These equations resemble first order state equations and can be used to construct the 3 port C field shown in Figure 5-5

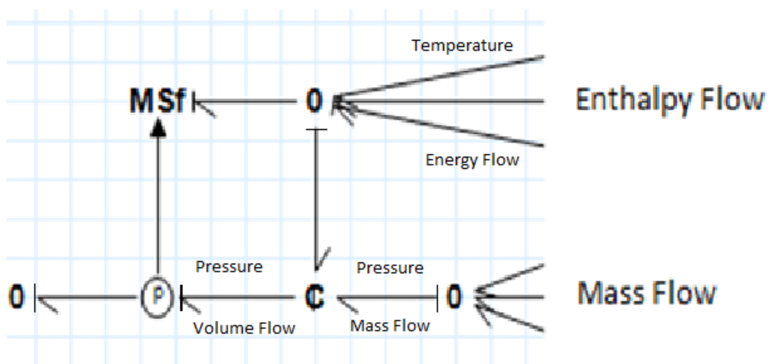

Figure 5-5 Thermodynamic accumulator

This three-port element can be used to link two models – one being a true bond graph and the other a pseudo bond graph – while satisfying all the different requirements on both sides of the model. This element is a core component of modeling any pneumatic system as it describes the flow of a compressible fluid into a variable volume chamber, and yields the pressure, temperature and work done by the fluid

The Thermodynamic Restrictor

The other element required to accurately model the flow of any pneumatic system describes the process of a gas flowing through an isentropic nozzle. Using the same pseudo bond graph variables derived for the thermodynamic accumulator (temperature and energy flow rate, and pressure and mass flow rate) we find that the mass flow rate and consequently the energy flow rate through an isentropic nozzle is a function of nozzle area, upstream pressure and temperature, and the pressure ratio.

$$\dot{m} = A\frac{p_u}{\sqrt{T_u}}\sqrt{\frac{2\gamma}{R(\gamma-1)}}\sqrt{p_r^{2/\gamma} - p_r^{(\gamma+1)/\gamma}}, \qquad \textit{Eq.7}$$

The relation is valid as long as the pressure ratio is larger than the critical pressure ratio

$$p_{r\,\mathrm{crit}} \equiv \left(\frac{2}{\gamma+1}\right)^{\gamma/(\gamma-1)}. \qquad \textit{Eq.8}$$

Where:

$\dot{m}$ is the mass flow rate

T_u is the temperature of the upstream flow

A is the flow area

R is the universal gas constant

P_r is the pressure ratio P_o/P_i

ɣ is the specific heat ratio C_p / C_v =1.4

- C_v is the specific heat at constant volume
- C_p is the specific heat at constant pressure

The energy flow rate associated with the mass flow rate is defined by

$$\dot{E}_h = c_p T_u \dot{m}. \qquad \textit{Eq.9}$$

These equations are then used to construct the thermodynamic restrictor which resembles a four port R field as shown in Figure 5-6

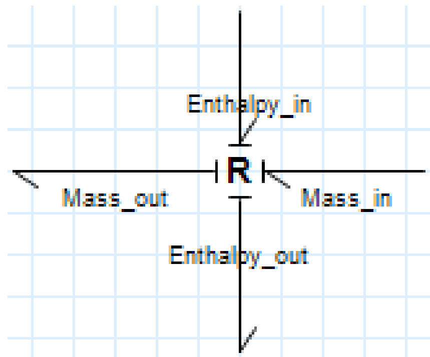

Figure 5-6 Thermodynamic restrictor

5.3 Modeling the pneumatic cylinder

The drilling simulator is built with two Festo® DNG-cylinders similar to the on shown in Figure 5-7. An initial model of the cylinder had each chamber in the cylinder modeled as a thermodynamic accumulator. The output on the true bond graph side of each accumulator is connected to a zero junction. The piston is modelled as an I element and its viscous friction force with the cylinder walls is modeled as an R element. Since these two elements are affected by the same velocity they are connected to a one junction. Finally, two transformers with a modulus equal the area of the piston are used to convert the volume flow rate and pressure outputs encountered at the previously defined zero junction to the force and velocity outputs expected at the piston.

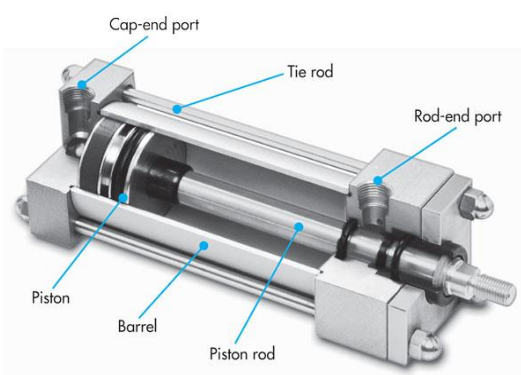

Figure 5-7 Pneumatic cylinder cross section (Festo Website)

On the pseudo bond graph side of the accumulator, a thermodynamic restrictor representing the leakage area through the piston's seals is used to model communication between the two accumulators. The restrictor also serves as a way to communicate the temperature of the fluid passing through it to the element that comes after it in the diagram. The model shown in Figure 5-8 describes a double acting pneumatic cylinder with its input ports sealed.

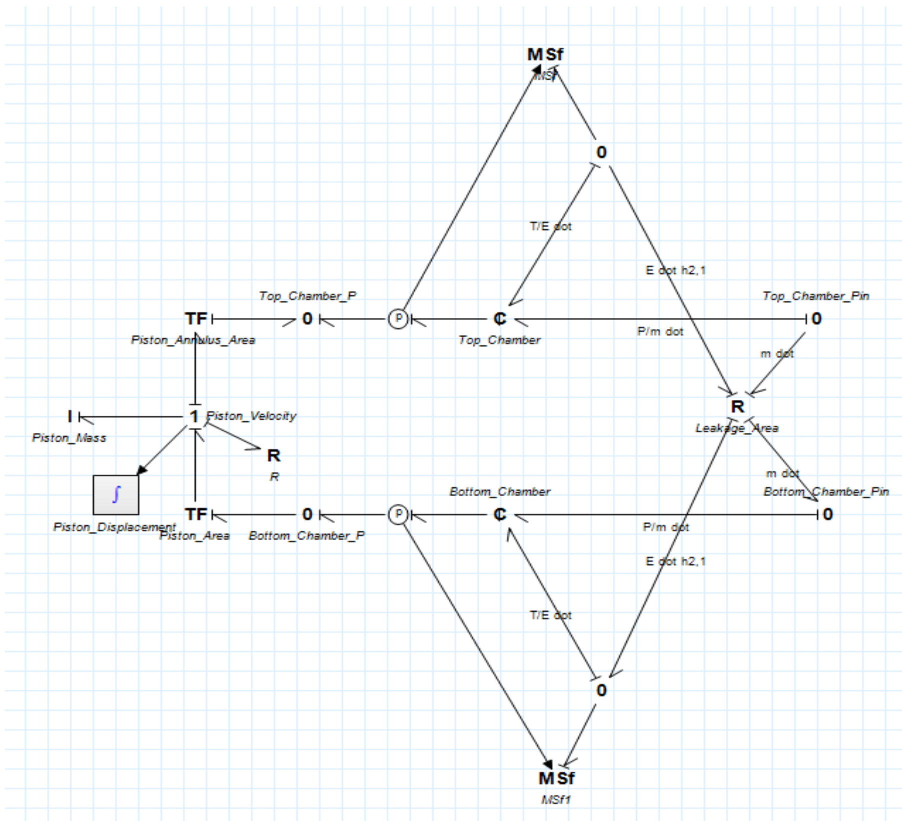

Figure 5-8 Double acting pneumatic cylinder with sealed ports

The initial values for the state variables in the accumulator were set to simulate the piston at the midpoint of its stroke, at 15°C temperature and atmospheric pressure. A sinusoidal force of 100 Newtons amplitude was applied at the piston, and the simulator was programmed to plot the piston velocity, displacement, upper and lower chamber's pressure, temperature and mass flow rate across the leakage area as shown in Figure 5-9 and Figure 5-10.

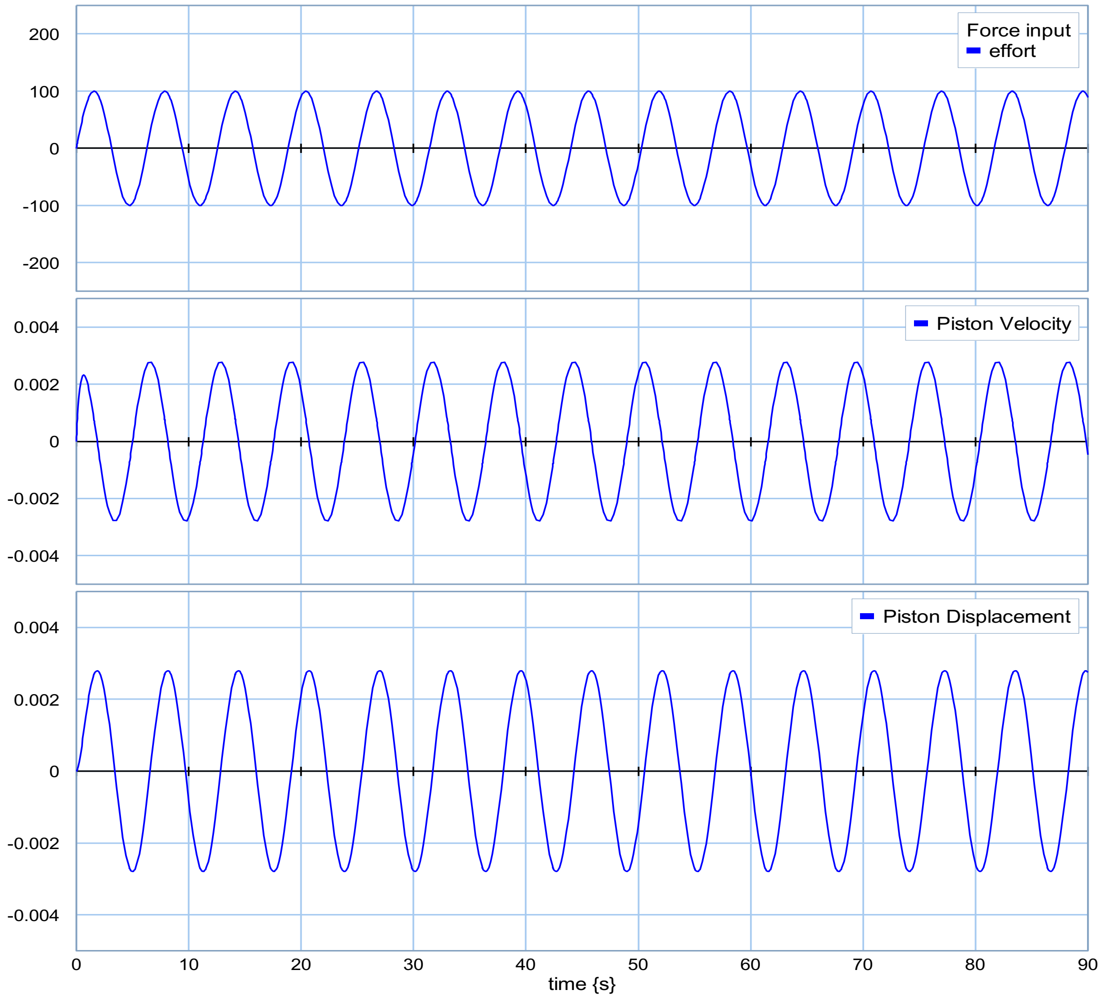

Figure 5-9 Input force, piston velocity, and displacement

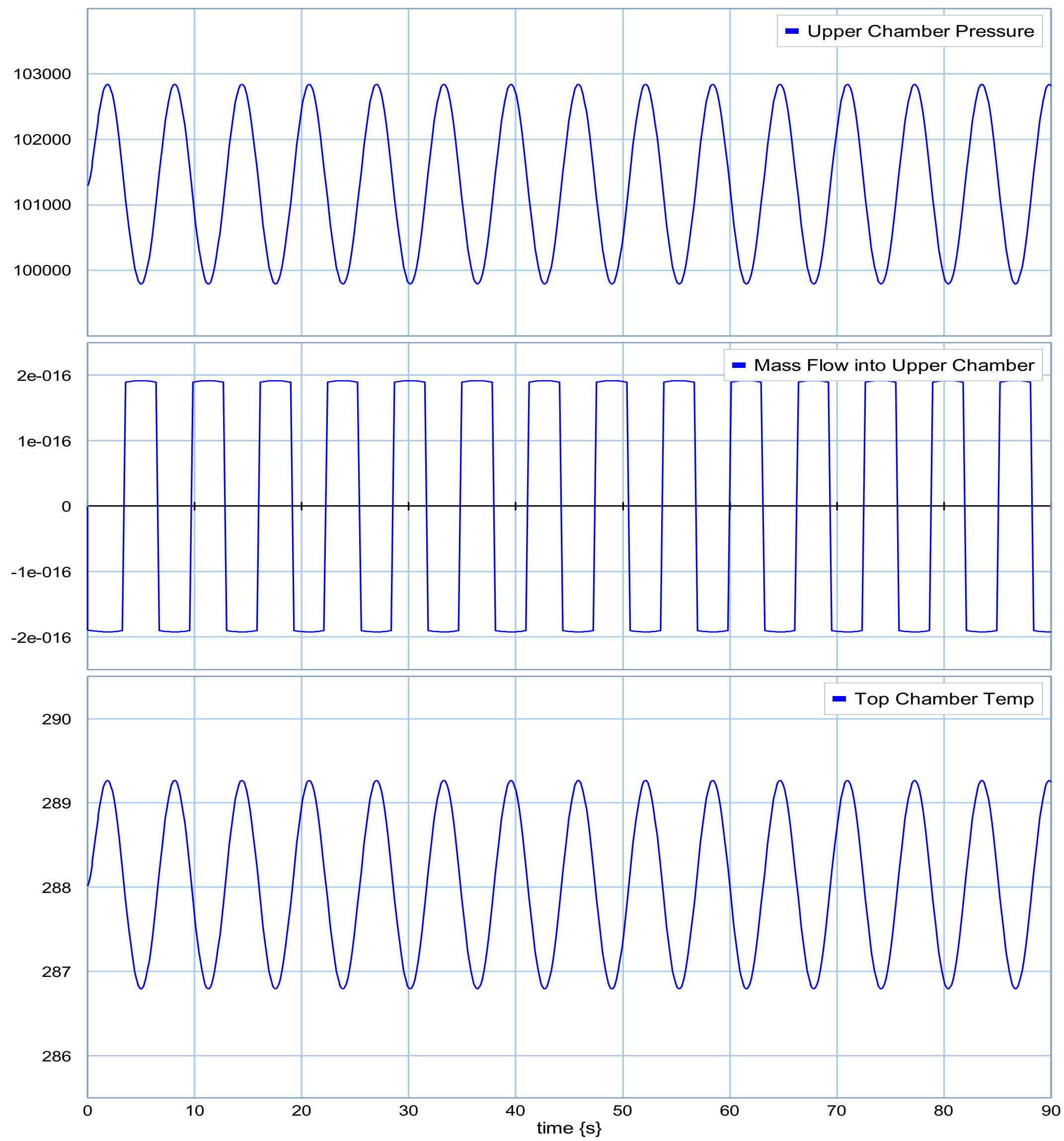

Figure 5-10 Pressure, Temperature, and mass flow rate in upper and lower chambers

The measured displacement at the peak force of 100 Newtons from the simulation is 3 mm, which implies a 37 KN/m air spring stiffness at the pre-defined conditions. The piston diameter is 0.2 meters, and the piston is at the stroke midpoint of 0.25 m. This diameter gives an area of 0.031 m^2, which in turn gives a chamber volume of 7.75×10^{-3} m^3. The resulting displacement's corresponding change in volume ΔV is 9.3×10^{-5} m^3. Since the change in temperature during the process is approximately two degrees Kelvin, it can be neglected, and the process can be considered isothermal. If we assume ideal gas behavior then the $P_1V_1=P_2V_2$ can be used to verify V_2 using the initial pressure of 101325 Pa with the initial volume, and the final pressure from the simulation. The final volume is calculated to be $7.63x10^{-3}$. The final volume corresponds to a ΔV of 1.2 $x10^{-4}$ m^3. The leakage between the chambers, based on machining tolerances, resulted in negligible mass transfer between the chambers and was removed for later models.

The drilling simulator employs two pneumatic cylinders with common advance and retract lines. Each of the lines is connected to a directional control valve that either connects the cylinder's chambers to a pressure regulator or to an atmospheric exhaust port. For the purpose of this study the pressure regulator has been modeled as a modulated source of effort, and the directional control valve with the associated lines have been modeled as a thermodynamic restrictor with the temperature ports connected to sources of efforts with the value of the ambient temperature, and the pressure ports connected to the pressure regulators as shown in Figure 5-11. Initial simulations showed a significant increase in the temperature of the chambers. Pneumatic systems are not prone to overheating during cycling air through their ports. The model was augmented with an R element and a one junction between the effort source representing the ambient temperature and the thermodynamic accumulators to simulate dissipation of heat through conduction of the variable surface area of the cylinder's chamber walls. The restrictor modeling the leakage between the chambers was removed and a C element using a nonlinear relation was added to the piston rod velocity junction to represent the ends of the stroke.

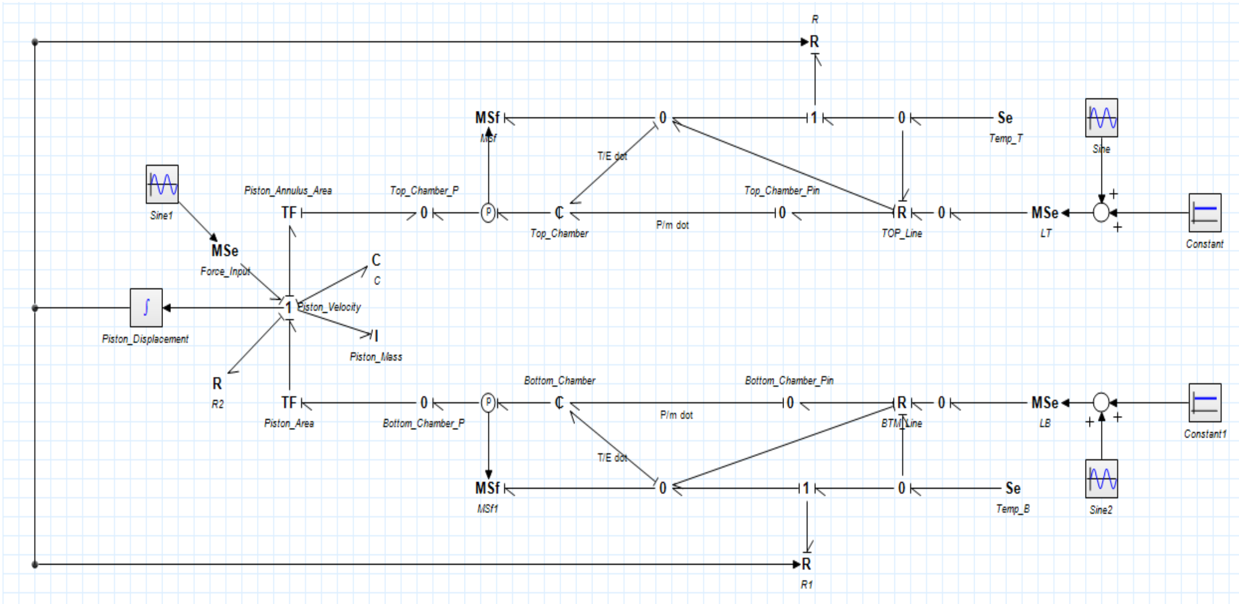

Figure 5-11 Single cylinder circuit with pressure actuation

The modulated sources of effort were set to two sinusoidal waves with the same frequency and amplitude but 180 degrees out of phase. The sinusoidal pressures oscillated between 1.5 and 4.5 bar. The resulting piston velocity, displacement, and chamber, pressure, temperature, and mass flow rates are shown in Figure 5-12 and Figure 5-13.

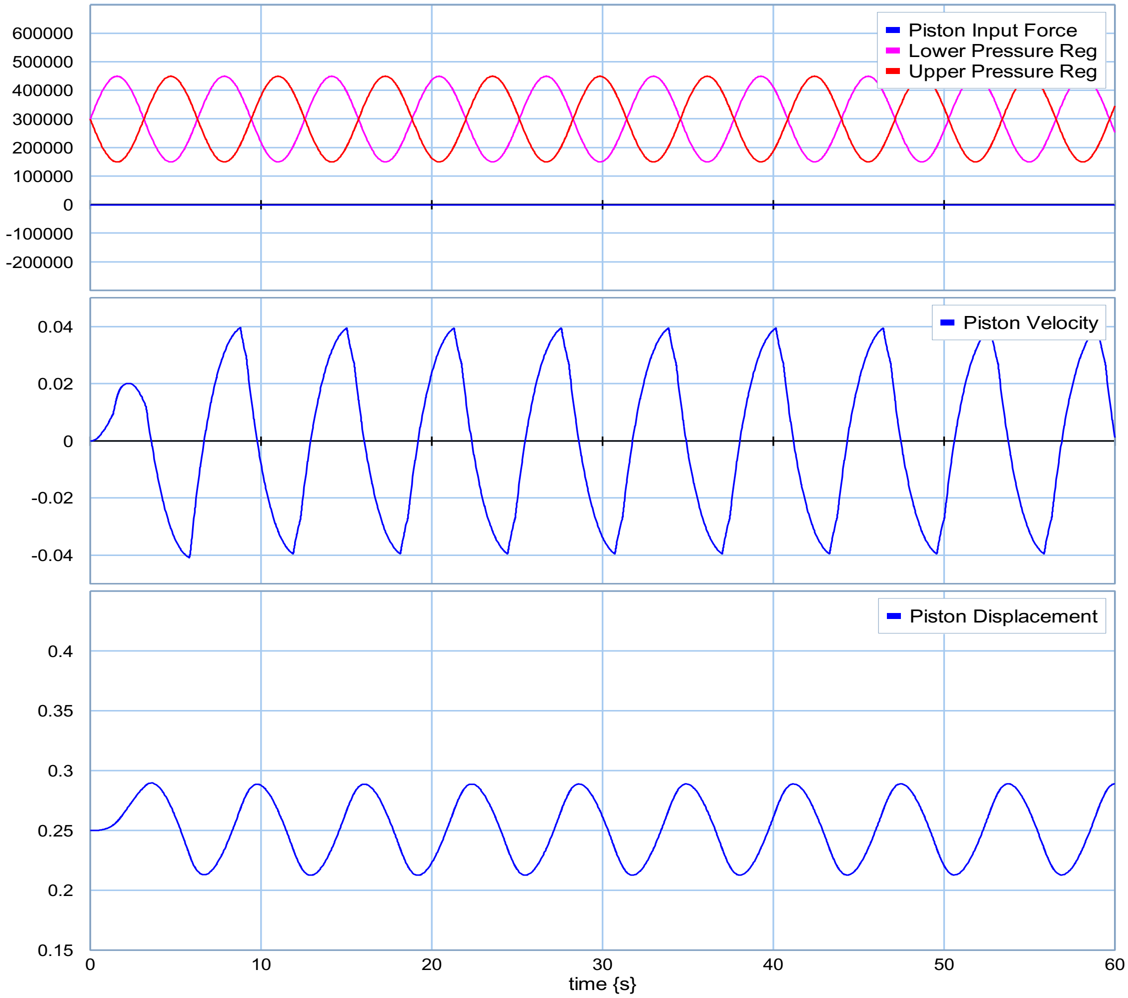

Figure 5-12 Input pressures piston velocity and displacement vs time

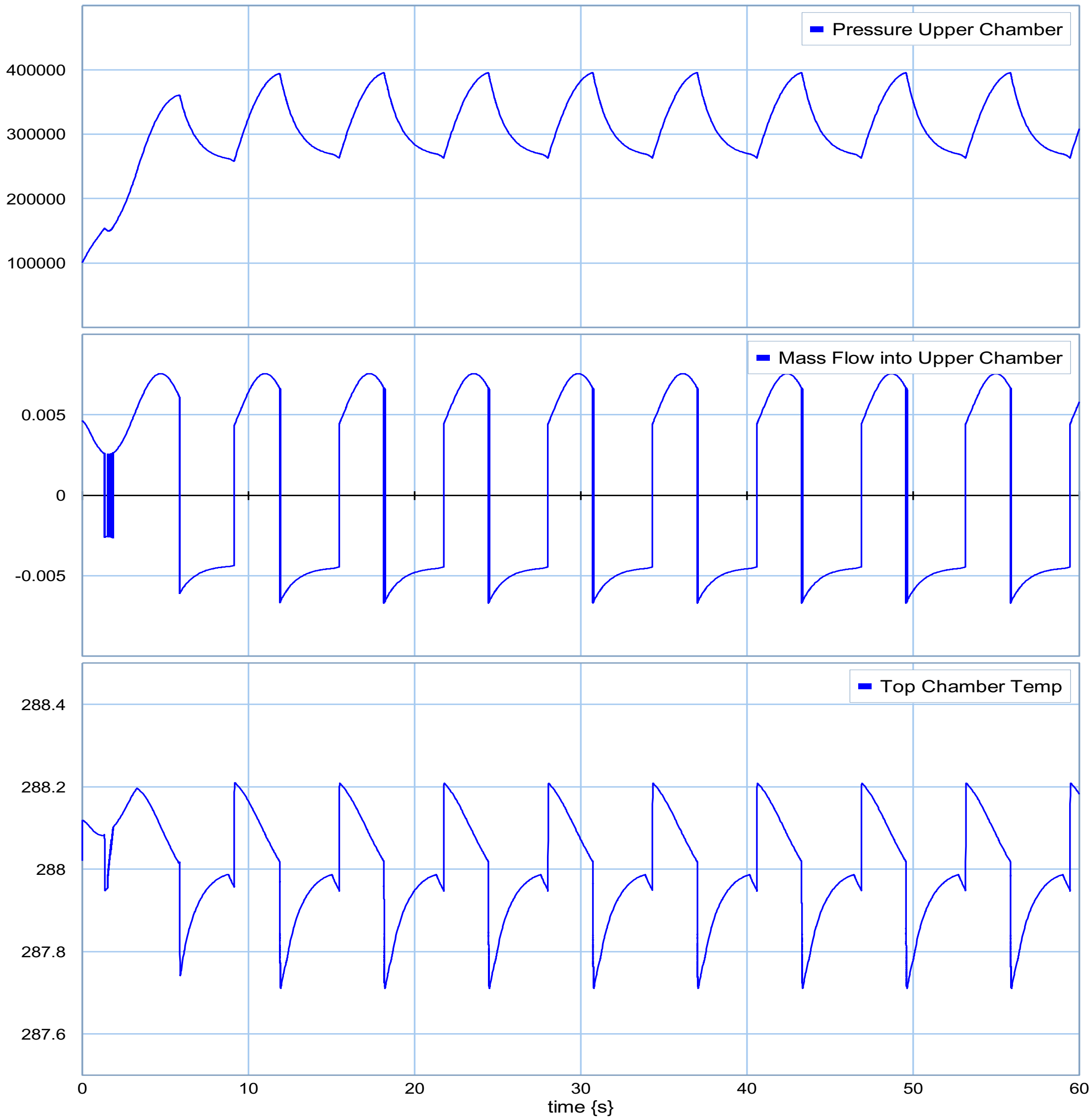

Figure 5-13 Pressure, Temperature, and mass flow rate in upper chambers

As the differential pressure between the input ports increases the piston is accelerated and moves forward. As the differential pressure starts to decrease, the piston decelerates and reverses its direction. In Figure 5-12 the piston advances further on the first stroke and slightly less on every subsequent cycle. This is due to the initial pressure build up from the initial state at atmospheric pressure to the average operating pressure.

5.4 Interaction between hydraulic and pneumatic systems

The drilling simulator's axial system consists of a mobile bridge connection with two pneumatic cylinders connected in parallel on one side, and the hydraulic system on the other side. The drillstring is located below the hydraulic cylinder, halfway between the two pneumatic cylinders as shown in Figure 5-12. The system was assembled in 20 Sim as two pneumatic circuits sharing the same input signals for the two cylinders, and a hydraulic system model. The velocity output of all three sub-models was connected to a one junction to enforce the constraint that all the three components must move at the same velocity. The mass of the drillstring and the viscous friction of the mobile bridge were modeled as an I and an R element as shown in Figure 5-14.

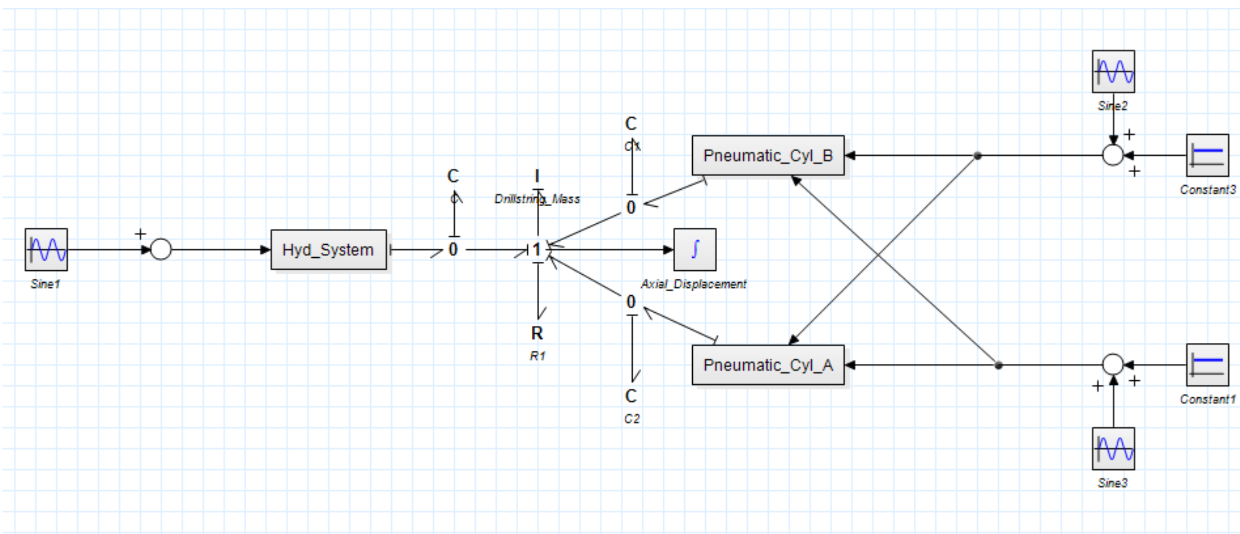

Figure 5-14 20 Sim model of the Axial System

5.5 Model Verification and Validation

In order to verify the model an experiment with the physical setup was conducted and used as a benchmark for the model. Since the pressure sensors on the apparatus are not designed to read pressures lower than atmospheric pressure the pneumatics were pressurized and moved to an equilibrium position approximately at the stroke midpoint. The initial pressure in the chambers was measured at 1.91 bars for the rod side (advance, upper chamber), and 1.57 bars for the rod less side (retract lower chamber). With the input valves to the pneumatic cylinders closed the hydraulic system was operated with a 2 Hz sine wave actuating signal that applied a 20 KN force on the connecting bridge. The hydraulic force caused an equal and opposite force to be developed in the pneumatic system, and the interaction between them caused the system to move in a 2 Hz sinusoidal pattern with an amplitude of 9.5 cm. The data recorded from the sensors is shown in Figure 5-15.

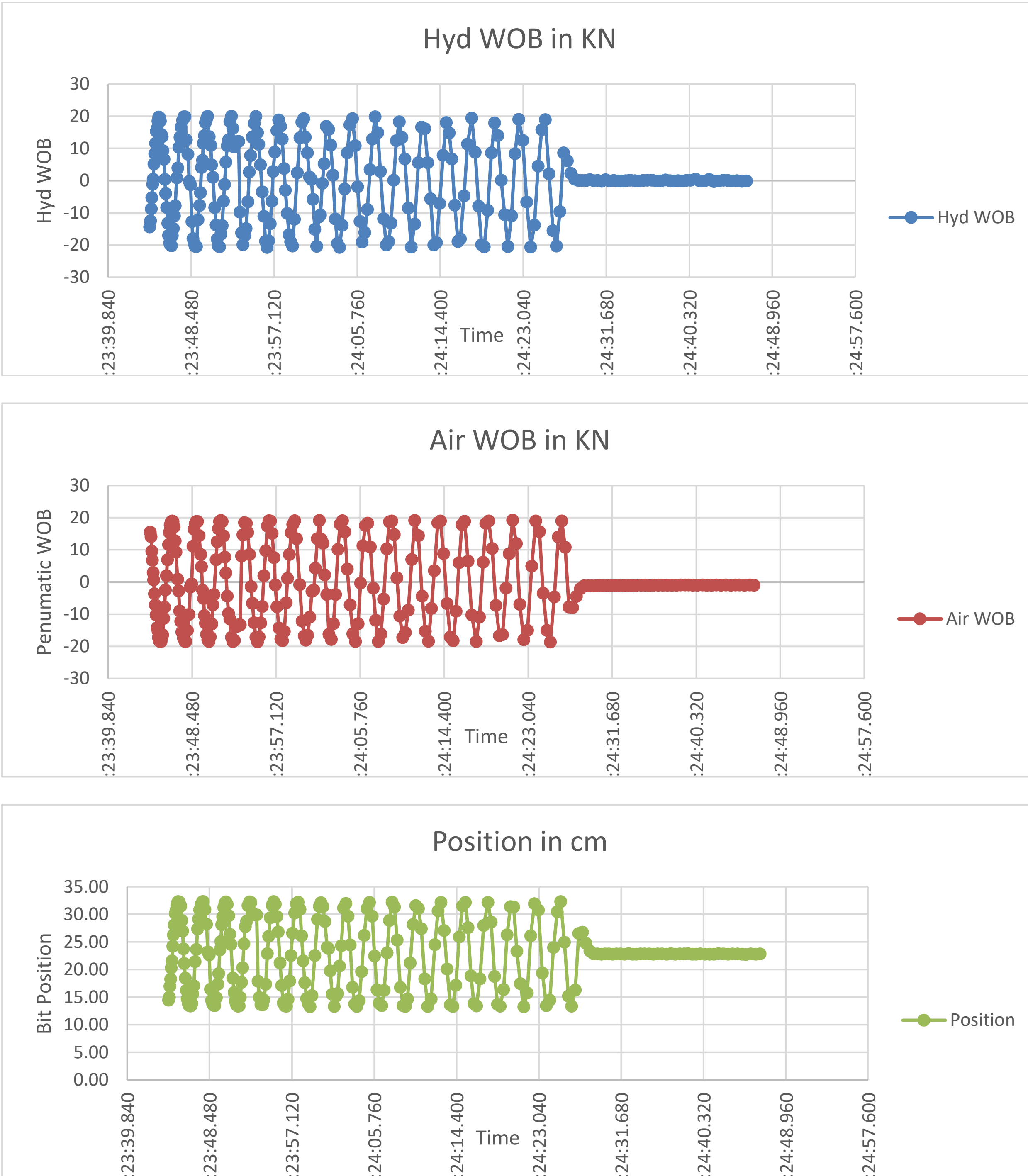

Figure 5-15 Sensor readout from apparatus

The same inputs were applied to the pneumatic model. The hydraulic simulation model has a position controller and was initially actuated with a position signal equivalent to the displacement results from the experiment. Discrepancies between the desired and actual position revealed a need for further tuning of the controller and servo-valve model. To compare simulation results with the experiments in which open-loop hydraulic force was applied (Figure 5-15), the hydraulic sub model was replaced with a modulated source of effort. The results are shown in Figure 5-16.

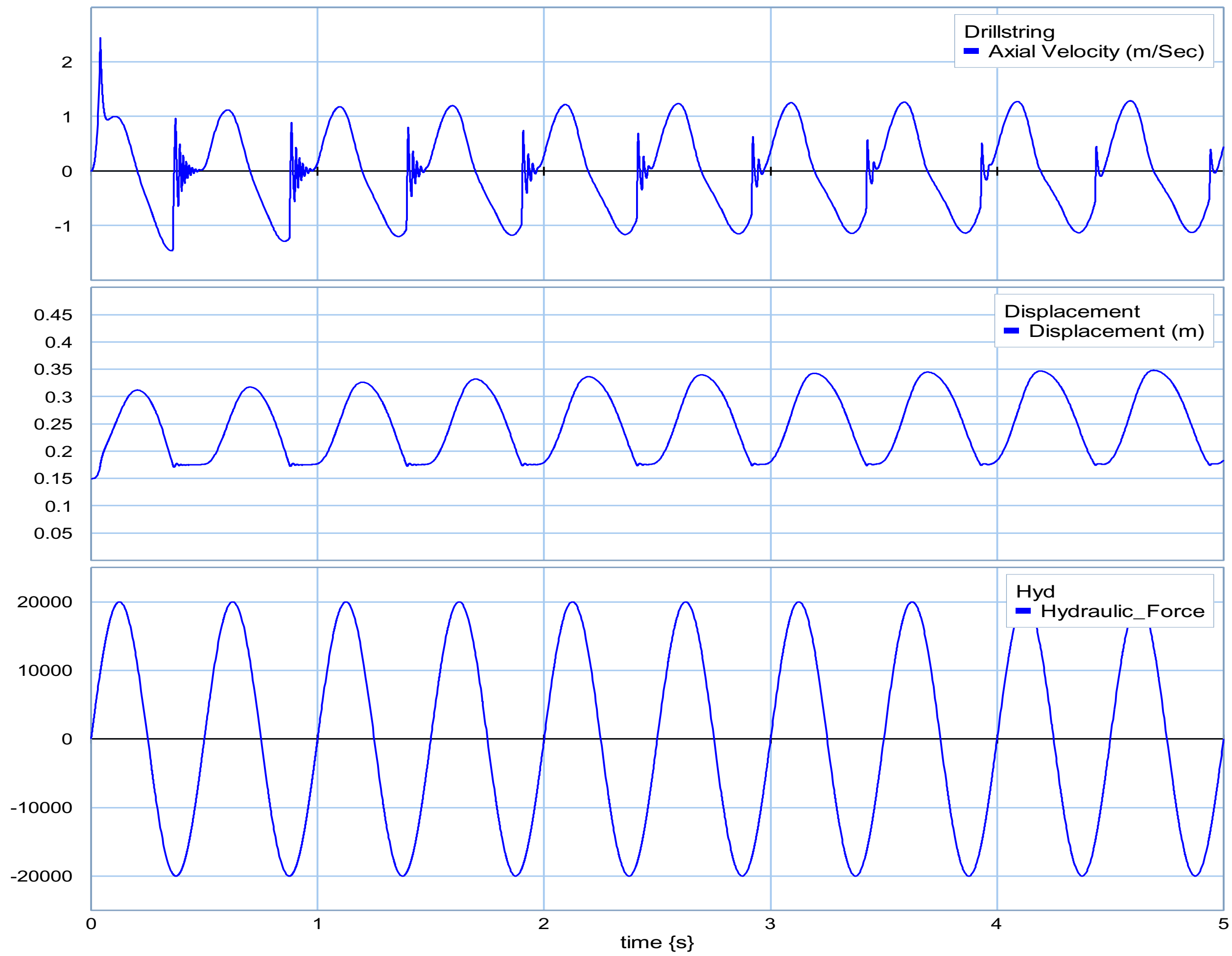

Figure 5-16 Simulation results with open-loop hydraulic force

The simulation result shows a pneumatic cylinder displacement that is consistent with the sensor readout from the experiment. The net axial force applied to the drill string is zero as expected since the two weights on bit from the hydraulic and pneumatic systems are equal in magnitude but opposite in direction.

5.6 Conclusions

A pseudo-bond graph simulation model of the pneumatic and hydraulic actuating components of an experimental apparatus, designed to impose realistic axial inputs to a rock drilling bit for oil and gas exploration or mining, has been presented. Notable model features include mass flow rate of a compressible fluid through a nozzle, work done by a compressible fluid in a variable volume chamber, and heat conduction through variable volume chamber walls. Initial models considered the leakage through the cylinder seals, but the effects were found to be negligible, and the final models assumed that the cylinder seals are leak free. Friction was modeled as linear viscous, and non-linear stiffening springs represent the mechanical limits of the piston. Thermal conduction to the surrounding environment is included to prevent unrealistic temperature rise during gas compression, and its effects on chamber pressure.

The models were validated through a series of simulations and experimental measurements. For a sealed pneumatic chamber, pressure values produced by the simulation were checked against manual calculations. Next, the hydraulic and pneumatic models were made interact with each other as a complete axial motion system model. The pneumatic cylinder chambers had their pressures set to create an equilibrium position, after which the hydraulic system was actuated to create open-loop cycling of the drill string and bit. The bit was cycled in air, and bit-rock interaction forces were not considered. The resulting displacement was simulated and compare to actual sensor read outs on the apparatus. Further tuning of the controller and servo-valve models, along with installation of more sensors on the apparatus, will allow validation against pressure and temperature in the sealed pneumatic cylinders.

Future work will combine a simple bit-rock interaction model with the axial motion subsystem, to verify that the drilling rig as designed is capable of providing the desired ranges of static and dynamic WOB. The drill rig will eventually become part of a hardware-in-the-loop system, with a high-order drill-string simulation model used to provide actuation signals to the hydraulic and pneumatic cylinders while drilling real rock.

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Chapter 6 Conclusions and Future Work

In this thesis two research topics were discussed, in the first part the digitalization efforts utilized by the Oil and Gas industry were investigated. The uses of digital twins as a method of forecasting future events and trying to overcome them was very evident from recent literature. The idea of augmenting RTOC's with digital twins and expert systems to overcome the loss of experience caused by oil price downturns is the focus of current research. The idea of using digital twins as a forecasting tool for maintenance is quite mature and is in its implementation stage. However, the use of digital twins to remedy operational issues is still in its infancy. A digital twin that can be used in the planning phase and can be used to automate operations in the operational phase is something that is needed and not covered in recent literature. This thesis presents a digital twin system for MODUs consisting of six components covering all critical focus areas that would benefit from automation. Since theses six components are quite diverse and cannot be covered in a single study, a single component was singled out and used as the focus of this study.

The development of an auto-driller system that collects real time data from rig sensors and relies on a database of geological models to eliminate geological uncertainties was selected as this component. An extensive chronological review of drilling optimization was carried out, and the results showed that there are four main approaches to optimizing drilling performance, empirically established correlation between ROP and drilling parameters, correlation with MSE, statistical methods, and analysis of performance through modelling of drill string dynamics.

An attempt was made to cast the components in an optimization problem, a nonlinear program that minimized a variant of MSE, showed good control over WOB, but failed to optimize rotary speed. Further investigation suggested that the use of optimal control would provide a better alternative. An evaluation of drill string models was carried out and a high-fidelity model was selected and verified against typical performance observed in the field, then the optimization problem was cast as a model predictive controller. Some difficulties were encountered related to the extreme nonlinearity of the bit-rock interaction present in the selected model. However, the model predictive controller shows potential in being able to perform real-time drilling optimization. Possible solutions on how to overcome the challenges encountered were proposed.

The second part of the thesis focuses on the development of a field scale drilling simulator capable of simulating drilling dysfunction by running a hardware in the loop simulation. The simulator was developed and tested to verify its ability to recreate field conditions encountered on a MODU and record high fidelity data from the experiments. The simulator is capable of investigating axial and torsional vibrations while drilling, it includes a high-pressure cell to simulate drilling under reservoir conditions and can simulate a gas kick by injecting air into the sample being drilled. The simulator is also equipped with a simple MPD system and sensor package. Initial experiments were conducted, and the system capabilities were confirmed with a single issue being highlighted, that the sensor package of the system needs to be augmented with a set of accelerometers, to ensure that high frequency vibrations are being captured correctly.

Moreover, a pseudo-bond graph model of the axial component of the simulator was constructed to be used as a tool for planning experiments. The model was built to consider all thermodynamic and heat transfer aspects relating to the use of pneumatic systems and was verified with actual measurements from the simulator that were captured in an experiment.

The next step for this research would be to further improve the model quality by applying the use machine learning to estimate hard to measure model parameters such as formation strength, bit wear and frication coefficients, and to complete the simplified formulation of the MPC controller and verify that it runs in real-time without compromising the fidelity of the model. A rework of the selected model converting it from the dimensionally complex DDE format into a simpler ODE format, and the reformulation of the MPC problem into a different format using the multishooting or colocation method, while using a solver with algorithmic differentiation instead of a numerical solver is proposed. Once a suitable formulation is reached, experimental verification using the HIL simulator can start. The resulting controller can then be gradually expanded to include the other five components identified earlier to produce the complete digital twin system proposed in chapter 2.