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Faculty of Technology, Natural Sciences and Maritime Studies

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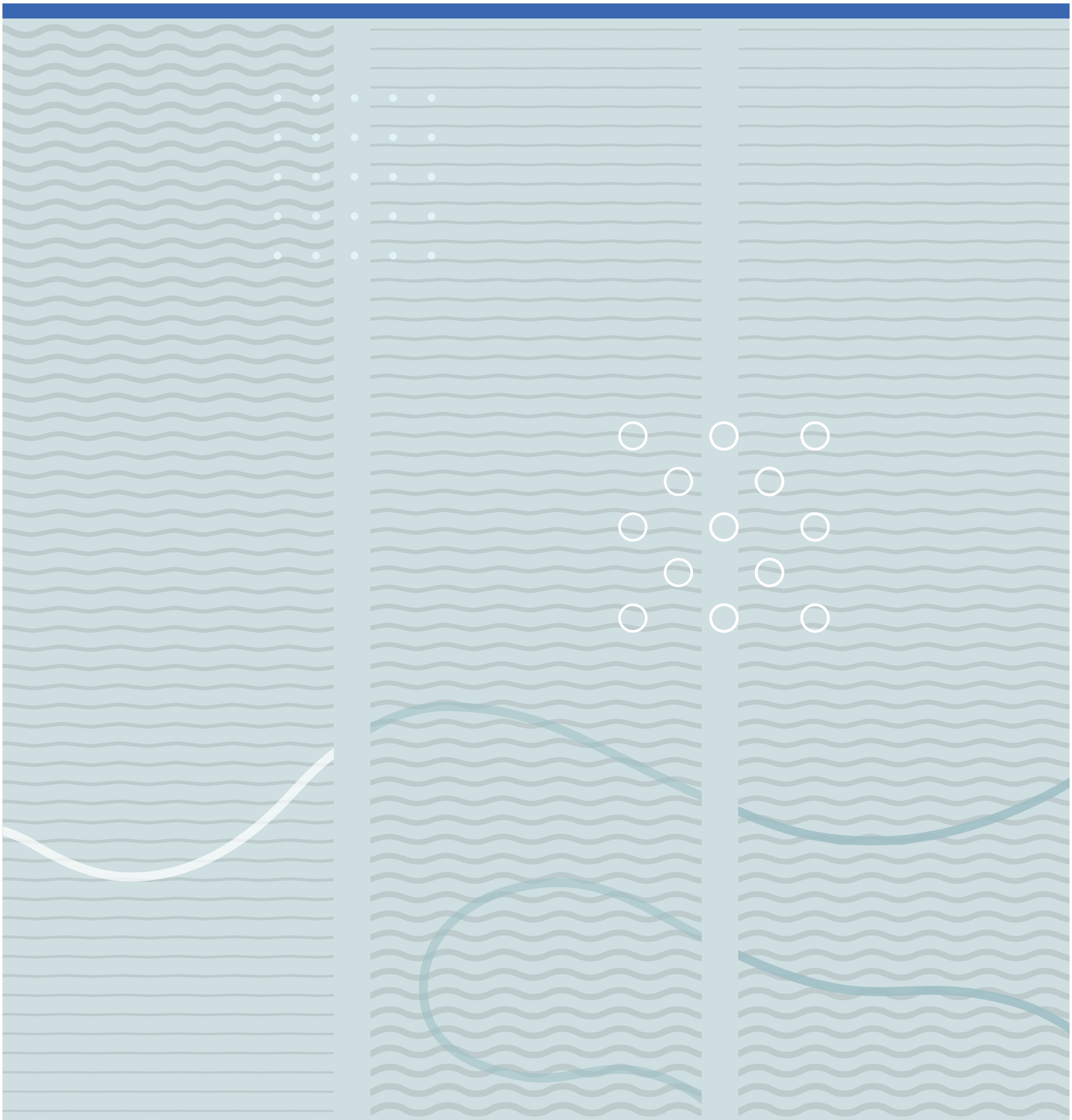
Morten Hansen Jondahl

Data Driven Models for Estimation of Drilling Fluid Rheological Properties and Flow Rate



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Data Driven Models for Estimation of Drilling Fluid Rheological Properties and Flow Rate

A PhD dissertation in
Process, Energy and Automation Engineering

Faculty of Technology, Natural Sciences and Maritime Studies
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Dedicated to the all the giants not in my reference list, whose shoulders upon which I stand

My fantastic wife and daughters, all my family members and friends.

"Per aspera ad astra"

Preface

This thesis dissertation is delivered to fulfil the graduation requirements of the degree philosophiae doctor (PhD) at the Faculty of Technology, Natural Sciences and Maritime Studies at the University of South-Eastern Norway (USN). The thesis work is part of a project initiated by USN, which received financial support from Norwegian Research Fund (NRF) and Equinor to conduct the research and to build and develop a lab facility to circulate model drilling fluid in an open channel with a Venturi constriction. The project is named Semi-Kidd (Sensors and models for improved kick/loss detection in drilling) and involves several faculty members as well as MSc and four Ph.D. students.

This doctoral thesis consists of a collection of scientific papers written during the PhD-work at USN. Therefore, this thesis is presented in two parts. Part I will state the research problem followed by the literature review. Then the scientific papers are presented and put in context to solve the research problem. In Part II the mentioned papers are presented in full text to support Part I. Paper 6 has since thesis evaluation been rejected from the IOP MST journal. Due to the timing of the feedback, the paper is presented herein as evaluated, but will be resubmitted to another journal.

I certify to the best of my knowledge that the work presented herein is my own original work, other contributions are acknowledged and that the use of the intellectual content of other researchers or contributors are made in good confidence according to scientific standards and norms regarding citation. The content of this thesis has not been submitted for any other degree or purpose.

I am grateful to have had this opportunity to expand my scientific knowledge field. The combination of this scientific work, with my previous four years' experience as a drilling engineer and offshore drilling measurements engineer has been especially rewarding. I have learnt a lot, and I am glad to add my small brick to the tower that is science. The best I can hope for is that it will prove a stable support to many more bricks yet.

Porsgrunn, April 2020

Morten Hansen Jondahl

Acknowledgement

The achievement represented by this thesis would not have been possible without great support. First, I would like to thank my main supervisor, associate professor Håkon Viumdal (USN), co-supervisors professor Saba Mylvaganam (USN) and Dr. Geir Elseth (Equinor and USN). They have all contributed their time, guidance, support and expertise in their respective fields, throughout my work. I would also like to thank USN and the Semi-kidd project for the opportunity to work on this research project, and for the opportunity to combine my previous knowledge of both science and the practical application of drilling technology with the new insights I gained through my thesis work. The Semi-kidd project has given opportunities to participate in an exciting project, collaboration with industry experts and receiving invaluable feedback throughout this work. It was also a pleasure to fulfil the duties as an intern at Equinor, participating in the testing of flow meters with an industrial application focus, rather than a purely academic approach. The experience was a rewarding and refreshing period of my PhD.

I appreciate my collaboration with Dr. Khim Chhantyal on the work with the open channel experiments and models. He was an inspiration as a researcher and PhD candidate, and was a great support in the early periods of this thesis work. MSc students Kenneth Nonso Mozie and Morten Hafredal were also great colleagues and a joy to work with on the ultrasonic drilling fluid experiments. Per Kristian Fylkesnes, Eivind Fjelddalen and Fredrik Hansen gave invaluable technical support for my experiments.

I would also like to thank my department heads at the Department of Electrical Engineering, IT and Cybernetics, Randi Toreskås Holta (former) and Svein Thore Hagen (current). On one of my first days at the office, Randi inspired and motivated me by saying: “Remember, the most important task of a PhD is to complete it”. This has been more important than ever in the last stages of this work.

My gratitude goes to my excellent PhD partners in the Semi-kidd project, Dr. Asanthi Jinasena, Dr. Prasanna Welahettige and Haavard Holta. Asanthi and Prasanna paved and lead the way, and I am glad to follow. I would also like to thank Xsens, Remi, Kenneth and Kjell Rune for the possibility to work with them for the testing of their ultrasonic flow sensor and collaborating on our paper.

Behind every individual or collective achievement, there is an indispensable support team, and for me that has been my family. It would not have been possible for me to pursue this PhD work without the excellent support, encouragement and help from my fantastic wife and best friend, Ingrid. I cherish the grounding perspective her and my young girls have given me, and the light and joy they have been in the dark and difficult periods. I admire my parents for their lifelong and unwavering support in my endeavours, failures and achievements. Together with the rest of my family and everyone who helped with babysitting and making it possible for me to dedicate my time and effort to my work, I thank you.

Abstract

Pressure control during well drilling operations includes management of the well pressure above the formation pore pressure and below the formation fracture pressure. If these boundaries are not kept, an influx of formation fluids or an uncontrolled loss of drilling fluid may occur. These incidents present serious risk to humans, assets and the environment. To avoid serious risks and accidents, detection of the influx (kick) and loss incidents is of vital importance in any drilling operation. The availability of sensor technologies to discover kick/loss incidents vary greatly for different drilling operations. Common for all is that dedicated measurements of the non-Newtonian drilling fluid can help the early identification of the possible occurrence of measurements of such incidents.

The inflow of drilling fluid is in most drilling operations well measured, either by pump output or flow metering on the flowline, such as Coriolis meters. The return flow is comparatively harsher for flow meters, as the return fluid flow contains formation cuttings and formation fluids. The common industry practice is applying a paddle flow meter, which gives a trend-based measurement that by human interpretation alongside other measurements may indicate anomalies in the return fluid flow. Secondly, a fluid level in the drilling fluid tank may be measured, as a level change can indicate a kick/loss incident. The response of this method is slow and inaccurate. Development of cost effective, fit-for purpose and in-line sensor technology for the return fluid flow will increase the capability for automation and reduce the time delay to detect kick/loss incidents.

This research work studies the applicability of a modified open channel for fluid return with a Venturi constriction. The subsequent level changes in the open channel may be measured and used to model the fluid flow rate. During this work, it was found that precise knowledge of the fluid properties is a requirement to some models, and beneficial to others. It is also vital in determining the volume of the kick/loss incident, and the subsequent correct procedures in handling the situation safely and effectively.

In this research ultrasonic characterizations of drilling fluids serve as inputs to models estimating the fluid rheological properties during drilling operations. The common industry practice of intermittent, offline and manual drilling fluid characterization is not satisfactory for automated drilling operations and continuous measurement systems, and improvements are needed.

Non-Newtonian drilling fluid flow is difficult to model precisely with mechanistic models. Data driven models are selected as suitable methods to handle the non-linear behaviours of these fluids when estimating fluid flow based on the level measurements. The models are trained and verified by using experimental data from a test flow loop. The data driven models are compared to other mechanistic models developed by colleagues that were verified using the same experimental setup.

Ultrasonic wave propagation is affected by the acoustic properties of the medium it propagates. By analysing this propagation in drilling fluids, the effect of the fluid rheological properties on the ultrasonic waves is studied in the present study. The work focuses on density and viscosity, as these are some of the drilling fluid rheological properties essential in the pressure control during the drilling processes. The relationship between ultrasonic properties and rheological properties are not fully described in literature, and data-driven models were identified as potential solutions. Three drilling fluid systems are diluted to yield in total 33 fluid samples that are characterized in ultrasonic transmission experiments, and their rheology is analysed. Data driven models are developed and verified using these data, to estimate the rheological properties based on the ultrasonic measurements.

The data driven models to estimate the fluid flow rate performed to expectation in the experimental setup. Several types of models were developed, but all had accuracies better than the industry standard set by NORSOK, at 5 % accuracy of measured value. Some of the mechanistic models outperformed the data-driven models, and the thesis work discusses the results and the strength and limitation of the models.

Data driven models proved to be an effective approach in estimation of fluid rheological properties. The two selected properties were estimated within the NORSOK suggested accuracy of 2%. The measurement principle with ultrasonic measurements and models has potential to be developed to apply to flowing systems and improve fluid flow models and improve availability of continuous drilling fluid properties measurements.

List of papers enclosed in the PhD-thesis

Paper 1

K. Chhantyal, M. H. Jondahl, H. Viumdal, and S. Mylvaganam, "Upstream Ultrasonic Level Based Soft Sensing of Volumetric Flow of Non-Newtonian Fluids in Open Venturi Channels," *IEEE Sensors Journal*, vol. 18, no. 12, pp. 5002–5013, Jun. 2018.

Paper 2

M. H. Jondahl, H. Viumdal, K. N. Mozie, and S. Mylvaganam, "Rheological characterization of non-Newtonian drilling fluids with non-invasive ultrasonic interrogation," in *2017 IEEE International Ultrasonics Symposium (IUS)*, 2017, pp. 1–4.

Paper 3

M. H. Jondahl and H. Viumdal, "Estimating Rheological Properties of Non-Newtonian Drilling Fluids using Ultrasonic-Through-Transmission combined with Machine Learning Methods," in *2018 IEEE International Ultrasonics Symposium (IUS)*, 2018, pp. 1–4.

Paper 4

M. H. Jondahl and H. Viumdal, "Developing ultrasonic soft sensors to measure rheological properties of non-Newtonian drilling fluids," *tm - Technisches Messen*, vol. 86, no. 12, 2019.

Paper 5

M. H. Jondahl, H. Viumdal, Asanthi Jinasena, and S. Mylvaganam, "An overview and outlook for drilling measurements, with focus on estimations of flowrate and rheological properties of return drilling fluid. The paper is submitted and is currently under review in Measurement Science and Technology (MST), IOP Publishing, November 2019.

Paper 6

K. Olsvik, M. Hansen Jondahl, K. R. Toftevåg, R. Kippersund, G. Elseth, and I. Kjøsnes, "Disruptive Clamp-On Technology Tested for Mud Measurement," in *SPE Norway One Day Seminar*, 2019.

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Abbreviations

ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
API	American Petroleum Institute
BHP	Bottomhole Pressure
CFD	Computational Fluid Dynamics
DP	Differential pressure
DT	Density transmitter
FT	Flow transmitter
LT	Level Transmitter
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
NCS	Norwegian Continental Shelf
NPT	Non-productive time
NRF	Norwegian Research Fund
OBF	Oil based fluid
P&ID	Piping & Instrumentation Diagram
PLR	Polynomial Linear Regression
PT	Pressure transmitter
RMSE	Root Mean Square Error
SLR	Simple linear regression
SVM	Support Vector Machine
SVR	Support Vector Regression
TT	Temperature transmitter
UR	Ultrasonic receiver
USN	University of South-Eastern Norway
UT	Ultrasonic transmitter
UVP	Ultrasonic velocity profiling
WBF	Water based fluid

Symbols

⍰	Channel inclination
γ_p	Yield Point
$\varphi_i(X)$	Kernel function
μ	Viscosity
$A(x)$	Relative amplitude
b	Bottom width
B	Bias array
c_1	Haldenwang empirical geometry constant 1
c_2	Haldenwang empirical geometry constant 2
C_{Chezy}	Chézy roughness coefficient
h	Fluid level
K	Geometry constant
k	The consistency index
n	Flow behaviour index
$n_{Manning}$	Manning roughness coefficient
N_{SV}	Number of support vectors
P_b	Wellbore pressure
P_f	Fracture pressure
P_p	Pore pressure
Q	Flow rate
R_h	Hydraulic radius
R_H	Haldenwang's Reynold's number
t	Time of flight
V	Average velocity
W	Weight array
x	Distance
X	Input array
Y	Output array
$\dot{\gamma}$	Shear rate
μ_p	Plastic viscosity
ρ	Fluid density
τ	Shear stress
τ_w	Average wall stress
τ_y	Average yield stress

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1 Introduction

There is a great focus on increased safety, efficiency and process control in the oil & gas drilling industry. The drilling process represents a substantial part of the financial costs to the development of an oil field, and poses great risk both financially, and to human life and the environment. Increasing the grade of automation in the drilling process has been identified by the Norwegian Research Council [1] as an area to reduce these risks and increase the safety. The OG21, the Norwegian Government's committee for securing efficient and environmentally friendly oil & gas value creation through education, research and development and commercialization, has also emphasized this focus on drilling process automation [2]. They also identify non-productive time (NPT) as a major cost in drilling operations. Decreasing this by early detection of kick/loss situations is the main knowledge gap to be addressed by the Semi-kidd project.

The Semi-Kidd (Sensors and models for improved kick and loss detection in drilling) research project has defined the research objectives of this thesis work. These are explained in chapter 1.3. The background and motivation are defined by an overview of the process of drilling, and the special challenge that non-Newtonian drilling fluids presents, when fluid flow and rheology properties are considered. The following subchapter will set the stage for the need of improved sensor and model technologies, and the challenges to overcome to achieve this. Then the objectives of the thesis work are described, and the thesis is outlined.

1.1 The drilling process

In the drilling operation of an oil & gas well there are many complex processes, and important considerations for operational purposes. Some of the considerations are for making the well a good producer, or making sure the target will be hit, i.e. the part of the reservoir where the well is to be placed. In addition, other situations during planning or execution phase may shift the focus of the drilling operation. However, the focus during drilling is well control. Well control is controlling the pressure in the well so that fluids from formation does not enter the wellbore uncontrolled. This means the formation pressure, or pore pressure (P_P), determines the lower limit for the wellbore pressure (P_b). At the same time, the formation integrity, the strength of the rock, determines the upper limit, referred to as fracture pressure (P_f). If P_b is greater than P_f, the rock formation might fracture, or old fractures might be reopened. This will cause the drilling fluid to flow into the formation. If this loss of drilling fluid is large enough, the hydrostatic pressure in the well will decrease, and in worst case, it can fall below the lower limit, causing the formation fluid to flow into the well. These two events are known as kick and loss.

To ensure well control, monitoring and estimating the pressure in the well is an integrated part of the drilling operation. Controlling the pressure in the well is during operation generally done by controlling the pump rate of the drilling fluid pumps. The added circulation pressure on top of the hydrostatic pressure will generally give the flexibility for controlling the bottom hole pressure (BHP) in most cases. Otherwise, the drilling fluid density can be adjusted, but this results in a longer response time. The composition of the drilling fluid needs to be adjusted, before it is circulated into the well to adjust the pressure. The former action, controlling the pumps, is represented by a quick and fast responding time to adjust the BHP. The challenge is to know when to adjust the BHP and by how much. This leads to the motivation for taking on this project. To gain this knowledge good reliable measurements of the drilling fluid system are needed. There is a need to know when a kick/loss is arising, and preferably quantify the incident, to be able to adjust the pressure in a quick, safe and efficient manner.

One of the more important measurements providing feedback to the well control system is the flow measurement of drilling fluid circulating in the drilling loop. Figure 1 displays an overview of the drilling system and the drilling fluid flow loop. The flow path of the drilling fluid can generally be divided into two parts, the high-pressure side, and the low-pressure side. The high-pressure side is where the drilling fluid is being pumped from the storage tanks on the rig, pits, through the pumps and through hoses and pipes into the drill string. Through the drill string and down into the well and through the drill bit. When the drilling fluid exits the bit, a lot of the high pressure supplied by the pumps has been lost to friction in the piping system, the drill string, and especially in the drill bit. Now the drilling fluid will return to the surface between the drill string and the borehole wall or casing, this space is called the annulus. When the drilling fluid returns to surface in conventional drilling, the fluid flows through an open channel, with no additional pressure applied to the drilling fluid column of the annulus. The drilling fluid picks up the cuttings of the rock generated by the drill bit operation. The rock cuttings are carried by the fluid flow on its way up the annulus. The temperature of the drilling fluid has increased throughout the system and reaches a typical average temperature at surface at about $60°C$. Furthermore, it may have had minor influxes of formation fluids or gases, i.e. oil, gas or water or a mix of these. These effects make the drilling fluid return flow to be a multiphase flow of abrasive nature. Thus, it is challenging to measure the return flow correctly, and due to the abrasive nature of the drilling fluid, these measurements should be done by non-intrusive methods. Measuring both the drilling fluid flow in, and out of the well will yield better information about the pressures in the well. This is because any loss or kick happening in the well will affect the drilling fluid flow out of the well. If these two measurements can qualitatively be compared, we will have a powerful tool in detecting kick\loss situations. This is just one step towards more automation and control of the drilling process. This is closely related to one of the focus areas the Norwegian government has set out for research in the oil and gas industry [3].

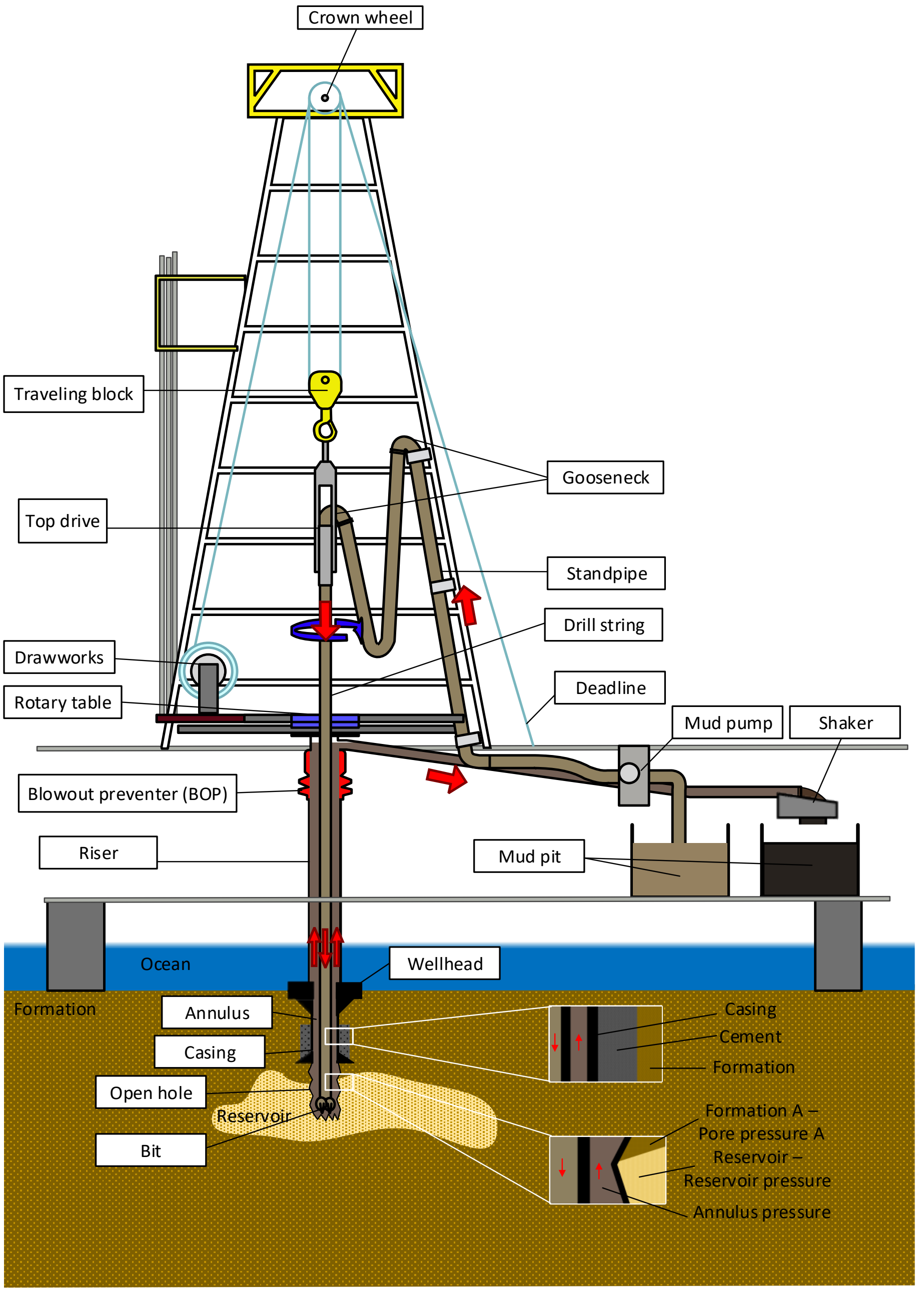

Figure 1: Overview of drilling system and drilling fluid flow loop

1.2 Rheological properties of Non-Newtonian drilling fluid

As mentioned in chapter 1.1 the non-Newtonian drilling fluids present a special challenge when considering the measurement of fluid flow and fluid rheological properties. The fluid is non-Newtonian in behaviour, and may also be multiphase, containing both the drilling fluid as designed, in addition to the well fluids and rock cuttings. Thus, it is abrasive in nature, in addition to having varying properties (viscosity is shear dependant, and in some cases temperature dependant) and its behaviour is difficult to express in exact mathematical models.

These challenges are encountered in all the research activities described in this thesis and are included in this introduction.

1.2.1 Viscosity

Non-Newtonian fluids are characterized by the non-linear relationship between the shear stress and shear ratio. Depending on the actual fluid, there are various models for the relationship which are applicable as seen in Figure 2. In drilling fluids, it is often best explained by either the Power Law or Herschel-Bulkley models. For reference, the standards set by the American Petroleum Institute (API) for testing both oil based fluids (OBFs) [4] and water based fluids (WBFs) [5] define the Bingham Plastic model as the norm for all measurements of viscosity. Non-Newtonian fluids can be described as either shear-thinning or shear-thickening [6], where the fluid is less or more viscous with increased shear rate respectively. Thus, the properties of the fluid will be dependent on the current state of the fluid, either stationary or flowing, and at what flow rate/velocity. For drilling fluids this behaviour is desirable, as a shear thinning fluid will keep cuttings suspended when it is still and thick [7].The models are further defined below, by their mathematical expressions.

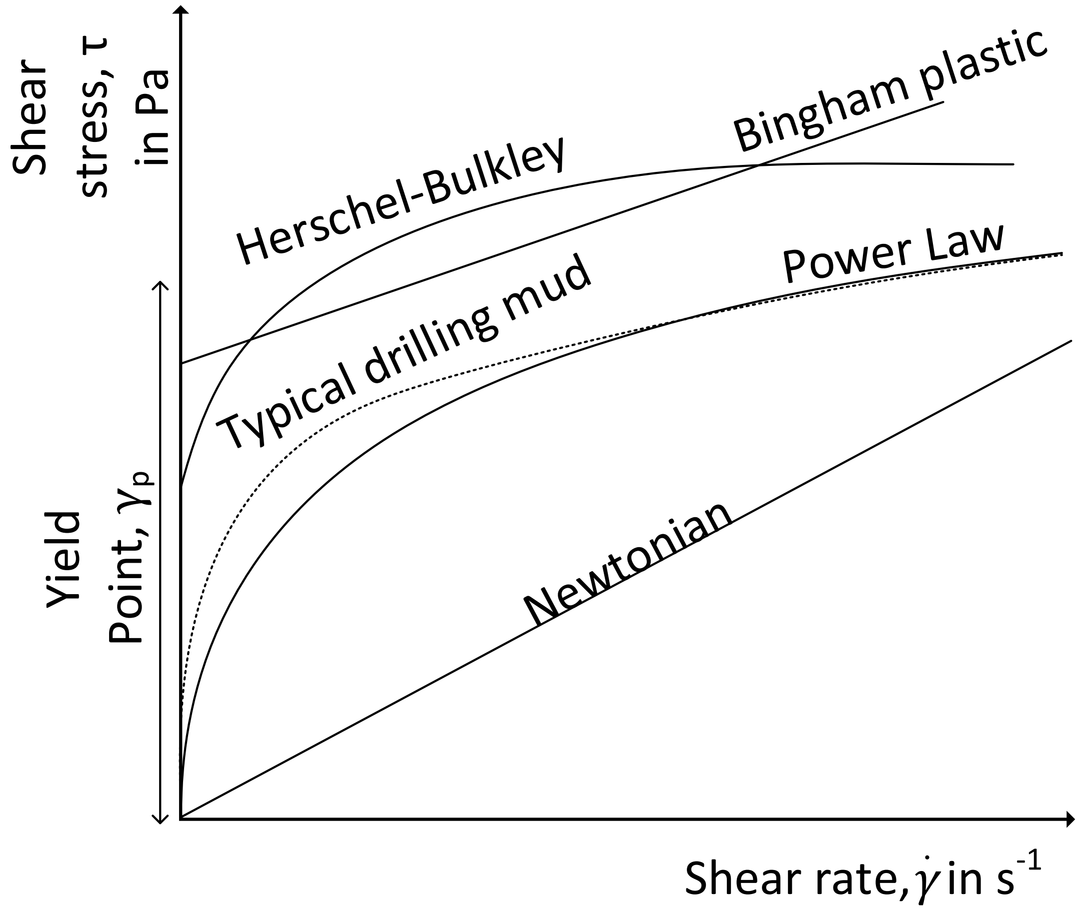

Figure 2. Comparison of different fluid rheology models. It shows non-linear behaviour of the Power Law and Herschel-Bulkley models, with the yield point to initiate flow in the Herschel-Bulkley and Bingham Plastic models. The curves are super positioned, and the models are defined in the text. Adapted after Caenn et al. [6] .

To define the viscosity of a non-Newtonian fluid, more than a single point measurement is required, as the viscosity is inferred by both the shear rate and shear stress. As viscosity is defined as the slope of the curves in Figure 2, a single point measurement is not enough. This is the reason for choosing a model (Power Law, Herschel-Bulkley or Bingham Plastic), along with measurements at selected shear rates. Thus, a few measurements can give the general shape of the curve, and viscosity at the relevant shear rate range. The models are defined as follows:

Newtonian fluid model,

$$\tau = \mu\dot{\gamma} \tag{1.1}$$

where τ is the shear stress and $\dot{\gamma}$ is the shear rate, with μ as the slope of the curve, and the viscosity of the fluid.

To include the non-linear behaviour of the non-Newtonian fluids, the Power Law introduces an exponential such that the shear stress is defined as,

$$\tau = k\dot{\gamma}^n \tag{1.2}$$

Where *k* is the consistency index and *n* is the fluid behaviour index.

The Bingham plastic model keeps the linear relationship, but adds the yield point as a bias, such that

$$\tau = \gamma_p + k\dot{\gamma} \tag{1.3}$$

where γ_p is the yield point.

For fluids with a linear relationship, the viscosity may be calculated by the slope of the curve,

$$\mu = \frac{\Delta\tau}{\Delta\dot{\gamma}} \tag{1.4}$$

Combining the yield point and non-linearity, we have the Herschel-Bulkley model defined as,

$$\tau = \gamma_p + k\dot{\gamma}^n \tag{1.5}$$

More refined models are described, that in some cases match true fluid behaviour more closely, but the models presented here are what are typically used to describe drilling fluids. They will generally follow Herschel-Bulkley behaviour, but the mentioned API standards assume the fit of the Bingham-Plastic when it considers the measurements of the viscosity. This is referred to as plastic viscosity, and the curve is sampled at selected shear rates to determine the plastic viscosity. For further details on non-Newtonian fluid models, the reader are recommended to review Aadnøy et al. [8] and Caenn et al. [6].

1.2.2 Density

The density of common drilling fluids is temperature dependent, and for a lot of the drilling fluids also pressure dependent, as for oil-based fluids the oil-component is compressible [6]. Furthermore, once the drilling fluid has passed the drill bit, and picked up any debris from drilling equipment in the wellbore along with rock cuttings, it has changed from the initial density, and the resulting fluid is more multiphase and abrasive in nature. As such, there are challenges in measuring the density, and the sensor systems used should be non-intrusive.

1.3 Objectives of the research project

The main objectives of this research project have been to develop methods and sensor systems to estimate the flow in an open channel flow with a Venturi constriction. In-line process measurement of the fluid rheological properties has also been identified as a secondary aim. Both have the potential to improve an early kick/loss detection system. And the secondary aim would also support the main objective, as several methods to estimate the fluid flow requires detailed knowledge of the fluid properties relevant to the models used.

1.4 Outline of the thesis

The thesis is structured after the objectives of this work. Chapter 2 includes the literature study for the thesis work, outlining the knowledge gap the work seeks to close. Chapter 3 will give an overview of the main objective of fluid flow measurement in the open channel with Venturi constriction, and it will review the results in Paper 1 in this context. Chapter 4 will give an overview of the experiments with drilling fluids, where a measurement principle to enable in-line measurement of the drilling fluid properties is assessed. This chapter relates to the Papers 2-4. Chapter 5 reviews the efforts of this thesis work and the results from the Semi-kidd research group. The results from the Semi-kidd project together with limitations and possibilities for future implementation in industrialized sensor technologies is discussed, supported on my own experience from working in the drilling industry. Chapter 6 concludes the thesis and presents the conclusions for this thesis work.

2 Literature study on prevailing measurement techniques

In this chapter the literature review the thesis work is based upon is presented. The developments on measurements of return drilling fluid flow and rheological properties are outlined back to the 1980s, and to the present ongoing developments as they are published in scientific literature. Along with the overview of the Semi-Kidd findings as they are presented in chapter 5, this literature review is submitted for publishing as Paper 5.

2.1 Rheological properties of return drilling fluid

On the drilling fluid properties measurements, first to mention is the API standards detailing the procedures to measure the rheological properties in all drilling operations. API RP 13-B1 [5] details the procedures to measure the drilling fluid properties of water-based drilling fluids. API RP-13-B2 [4] details the same for oil-based drilling fluids. These give the procedures for manually measuring the fluid rheological properties offline. The density and viscosity are deemed most critical, and is generally measured every 6 hours, whereas the complete set of measurements are performed every 24 hours. Thus, the measurements are poorly suited for control and monitoring systems where continuous, discretely reported measurements in an interactive system is needed. The need for automation of the measurement of fluid properties, and especially density, viscosity and other rheological properties have been discussed over the course of several years. Godhavn et al. [9], Broussard et al. [10] , Cayeux et al. [11] emphasize the need for these measurements. The purpose of the measurements is twofold, as the rheological properties are needed as input in hydraulic models for drilling process control. Next, they are also needed in the efforts to keep the drilling fluid properties within specifications. Similarly, there are two fields of research focused on the development of this sensor technology. The first aims at modelling and controlling the drilling process.

The other is the effort to automate the process of mixing the drilling fluid and controlling its properties.

In 1990 Podio et al. [12] showed that there is a relationship between acoustic attenuation, sound velocity and rheological properties of drilling fluids, as they sought to understand the effect of drilling fluid on acoustic measurements downhole. They indicated that this dependency can be used to determine fluid properties, although that was not their focus. At the same time Crowo [13] explored the same relationships, but aimed at determining the fluid density by using the measured sound velocity. In addition, Pope et al. [14] in 1992 showed that the density could be estimated by analysing the ultrasonic (US) resonant peaks in the frequency domain.

The pipe viscometers had already been outlined and discussed by Rogers et al. [15], and were tested in field experiments by Maglione et al. [16] . In 2003, Lourenco et al. [17] used the pipe viscometers to study the effect pressure and temperature had on the drilling fluid properties. As the drilling fluid is non-Newtonian, these environmental properties may change the fluid properties compared to the specifications and the designed mud at the surface conditions.

Furthermore, a densimeter that applies acoustic impedance measurements as well as sound velocity to give slurry fluid density has been described in literature by a group around Bamberger and Greenwood [18]–[21], but it is not stated whether the slurries are non-Newtonian or not, and the applicability to drilling fluids is therefore questionable.

Another approach was demonstrated in 2009 by Saasen et al. [22], where the measurements as described by the API standards mentioned above, where automated. An automated measurement system was constructed which picked a sample and measured the rheological properties by automatically sampling the fluid from the suction pit (upstream of the pumps) and running it through a bypass line and the measurement system. The system has been tested in field trials on the Norwegian

Continental Shelf (NCS). Other approaches are made by Broussard et al. [10] and Miller et al. [23]. Yet another approach has been discussed in several papers and reports [24], [25] where differential pressure meters in the standpipe are utilized to characterize the rheological properties of the drilling fluid. Yet, to the best of my knowledge none of these have become prevailing and widely applied. Thus, there is a possibility to introduce an alternative sensor technology, which will be detailed in Chapter 4, as a part of this PhD work.

2.2 Return fluid flow rate

As stated above, the measurement of drilling fluid flow out of a well is an important measurement. However, due to the challenges mentioned, the measurement has been trend-based, and not an accurate measurement. This means that the prevailing industry standard of using a flow paddle [26], does not measure flow rate accurate enough for automatic control and early kick/loss detection methods. Figure 3 shows the measurement principle of the paddle meter. The paddle deflection can be measured using either a rotary encoder or strain gauges. The flow paddle was in 1992 described as the industry standard by Schafer et al. [27] while Le Blay et al. [28] states it still is in 2012. To the best of my knowledge, this is still true. Due to the variation in the return fluid flow, depending on both the fluid properties, and if the fluid flow is enough to fill the pipe or not, the calibration of this flow meter is unpractical, and the measurement cannot be used quantitatively. The measurement is used for trending, by interpreting the trend against operations and other measurements on the drilling system, such as the pump rate, drilling speed, the operator can decide if the drilling fluid flow out can be an indication of any kick or loss situations [27]. In addition, the level in the drilling fluid pit (see Figure 1) is monitored [29]. Since the drilling fluid system is a closed cycle, differences in the drilling fluid flow in and drilling fluid flow out, will cause a change in the fluid level of the pit. This display a rather slow response, and the delay results in a larger influx volume, increasing the risk of a harmful incident.

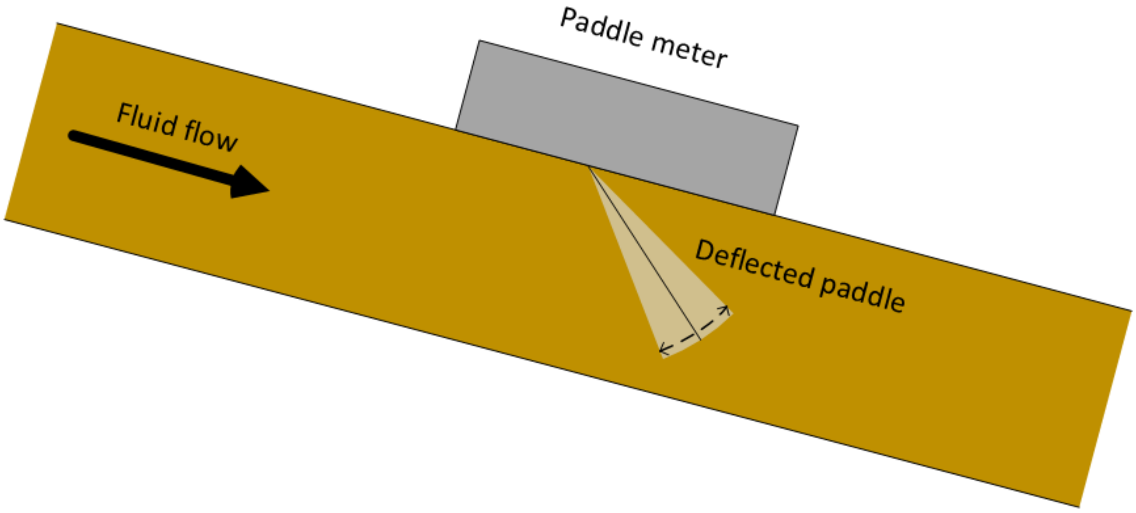

Figure 3. Flow paddle meter principle. The fluid flow will deflect the paddle differently depending on the flow rate/speed. It will also work if the pipe is partially filled but will only work as a trend-based measurement that needs human interpretation, as calibration is unpractical.

Already in 1987 Orban et al. [29] identified some new developments in fluid flow measurement, where they described a flow meter using ultrasonic level measurements and an ultrasonic Doppler sensor to calculate the volumetric flow. In the same year, Speers et al. [30] describes the delta flow method for kick/loss detection, as well as new magnetic flow meters for both inflow and return-flow. The delta flow method can in short be summarized as

$$\Delta Q = Q_{mud,in} - Q_{mud,out}$$

$$\begin{array}{ll} \Delta Q \approx 0 & \text{normal operation} \\ \Delta Q > 0 & \text{loss} \\ \Delta Q < 0 & \text{kick} \end{array}$$

Orban et al. [31] then set out to combine their based sensor with this delta flow method and they report improved detection time of simulated kick incidents in a field test. In 1988, Johnsen et al. [32] developed and tested a flow meter based on measuring the forces due to fluid flow through a J-bend. They had good results for the flowmeter in their original publication, reporting on further developments has been lacking since. To the best of my knowledge, this J-meter, as it is referred to in industry, and is found on some rigs, but remains unreliable and like paddle meter in reliability and accuracy. In 1992, Schafer et al.[27] conducted an independent evaluation of proven and emerging technologies for flow metering during drilling a geothermal well. For the outflow, they compared an acoustic level meter and a rolling wheel flowmeter to the common paddle meter. These are both non-direct measurements, and as the paddle meter only indicates relative changes in the fluid flow and are calibrated to the inflow meter. The next apparent development is reported by Schubert et al [33] in 1998, describing a pulse-echo system to detect the fluid level in a wellbore in case of total loss of return. This is a case where the fluid losses are so great that no fluid is returned to surface, and the fluid level in the annulus is the only indication of the severity of the loss situation. Thus, it is only of use in a severe kick/loss incident, and not as a measurement of the return fluid flow rate

Nayeem et al. [34] describes developments where downhole data is combined with inflow measurements to give indications of kick, yet no measurement of the return fluid flow rate.

Kotzé et al.[35] describes in 2016 a system capable of measuring the fluid flow rate and rheological properties using a sensor system combining ultrasonic velocity profiling (UVP) and differential pressure (DP) measurements. The UVP is furthermore a combination of time of flight and ultrasonic Doppler measurements. The effort to develop the system seems from the published papers to have been conducted since the early 2000s. The company promoting this technology lists drilling fluid measurements as a case study on their webpage [36] but no tests results are found in literature.

In [37], a modification of Lamb wave based non-intrusive and non-invasive flow sensors are described meant for multiphase flow measurements, and determination of gas/oil/water fractions. I have been involved in testing this sensor for the purpose of determining the flow rate of drilling fluid, and the publication is enclosed as Paper 6. The sensor is a non-invasive ultrasonic sensor, applying novel combination of helically oriented ultrasonic wave measurements with common straight-line reflection measurements. In short, the technology is promising, but needs more development to handle a wide range of drilling fluid flow rates, as well as testing for a variety of fluid properties and inclusion of cuttings. It may be considered at the same stage of development as described in [35], where the flow meter's basic principle has been demonstrated successful for a similar application but needs specific development to achieve success for this application.

There are also some developments which are not reported in scientific papers. One example is the Valcom flow meter, developed in cooperation with prof. Alimonti [38], [39]. This technology appears as a commercial solution sold by Valcom, but without any published papers proving the operation of the technology. Other technologies might be developed behind closed doors, as the oil service industry is highly competitive, where reporting during development of new technologies can be limited. I must limit my work to consider the scientifically supported developments, and this thesis reflects that, and any omissions due to this limitation must be excused.

2.3 Open channel Venturi with Ultrasonic level sensors

The Venturi test rig at University of South-Eastern Norway (USN) has been the focus of several works done in this field of study the past years [40]–[46]. Applying the Venturi effect to measure flow rate has been done effectively in different systems [47] and is defined in ISO standard [48]. The hypothesis of the Semi-Kidd research group, which I have been a part of, is that this principle can be applied to non-Newtonian fluids to estimate the fluid flow rate. The Venturi rig at USN applies this principle in an open channel, to be tested with model drilling fluids. Thus, the change in fluid level is the effect of the Venturi, and not a pressure loss as seen in pipes with Venturi constrictions. Ultrasonic or radar level meters are applied to measure changes in the fluid level, and by using a soft sensor this has been shown by Chhantyal et al. to estimate the flow rate

[45]. They applied several empirical models to estimate the flow rate and found that there is a trade-off between the more accurate model being more computer intensive than the second-best model. However, both had mean absolute percentage (MAPE) values less than 2%. Some work has also been carried out for master theses, namely Adeleye [43] and Ejimofor [44], where empirical approaches to estimating the flow rate has been carried out. These works show good potential for an empirical approach. The test rig has also been the focus of work where a mechanistic approach has been taken. Agu et al. [41] found that a 1-D model based on numerical solution of the Saint-Venant equations could estimate the flow rate. Two models were developed, one for steady state and one for unsteady state.

3 Flow measurements in open channels

As described in chapter 2.2, there is a need for developing measurement technology for the measurement of return fluid flow. This will enable better methods to detect kick/loss incidents, where analysis of the fluid flow into and out of the well and any discrepancies between these are of importance. The main idea of the Semi-kidd project has been to apply a Venturi constriction to an open fluid flow channel. The subsequent changes of fluid levels in this channel can then be measured. Then the fluid flow rate may be estimated using different models describing the relationship between the fluid levels at different points in the channel and the fluid flow. Here the background for developing these models are described, along with a short overview of them. The results are presented and discussed. This part of the work has been published in Paper 1 [49].

3.1 Open channel flow measurement theory

Any fluid flowing with a free surface is considered an open channel flow. Thus, the flow is gravity driven. One natural example of open channel flow is a river. The inclination of the riverbed, the width of the river and the texture of the riverbed and the banks are all affecting the river flow. The same applies in industrial applications, such as sewer systems or drilling fluid flow channels. In these applications, the inclination is still a governing factor, along with a friction factor related to the roughness of the channel bottom and walls. Following are two models describing the open channel flow with these, and other parameters. They are limited by assumptions of uniform channels and fluids with Newtonian properties. These are the foundations for open channel models, and the more developed models in chapter 3.1.2 and 3.1.3, where first non-Newtonian fluids are considered, and then the Venturi constriction.

3.1.1 Newtonian fluid flow models

A model describing the average velocity as a function of the friction factor and inclination angle of an open channel was developed in 1768 by Chézy [50, p. 699] The model is referred to as the Chézy equation,

$$V = C_{Chezy}\sqrt{R_h \tan\Theta} \tag{3.1}$$

Where V is the average velocity of the fluid, C_{Chezy} is a roughness coefficient for the channel surfaces, R_h is the hydraulic radius, and Θ is the channel inclination. In 1889 Robert Manning [50, p. 700] developed a similar model, using a different coefficient and applying the hydraulic radius somewhat different.

$$V = \frac{1}{n_{Manning}}(R_h)^{2/3}\sqrt{\tan\Theta} \tag{3.2}$$

Where $n_{Manning}$ is the roughness coefficient for the channel.

These are the basic models for open straight channel flow, with Newtonian fluids, which also needs to be tuned for the roughness coefficients of the respective models. Thus, more refined models are needed as non-Newtonian fluids are common in many industry applications, and especially in drilling industry.

3.1.2 Non-Newtonian fluid flow models

More recent research has focused on developing models for open channel flow that applies also to non-Newtonian fluids. The work of Burger, Haldenwang and Alderman have been reported in several published papers [51]–[54]. This model takes the fluid rheological properties into account and is expressed differently for average velocity in laminar (3.3a) and turbulent (3.3b) flow.

$$V = \frac{R_h}{2}\left[\frac{(16/K)\tau_w - \tau_y}{k}\right]^{1/n} \tag{3.3a}$$

$$V = \sqrt{\frac{2\tau_w}{pc_1(R_H)^{c_2}}} \tag{3.3b}$$

where
$$R_H = \frac{8\rho V^2}{\tau_y + K\left(\frac{2V}{R_h}\right)^n} \tag{3.4}$$

K is a geometry constant (values for typical geometries are given by Burger et al. [51]). τ_w is average wall stress, τ_y is average yield stress, k is the consistency index, n is the flow behaviour index, ρ is the fluid density, c_1 and c_2 are empirical geometry constants, also given by Burger et al. [51]. R_H is Haldenwang's Reynold's number [53].

With this, the flow upstream of the Venturi constriction may be modelled. However, as the geometry of the channel is easy to obtain and experiments like Burger et al. [51] may be conducted to find these constants, the varying fluid properties need to be determined by rheological measurements.

3.1.3 Fluid flow measurement in open channel with Venturi constriction

To relate the modelling of an open channel flow with the effect of a Venturi constriction, ISO-4359 [55] defines one model based on a single upstream level measurement as

$$Q_v = C_d C_s C_v \left(\frac{2}{3}\right)^{3/2} \left(\frac{g}{\alpha_1}\right)^{1/2} b_2 h_1^{3/2} \tag{3.5}$$

Where Q_v is volumetric flow rate, C_d is coefficient of discharge, C_s is shape coefficient, C_v is coefficient of velocity, b is the bottom width of the channel, g is gravitational acceleration, h is fluid level, α is kinetic energy correction factor or Coriolis coefficient. Subscript 1 relates to the upstream section, and subscript 2 relates to the throat (constriction) section. A sketch outlining some of the parameters of this model and their relation to the channel is shown in Figure 4.

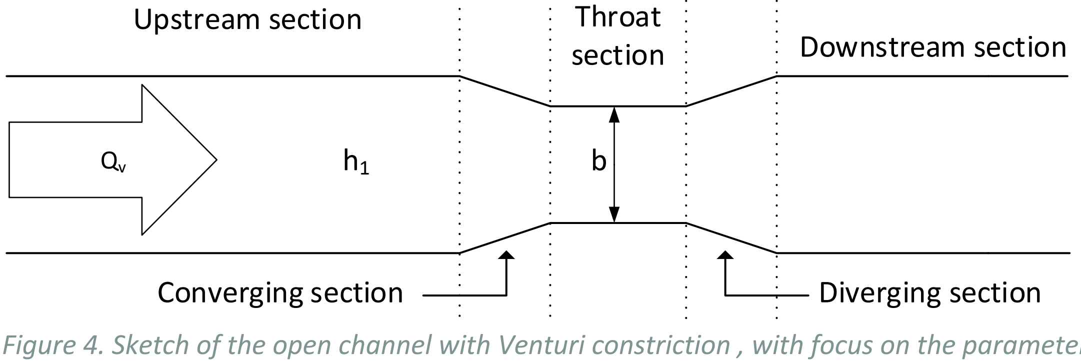

Figure 4. Sketch of the open channel with Venturi constriction , with focus on the parameters and sections related to the model described in eq. 3.5. This is not to scale.

The Venturi principle for open channel flow measurement is defined by ISO 4359 [55]. The standard details the design of the channel, regarding the material selection and the relationship between its various dimensions. The standard also states the measurement calculations and presents tables of the coefficients related with common channel designs. It does state that the models defined are only applicable if the flow upstream of the throat is subcritical, and the flow in the throat is critical. Another limitation is that the fluid flow should be slow changing, without the standard specifically stating what is a slow and what is a fast change of flow rate. As the fluid flow measurement with the aim of improving kick/loss detection, it is desirable to achieve as quick a response as possible, to as small as possible changes in the fluid flow. This will enable the most precise and flexible kick/loss detection algorithms. The standard does not take fluid rheological properties into specific considerations. The models presented does include calculation of Reynolds number, but the specifics of the fluids are not considered. Thus, there is a need to develop alternate models for the application described in this work.

3.2 Venturi channel flow measurements at lab facility

The work on measuring the flow of model drilling fluids in an open channel has been published in Paper 1 [49]. The lab facility at USN was constructed to explore the viability of the Venturi constriction and applying different models and measurements on fluid levels in the channel to estimate fluid flow. The focus of this thesis work was to develop data driven models to estimate the volumetric fluid flow using ultrasonic level sensors placed above the open channel in combination with other process measurements.

Figure 5 outlines the piping and instrumentation diagram (P&ID) of the rig with the relevant sensors used. The level sensors in the open channel are movable along the channel, and different configurations may be considered depending on the model used for flow estimation.

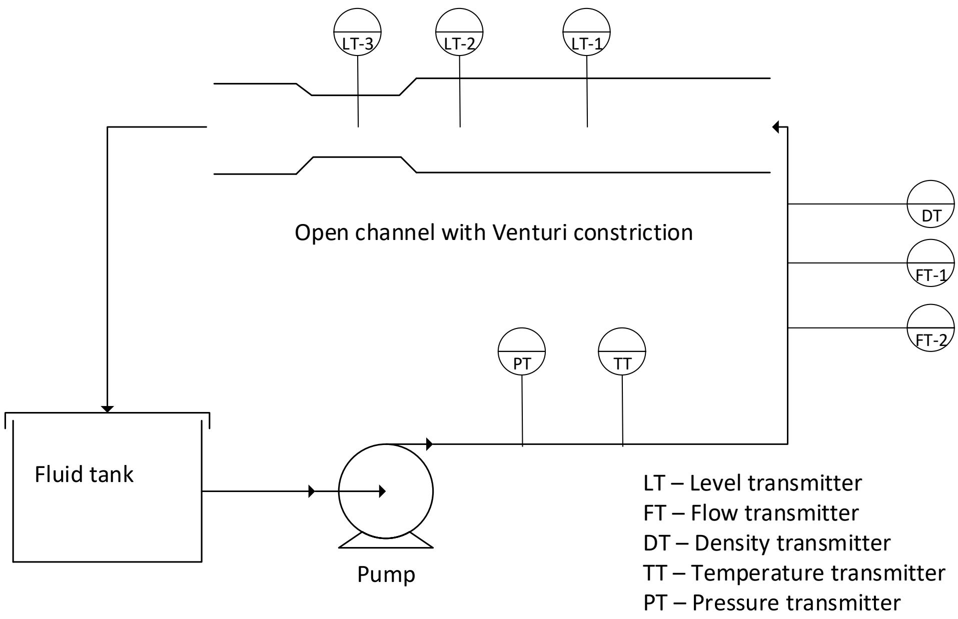

Figure 5. P&ID of the flow loop rig. The flow direction as indicated by the arrows and sensors with tags as shown. The level transmitters used are ultrasonic, and the two flow transmitters are two Coriolis meters. One is used for reference, and the other used for the control of the pump.

The setup consists of two fluid tanks, a pump, piping and an open channel with a Venturi constriction. In addition, the flow loop has different sensors installed, as indicated by the P&ID. The fluid is pumped from the tank up to the open channel, where gravitational flow leads the fluid through the open channel and the Venturi constriction before returning to the tank. This experimental setup has been the focus of many research works on the flow of model drilling fluids and has resulted in several published papers [37], [49], [56]–[62], [62]–[73]. Part of the experimental setup is shown in the photo in Figure 6. The view is along the flow direction, toward the Venturi constriction. In this specific photo, there is an ultrasonic level sensor as well as a radar level sensor in the background, which was tested for some other experiments.

Figure 6. Partial view of the open channel with Venturi constriction. The flow direction is away from the viewer, with the Venturi constriction ahead, with two level sensors suspended above the channel. Photo by A. Jinasena.

The channel is in total 3.7 m long and is trapezoidal in shape. The bottom width varies, as the constriction is narrower. Figure 7 shows the dimensions for the channel used in these experiments. The setup is capable of circulation of a mass flow rate ranging from 250 to 450 kg/min, which gives volumetric rates in the range 180-400 litres per minute depending on the fluid in the system. The fluids are described in chapter 3.2.2. These flowrates are in the low range when compared to drilling operations offshore. Typical flowrates can range from 500 to 3000 litres per minute. In addition, the flow return channel will be of different dimensions and design, and the experiments performed in the lab at USN would still need to be verified by pilot or field scale tests to prove the applicability of the concept to the industry.

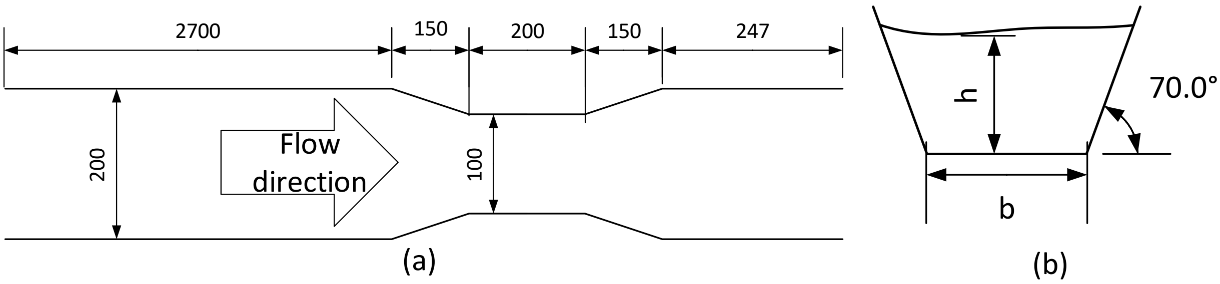

Figure 7 Dimensions of the open channel with Venturi constriction , all dimensions are in mm, and the drawings are not to scale. (a) is the top view, with the width of the trapezoidal channel indicated by the bottom width. (b) is the cross-sectional view, with b the varying width of the different sections, and h the varying fluid level. Sketch and measurements from Glittum et al. [40]

3.2.1 Sensors in the model drilling fluid circulation system

In the system, several sensors are installed, as can be seen by the above P&ID. Table 1 details the sensors, and their accuracies. The Coriolis mass flow meter with tag FT-2 is used as a reference for the volumetric fluid flow estimations. FT-1 is used in the control system for the rig, to adjust the pump output to the setpoint.

Table 1. Details of sensors installed in the model drilling fluid circulation system. and their accuracies. The tags are referenced to the P&ID in Figure 5. The details are based on information from the sensor manufacturers.

TAG	MODEL	MEASURAND	RANGE	ACCURACY
LT-1, LT-2, LT-3	Rosemount Ultrasonic 3107	Level	0.3-12m	0.025 m
PT	Smart Pressure Transmitter PCE-28	Pressure	0-7bar	±0.1% of measured value
FT-1	Endress+Hauser Promass 83I Coriolis meter	Mass flow Viscosity Density	0-1000 kg/min	±0.1% of measured value
TT	Endress+Hauser RTD Thermometer omnigrad TST41N	Temperature	0-100°C	±0.19°C @ 20°C
FT-2	Endress+Hauser Promass 63F Coriolis meter	Mass flow Density	0-1000 kg/min	±0.1% of measured value (mass flow) ±0.01 g/cc
DT	S-Tec DT-9300 Density transmitter	Density	Can measure all liquids and slurries.	Typically less than ±0.2% of highest density over 20s

3.2.2 Model drilling fluids – their design and properties

In the lab facility the circulation system is not designed to handle particulates in the drilling fluid, and it is also an open system in a lab that hosts other researchers and their equipment. For that reason, fluids that models the behaviour and properties of the drilling fluids used in drilling operations are used. The model drilling fluids consists of three main parts, tap water, xanthan gum and potassium carbonate (K_2CO_3). The xanthan gum is the viscosifier in the mix, and the potassium carbonate is the densifier. The fluids used in the study are mixed in the lab, and the compositions are given in Table 2. The model drilling fluids are designed to emulate industrial drilling fluids with respect to their densities and viscosities only. Drilling fluids used in industry might be designed with focus on more properties, including but not limited to filtration properties, alkalinity, lubricity and corrosivity [6]. Several considerations are taken for each drilling operation to consider the design of the drilling fluids that is not considered for the model drilling fluids used in this work. Normal range for density of drilling fluids is 1100 – 1800 kg/m^3, and the normal range for plastic viscosity is 0.005-0.050 Pa·s. The rheological characterizations of the fluids have been performed using professional fluid measurement equipment (Anton Paar Modular Compact Rheometer MCR 502).

Table 2. Model drilling fluids composition. The additives to the water base are given as percent weight, and density in kg/m^3. Fluid 1 is tap water, but the circulation system is not cleaned up between use of the different fluids, so the water will pick up some residuals from the last fluid used. Flow index, n (dimensionless), and consistency index, k in Pa are the parameters used in the rheological models Power Law and Herschel-Bulkley.

Fluid	*K_2CO_3 % vol*	*Xanthan gum % vol*	*Density, ρ kg/m^3*	*Flow index, n*	*Consistency index, k Pa*
1	-	-	1015	0.97	0.01
2	18	0.07	1145	0.63	0.05
3	21	0.07	1190	0.64	0.04
4	29	0.21	1240	0.47	0.23
5	73	0.22	1340	0.82	0.03

3.3 Developing fluid flow models and their performance results

As the models described above for non-Newtonian drilling fluids are limited, the work published in Paper 1 [49] focused on development of alternate models to estimate the drilling fluid flow. The work has focused on machine learning (ML) models, using variable inputs, based on fluid level. Experiments were performed to find the best suitable configuration of level meters in our lab setup, both regarding of the number of level measurements, and the placement along the channel in the flow direction.

Considering the possibility of a non-linear relationship between the fluid levels in the flow channel and the fluid flow rate, both linear and non-linear models were developed. The linear models used were simple linear regression (SLR) and polynomial linear regression (PLR). These are simple, but effective models and served as a good starting point to consider the model development. For the non-linear models three types of ML models were developed. These included artificial neural networks (ANNs), support vector regression (SVR) and adaptive neuro-fuzzy inference system (ANFIS). Paper 1 details the experiments made to collect both training data for the models, but more importantly for their validation. As this study is part of a proof of concept for the measurement principle applied to non-Newtonian drilling fluid, the validation results are the most important. As the models are applied to measurements within their training range, but not used for training the models, they can be validated. As Paper 1 shows, several model types and configurations are applied to the same data, to be comparable.

The key findings from this work are twofold. First, the promising results from the validation of the data driven models that are based upon our lab experiments. These results are shown in Table 3, pointing out the results of the ANN with one single level measurement and the PLR as the most successful models. Included in the table is also the Norwegian requirements for the drilling parameter measurements [74] which is 5.0% accuracy of the measured return fluid flow. This standard does not specify accuracy requirements for the fluid flow into the well, as this is often related to the measurement on the pumps. This is specified by the counting of strokes and is hard to relate to the accuracy of the computed pump output. However, the Coriolis meter is common as the inflow measurement system, and typically these meters have accuracies below 0.5%. As Table 2 shows, the results from the developed models are within the standard requirement, but not comparable to a Coriolis meter. The common industry measurement of return fluid flow is based on the paddle meter, which does not have a specific accuracy, as the measurement is trend based and relies on interpretation and comparison to other measurements such as the drilling speed (rate of penetration), the pump flow in and the position of the bit and if the drilling fluid properties are adjusted. The main reason for this is that the paddle meter is only used to detect changes in flow, to discover kick/loss incidents. As such, the results from using the Venturi constriction in the open channel and ML models are promising in introducing quantified measurements of the return fluid flow in the drilling process.

Table 3. Performance of different machine learning models estimating the volumetric flow rate. The reported performance is MAPE in percent and root mean square error (RMSE) in litres per second.

Machine learning models	*MAPE [%]*	*RMSE [l/s]*
Simple linear regression	4.76	0.24
Polynomial linear regression	2.09	0.16
Support vector regression	2.37	0.17
ANN (single level input)	2.05	0.16
ANN (three level inputs and density)	2.44	0.16
ANN (three level inputs)	2.25	0.16

The next important finding is from extrapolating the results from these models. This was done to extend the range of the models to flowrates like the actual flowrates in field applications. The extrapolated models were compared to the ISO standard upstream level-based model as defined in 3.1.3 and eq. 3.5. In this regard, the results were less consistent, as the graphs (Fig. 12) in Paper 1 shows. The important observation is that considering this extrapolation, the best performing model was in fact simple linear regression, as the other models failed to follow the trend of extrapolation.

4 Estimating drilling fluid properties using ultrasonic measurements

This section of the thesis will put the work of Papers 2-4 [63], [64], [72] into context and outline the most important parts of the work. For full details, please review the papers.

The objective of this part of the work has been to explore a measurement principle for estimation of rheological properties based on ultrasonic measurements. As shown in Paper 1 [49] some models require knowledge about the fluid rheological properties. This is also relevant to other parts of the Semi-kidd research group efforts, focusing on mechanistic models that relies on specific knowledge of the fluid rheological properties.

4.1 Ultrasonic waves in non-Newtonian fluids

Measurements using ultrasonic waves are often used in various flow metering techniques, e.g. for the fiscal flow metering in oil & gas industry. In this application, accurate measurement of the oil, gas and water content in a multiphase fluid stream is in focus. As Podio et al. [12], Crowo [13] and Pope et al. [14] has shown, the acoustic characteristics of a fluid are related to the rheological properties density and viscosity of non-Newtonian fluids. As Dukhin et al. [75] writes about the acoustic theory of particulates (fluids with particles in suspension) “Despite 100 years of almost continuous effort by many distinguished scientists, there is still no single theory that meets all of these requirements”, referring to three central requirements about the particle size distribution, particle-particle interactions, and numerous ultrasound interactions such a theory should encompass. Together with the non-Newtonian behaviour of drilling fluids this proves that defining such a theory is a great challenge. Considering the acoustic attenuation and sound velocity it is possible to describe a relationship with the density and viscosity of the non-Newtonian fluids, but no model has been found in literature. Therefore, the ML techniques that rely on data to develop the models, rather than explicit mechanistic models, are well suited for the task.

Paper 2 [72] details the first experiments performed, measuring ultrasonic wave propagation in a drilling fluid sample, and the exploration of the relationship between acoustic properties and rheological properties. In this work, a relationship between the attenuation and density and viscosity of the fluid sample was apparent. Its non-linear behaviour made it suitable for use in ML models. Paper 3 [64] and 4 [63] follow this development, with additional experiments on two new fluid samples and exploring different ML model types. In the following sections, the experimental setup is explained briefly, along with the main results from the last paper, where the developed ML models were applied using the full set of fluid samples to evaluate the model performances.

4.2 Experimental setup for ultrasonic characterization

Ultrasonic through transmission modalities were used to record the transit time and sound velocity of three drilling fluids systems. In collaboration with the drilling fluid manufacturer, a scheme was detailed for diluting the fluids to increase the potential for data collection. Each of the three samples were diluted in total 10 times, thus granting 33 fluid samples with different rheological properties. The amplitude and time of flight of the ultrasonic pulse was carefully measured at different distances. Precise laboratory measurements of the fluid rheological properties were used as the reference for the developed models. The details of the fluids are given in the attached Paper 4, Table 1.

Some results based on ultrasonic transmission was reported by K. N. Mozie [60] using the experimental setup for the measurements of ultrasonic wave propagation. The near-field effect was quantified and established the measurement procedure for the further experiments. M. Hafredal [59] applied this procedure to one of the drilling fluid systems, which is also used in Paper 3 and 4.

The objective of the experiments was to explore a measurement principle that may be applied to the drilling fluid storage systems. The future goal of developing a measurement principle for the potential of a non-invasive system that can be installed on the outside of the return flowline, which will present new challenges. The initial motivation for the ultrasonic measurements in the drilling fluids was to evaluate their ultrasonic attenuation. In that way the feasibility of ultrasonic based fluid properties sensors could be evaluated. As shown in chapter 2.2 there are several developments on fluid flow sensors using ultrasonic waves. If these sensors also could apply the ultrasonic measurements to the fluid rheological measurement, the potential for a change to the industry common practice is increased. The clear change in the ultrasonic attenuation with respect to both the distance and the fluid rheology, showed a promising potential for rheological characterization

The setup featured a tank for holding the fluid, a frame for submerging an ultrasonic transmitter (UT) and a receiver (UR) into the drilling fluid. Three transmitter/receiver pairs with different frequencies (0.5, 1.0 and 2.25 MHz) were used, as well as the transceiver for generating the ultrasonic pulse and measuring the received pulse. The setup is shown in Figure 8.

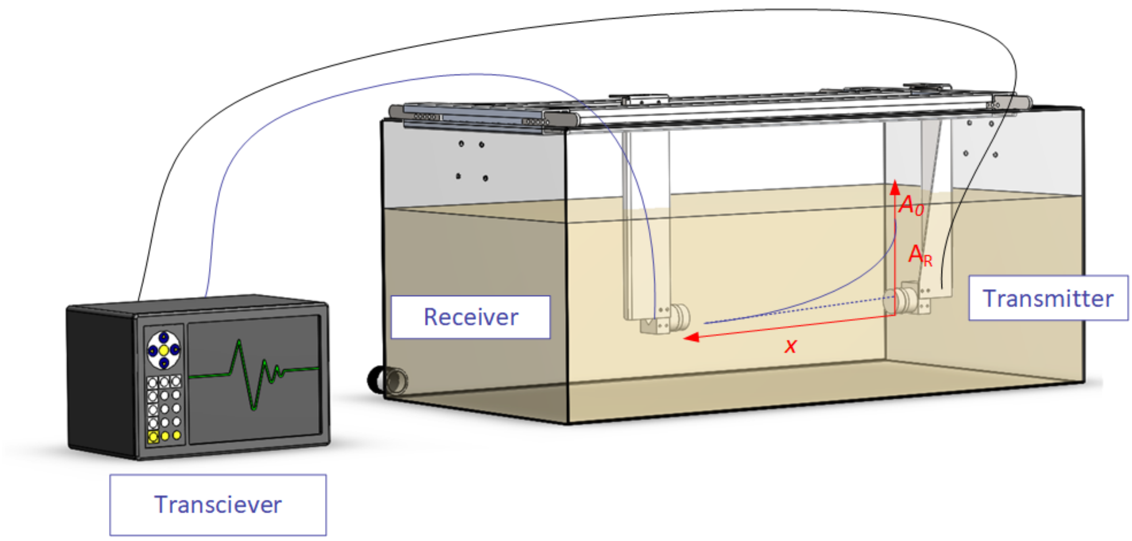

Figure 8. Experimental setup to measure ultrasonic wave propagation in drilling fluids. The signal is transmitted and received along the x-axis, and this distance (x) is varied to increase the database for training the machine learning models. The received amplitude (A_R) is measured in addition to the transit time, and with the measured distance along the x-axis the sound of velocity is calculated. The amplitude is expressed as a ratio of the reference amplitude at A_0, recorded at x=3 cm.

In all the drilling fluid systems the measurements were done with the three pairs of UT/UR. The two first papers (Paper 2 and 3) used the data from all three pairs in developing the rheological models, while in the latter work (Paper 4) the measurements made with the 0.5 MHz UT/UR was chosen, as this work focused on several models, and to effectively compare the model types, this most promising frequency was selected.

In addition to the varied fluid samples (33), the data collection was increased by varying the distance between the transmitter and receiver. Calculations of the near-field effects of the transmitter/receiver pairs by Mozie [60] established a procedure using x=*3 cm* as the reference distance for the amplitude, as this avoids any near-field effects. It was assumed that the scattering effect was occurring due to the particulates in the drilling fluid. This effect is expected to increase in the field application, as rock cuttings also will be present in the drilling fluid. This scattering will result in a great loss of transmitted signal, as a lot of the signal is lost between transmitter and receiver due to misdirection by the particulates. Depending on the volume fraction of the particulates, this scattering could also result in multiple reflections reaching the receiver, resulting in a noisier signal. Thus, a peak measurement that is both lower and noisier must be expected in such a fluid. This effect is not quantified in the experiments, as focus is on the acoustic measurements for training the ML models. Thus, any influence of scattering will also be part of the models trained, to the degree that the scattering affects the transmitted signal.

4.3 Description of models for the estimation of drilling fluid rheological properties

In this chapter the models used to estimate the rheological properties of the drilling fluids in the experiments are briefly described. In this work focus is on developing three machine learning models based on the three experiments. Paper 2 [72] explores the possibility of using regression models on the first fluid experiment, while Paper 3 [49] explores applying ANN to two of the experiments. In the end, Paper 4 [63] reviews results from all three experiments, and considers three types of models, ANNs, SVR models and an ANFIS models.

The models described are all ML models. This means they are data driven and are not represented by mathematically expressed physical relationships between inputs and outputs. The models are trained using datasets consisting of input and outputs. The datasets are divided into training, validation and test subsets. A detailed overview of the workflow in collecting data, dividing the dataset and performing training, validation and testing of the ML models are given as a general overview applicable to all three model types, in Paper 4, Figure 6.

The inputs of the models, and the two possible outputs are given in Table 4 and Table 5, respectively. The inputs are measurements from the experimental setup as described above, while the targets for the outputs are from the rheological characterization of the lab analysis. The models were designed to give only one of the outputs, such that for any model architecture, it was trained once with density as the target output, and in the next model plastic viscosity was the target output.

Table 4: Input variables to machine learning models

Input	Symbol
Time of flight	t
Distance	x
Relative amplitude	$A(x)$

Table 5: Output variables from machine learning models. Models are designed for each output, such that any model outputs one rheological property.

Output	Symbol
Density	ρ
Plastic viscosity	μ_p

4.3.1 Artificial neural networks - a short review

For ANN, the models trained are simple compared to more common uses of ANNs. The number of inputs used in this work is only three, while typical application of ANNs can be image analysis and categorization, where the inputs may be several thousands. As the work in Paper 2 [72] on linear regression showed, there is a clear non-linear relationship between the increasing distance between transmitter/receiver, and the measured amplitude. The hypothesis was that this non-linearity would be modelled well by ANN.

ANN is a ML model branch that features networks of interconnected nodes, to compute output based on input. The nodes, and the connections between the input and output are designed to each application, with varying number of hidden layers and number of nodes in each layer. In addition, an activation function is chosen to calculate the output from one layer into the next, or to calculate the output. The principle of such a network is shown in Figure 9. Here a network with one hidden layer is shown similar to the ones that were used in this work, although configurations with several hidden layers are common, depending on the application. The input variables are connected to the hidden layer, and the weights (*w*) decides the influence of each input node to each hidden layer node. Next the product of each associated weight and preceding node is evaluated in the hidden layer node, and the activations function propagates this to the next layer, in this example the output node. The process, known as feedforward can be vectorised and defined as [76]

$$ {}^{1}Y = {}^{1}f\left({}^{1}W \cdot X + {}^{1}B \right) \tag{4.1} $$

$$ {}^{2}Y = {}^{2}f\left({}^{2}W \cdot {}^{1}Y \right) \tag{4.2} $$

where *Y* is the *p* by 1 vector of outputs, *W* is the n by m array of weights, *X* is the *m* by 1 vector of inputs, and *B* is the 1 by *n* vector of bias. *n* is the number of hidden neurons, *p* the number of outputs and *m* is the number of inputs. *f* represents the activation function used. Preceding superscript 1 and 2 refer to the layers.

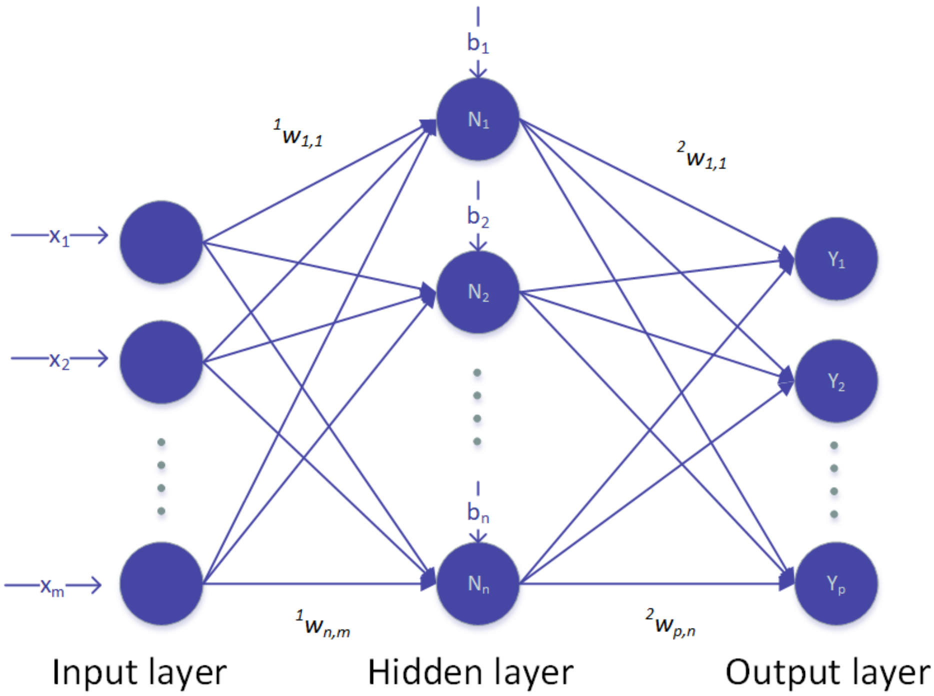

Figure 9. Sketch of ANN with one hidden layer, m inputs and p outputs, with n hidden neurons in the hidden layer. The connections between input nodes, hidden layer nodes, and the hidden layer nodes and the output nodes are weights. Adapted from Haykin [77].

The artificial neural network models were applied in two steps. First for the use in Paper 3, where two fluids where characterized, both WBF. This would be a first test to evaluate the use of ANN before the third fluid system had been characterized. The results were good, and ANN was used in our last and final evaluation of the chosen ML on the full dataset.

For descriptions of ANNs the reader is referred to Paper 4, and detailed description by Haykin [77]. The ANNs were trained using MATLAB Neural Networks Toolbox 11.0 and Statistics and Machine Learning Toolbox 11.2. The code generated by these toolboxes was then reworked to perform meta-parameter training, i.e. optimizing the size and structure of the ANN. This involved retraining the networks several times and finding the optimum performing network, by searching for the number of hidden neurons. The best performance was achieved when restrained between 3 to 50 hidden neurons.

4.3.2 Support vector machines - a short review

Support vector machine (SVM) models were developed as an alternative to ANNs. SVMs solve non-linear problems by mapping the dataset into a higher dimensional space, the feature space. This is done by applying a kernel function, which can be of several designs. In our application, it was decided to use a Gaussian kernel function after trial and error with several kernel functions. In the feature space, the original dataset may be estimated by a linear regression. This solution is then brought down to the original space, and the model is described. The application of SVM as a regression model [78] is referred to as SVR and is described by

$$Y = \sum_{i=1}^{N_{SV}} \left(w_i \cdot \varphi_i(X) \right) + B \tag{4.2}$$

where $\varphi_i(X)$ is the kernel function, i.e. the mapping function from the input space to feature space. *B* is the bias array, *X* is the input array, *Y* the output array, *w* is the distance of each point from the error margin and N_{SV} is the number of support vectors.

4.3.3 Adaptive neuro-fuzzy inference systems - a short review

ANFIS are systems combining fuzzy inference and neural networks. This hybrid system is tuning the membership function parameters and fuzzy logic rules by a neural network. The fuzzy inference system is initially designed by the user, and the neural network performs parameter-optimization based on the training dataset given.

This model type was explored, as it is another common ML model, in addition to the two other selected models. It combines the data-driven learning of the neural network with user input of designing the fuzzy logic inference system.

The model was developed by using the MATLAB toolbox for Neuro-fuzzy design, and as for the two other models, the dataset was the same, divided into training and test set. The algorithm used by MATLAB selects cross validation data from the training set to avoid overfitting. The details of the training algorithm are given in Paper 4.

4.4 Results from models used in estimating drilling fluid rheological properties

In presenting the results from the different ML models, focus is on the ANN results. These showed the smallest MAPE, both for the two types of output (density or plastic viscosity) and for the two types of input data drilling fluid type (WBF or OBF). The results are summarized in Table 6. The models were compared using an independent test data set from the experiments. Furthermore, the training time was evaluated in addition to the processing time for the test dataset estimation. Since the number of inputs are limited to three, and the datasets in general were small, approximately 1000 samples, the elapsed time for training was not a problem, ranging from 1.7 to 2.5 sec. The time to process the estimations for the test data ranged from 0.02 to 0.05 sec. These elapsed times were recorded using a normal work-laptop with no significant hardware, and other software running could have affected the times, so for the reported results, the computational efficiency of both training and evaluation is negligible.

Full overview of the results is given in Paper 4, but the key finding is that the ANN was the best performing model for both density and plastic viscosity. The two other types of models were not too far off, which supports that the ANN model is valid, and that it is not just coincidence that the model predicts the outputs with the reported error. As repeated training was performed 1000 times to find the best performing model, this could happen, a lucky combination of the parameters could give well performing models, but as the results show, each of the model types perform with error values in the same order of magnitude.

Table 6: Performances of ML models estimating drilling fluid rheological properties. MAPE in %, for all best models of each type for two fluid systems

Model type	OBF MAPE, %	WBF MAPE, %
ANN Density, ρ	1.17	0.69
ANN Viscosity, μ_p	4.66	4.07
SVM Density, ρ	2.87	1.27
SVM Viscosity, μ_p	13.6	22.2
ANFIS Density, ρ	1.79	1.52
ANFIS Viscosity, μ_p	10.60	19.5

The results are limited by the method used for collecting the training set. The decision to dilute the three original fluid systems gave increased training dataset, but it can be considered a dependent dataset, as the dilution would be dependent on the fluid it was diluted from. There might also be some errors in the way the dilution was performed compared to the practical methods applied in the field for these fluids. The facilities to replicate exactly the drilling fluid mixing process was not available during this thesis work.

The training data set range spans well for both density (1180 to 1750 kg/m^3) and viscosity (0.0042 to 0.0397 Pas). This is within the range of expectation in field applications, and thus the models are valid. However, the composition of the drilling fluid has not been generalized, as in the field, the composition may be specific to one section of a well. Despite these limitations, the dilution and the resulting range of properties measured here shows the validity of the developed models when applied to a limited number of fluids. It can not be concluded how well the developed models generalize different drilling fluid systems, but once trained on a system, with good range of training data, their performances are promising. In the field, the generalization to various fluids may not be necessary, as common drilling process operations might allow for collection of training data on the actual drilling fluid system used in the current operation.

5 Semi-kidd findings and their future

The literature review of recent developments along with some historical developments regarding the two measurements: return fluid flow and in-line fluid rheology, are published in Paper 5 (submitted and currently under review in Measurement Science and Technology (MST), Institute of Physics (IOP) Publishing, December 2019.) This review has been presented in general terms in chapter 2, and the following chapter will take some of the main findings in Paper 5 and discuss the results, possibilities and limitations of both this thesis work, and the other theses from the Semi-kidd research project. It will end with conclusions and recommendations for future work

The main technological idea of the Semi-Kidd research group is to improve kick/loss detection by developing sensors and models for estimation of the return fluid flow by using an open channel with a Venturi constriction. The first research objective in this thesis work was to explore the application of machine learning models, estimating the fluid flow in the open channel based on the level measurements at different locations in the channel. The second objective was to explore the estimation of the fluid rheological properties, as measurements of these could further increase the quality of kick/loss detection by improving quality of the flow rate estimation models. In addition, it could also enable other automation and digitalisation efforts in the drilling process.

5.1 Results from estimations of flowrate and fluid rheological properties

The main findings from Paper 1 is proof of concept for flowrate estimation with several configurations both regarding sensor placement in the channel, and with different ML model types. Based on this Chhantyal [79] presents the ANN model as the best performing ML model to estimate the fluid volumetric flow in the open channel. Furthermore, some additional challenges to be solved are identified, one of which is estimation of fluid rheology. The results show that the best performance is achieved by using a single level measurement, upstream of the Venturi constriction and an ANN model. When the model is extrapolated outside the range of the training dataset, it is not comparable to the standard model of the upstream. In such a case, the SVR and PLR models were more flexible, performing well outside their training range. As such, the best model, when deployed in the field would be application dependent, considering the expected range of flow, and opportunity to train the model using the full expected range of the input variables. The models were reported with mean absolute percentage error in the range 2.05-2.37% of the measured value for the test data set, which is good compared to the NORSOK standard requirement of 5 % [74].

Based on the same experimental setup, and similar data from the flow channel, other methods to estimate the fluid flow rate of the return flow have been developed, the selected best methods and their performance are summarized in Table 7. A. Jinasena [80] details work on the estimation of state parameters, and applying mechanistic models to estimate the fluid flow rate. One important challenge to address was the processing time of the mechanistic model. For the mechanistic models to be quick enough, several approaches must be taken to make them effective enough for real-time use, where the aim has been to develop models to provide estimations with 1 second updates. In [80] several schemes to solve the hyperbolic PDEs in the models are explored. The orthogonal collocation method is used along with a fit-for purpose friction model to estimate the fluid flow rate in the open channel. This method outperforms the ML models in Paper 1, with a reported 1.7% MAPE.

P. Welahettige [81] combines experimental findings and computational fluid dynamics (CFD) simulations to evaluate estimations of the fluid flow rate using mathematical mechanical models. A model based on 1D Saint Venant equations that gave an estimation average error of 4.1% with optimal placement of the level sensor upstream of the Venturi constriction. With the simplification to the 1D model the model is fast enough to be used real-time, while the extensive 3D CFD modelling and other experimental data validated the performance results.

Table 7 Overview of performance results on models estimating fluid flow in open channel with Venturi constriction based on level measurements. The NORSOK standard is used as a reference to show that all models have potential. The performance is given as MAPE value compared to Coriolis reference measurement.

Method	MAPE
NORSOK Standard requirement [74]	5.0%
ML model, ANN [49]	2.1%
State estimation model [67]	1.7%
1D Saint Venant model [57]	4.1%

For the ML models, a lot of the algorithm and training efforts goes into regularization and to avoid overfitting the model. Although outperformed here, ML models may be competitive against the mechanistic models presented in [80], if applied on an industrial scale. There would be potential in building an algorithm to train the ML models during certain operational tasks and make the models more flexible and quicker to adapt to operational changes. This could also be done with the mechanistic models, where a scheme was written to increase the states included in the model, to adapt to the different operations, and allow the model to be updated during the operation without specific changes by operators. This would resemble a grey-box machine learning approach, where some parts of the model would be mechanistically described but tuned by an algorithm based on machine learning techniques.

Reviewing these three approaches to the same problem, using the same experimental setup and fluids, it has been shown that the application of an open channel with Venturi constriction, and models using level measurements in the channel as inputs has potential. These experiments and models developed in the lab have all different, but promising performance results in the same order of magnitude. The selection of which method would be best suited should be further researched at field scale and with field conditions. The lab experiments performed at USN are scaled down in terms of the volume and flow rate of the fluids. Furthermore, the fluids will also be different, as the model drilling fluids used at USN are similar in some of the rheological properties, but not all. The mechanical design of the lab channel will also be different from the various adjustments that needs to be done in any rig installation. As such, any model chosen will still have to be tuned to the specific rig design.

For estimation of the fluid rheological properties of drilling fluids, the main findings are presented in Chapter 4.4. Here the proof of concept of a measurement system measuring the rheological properties of non-Newtonian drilling fluids by using ultrasonic measurements in a tank is presented. This measurement principle should be developed further to apply to inline flowing systems. Then the continuous measurement of density and plastic viscosity may be used to enhance the proposed models to estimate the fluid flow rate in the return channel. If this can be achieved, the differences between the model approaches might change, and makes it challenging to evaluate which approach would be best suited to field application.

Participating in the work with Xsens and their ultrasonic technology, gave insight into a different approach than the open channel with Venturi principle. The work is enclosed as Paper 6, where the testing of the ultrasonic sensor technology developed by Xsens is described. This thesis work includes the participation in this testing, and in analysing the results and reporting them in a conference paper. This collaboration is what lead to the idea that applying the techniques explored in chapter 4 can be applied to ultrasonic flow meters. Due to the time constraints in this thesis work, it was not possible to pursue this idea in further collaboration.

5.2 Future developments

5.2.1 Implementation of the open channel sensor system

From my experience working in the drilling industry, the rig design will impact the specific design of the sensor system when applied to any rig. In addition, it will also have to adapt to different operational conditions when installed. During the drilling of an oil well, the different sections of the well require differences in both the drilling fluid design, the constraints on typical operational parameters. For instance, during drilling one section of the well, the inflow rate might be limited to 1500-2500 l/min for various operational and geological purposes, and the drilling fluid will have densities in the range 1500-1550 kg/m$^{3.}$ In the next section, it might be down to 1000-1100 l/min inflow rate and 1300-1350 kg/m^3. Within each section, the setpoint for the flowrate and densities might be changed either gradually or stepwise. Any model to be used to measure the return flowrate needs to be able to adapt to these changes in the process on the fly, without downtime in the delivery of real time measurements. At the same time, they still need to detect changes in fluid flow rate to alert any kick/loss incidents as soon as possible.

The construction of the channel itself, and the Venturi constriction must be made fit for purpose to any rig it should be implemented on. Principal sketches, showing the possible implementation on a land rig is shown in Figure 10 and Figure 11 . Although the work presented in this study focuses on offshore drilling operations, for the simplicity of the illustrations a land rig is used, as an offshore rig would be too complicated to show effectively in such illustrations.

The rig specific design will dictate the upstream and downstream length from the constriction. As these lengths change the flow regime in the channel, analyses similar to those presented in [81] should be used to explore the possible design solutions to find the best possible implementation. Once the modifications are done, the optimal model should be chosen and tuned to the actual set up. Both are challenges not tested during the lab experiments of the Semi-Kidd group. The next important step would therefore be the first user step, and to see what changes must be done in implementing the system, and if it works as well under field conditions as in the lab.

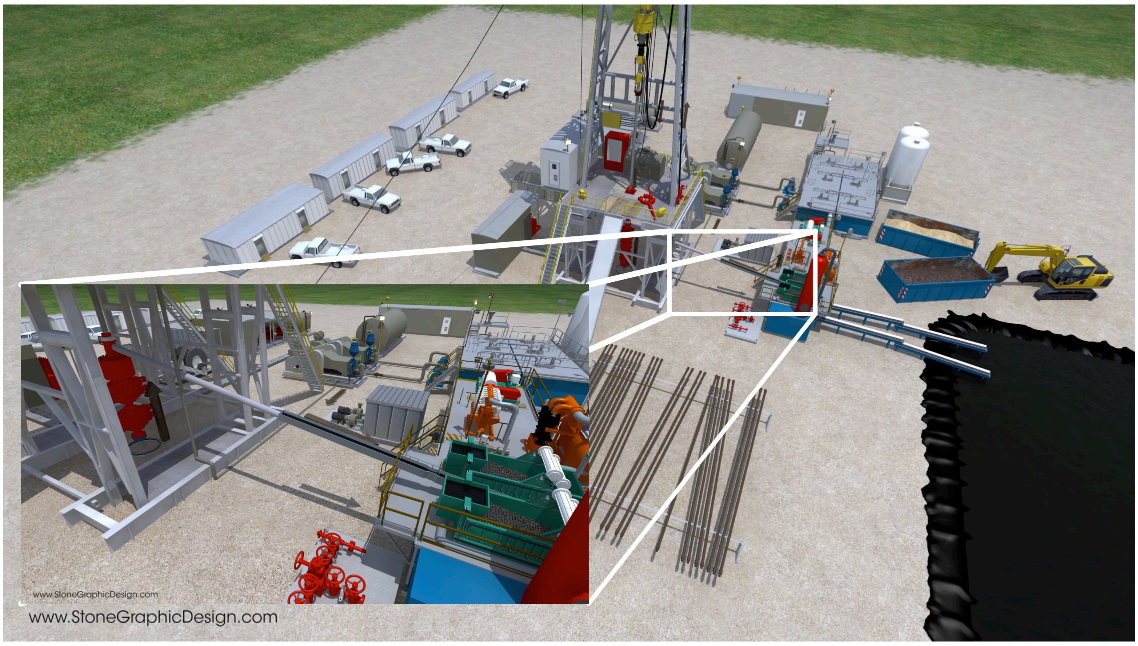

Figure 10. Overview of land drilling rig common layout. The inset focuses on the return drilling fluid flow line, where the open channel may be placed. In the lower right corner, the flow is divided into the shakers, that start the drilling fluid treatment system. Illustrations by Stone Graphic Design

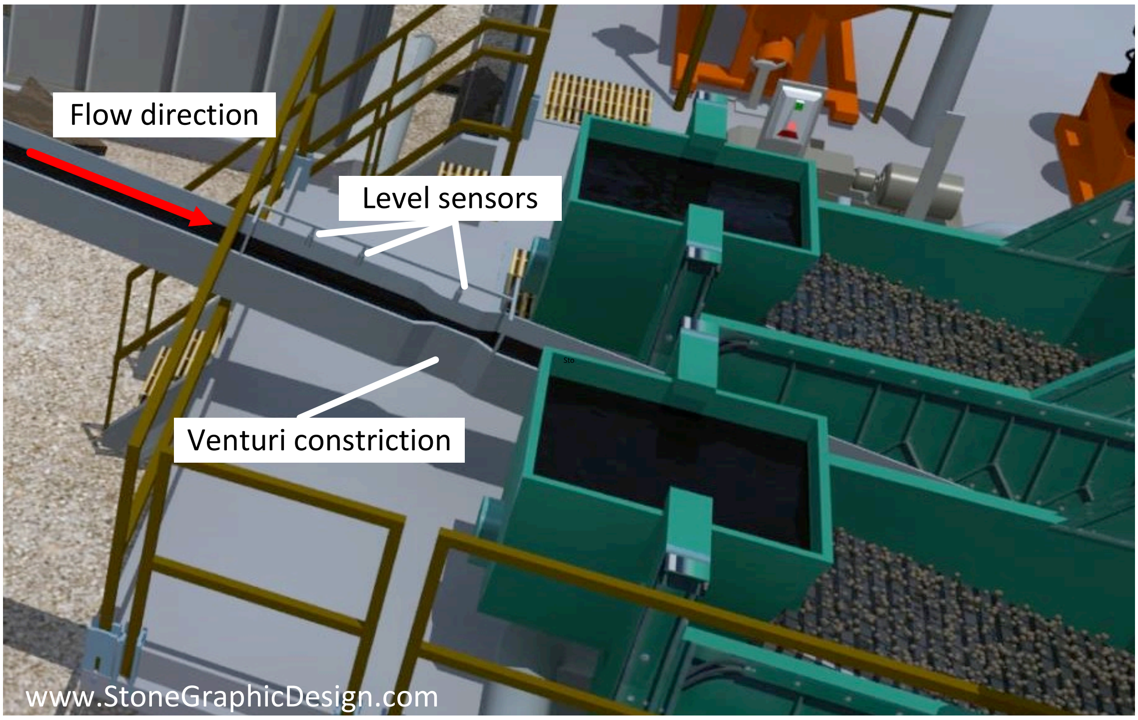

Figure 11. The open channel is part of the fluid return line, that represents the equipment change needed to apply the Semi-kidd technology for estimating the fluid return flow, by measuring the fluid level in the open channel with the Venturi constriction. As has been discussed, several level sensor placements have been suggested for various models. Here it is shown with two upstream level sensors, and one in the constriction. Illustrations by Stone Graphic Design.

5.2.2 In-line real time continuous monitoring of drilling fluid rheological properties

The measurement principle for estimating drilling fluid rheological properties needs further developments before implementation can be considered. The next development step is application to a flowing system, using ultrasonic sensors located either outside a pipe, or embedded in the pipe. There is an earlier effort where this was achieved by Gurung et al. [82] on model drilling fluids. Furthermore, several flowmeters for other purposes, for instance multiphase flow measurement, or gas measurement, have overcome the challenge of placing the sensors on the pipe wall, so I am confident this challenge can be overcome also for drilling fluid. Through the collaboration with XSens, on testing their flowmeter at the drilling fluid circulation system at Equinor, Porsgrunn, it seems that the measurement principle may be combined with development of sensor systems for flowrate estimation. Cooperation with any company developing similar solutions could therefore be a beneficial next step to further develop this measurement principle.

Refining the measurement principle and increasing the collection of data for input in the models is another step that should be considered. Sampling the frequency spectra of the received signal would enable more complex data, and possibly better models. This could also help in generalizing the models, increasing the accuracy to several fluid systems and a greater range in the estimated rheological properties.

To combine this measurement principle with the open channel system for flow rate estimation is a different task. The rheological properties measurement system should be fitted to an open channel flow, with variable depth. As such, placement of the UT/UR should be considered thoroughly. In open channel flow, with low inclination, the build-up of cuttings and grime could be a problem, but CFD simulations by Welahettige et al. [62] supports a claim that cuttings build up will only be a minor problem along the edges in the channel, and otherwise not affecting the channel flow significantly. Figure 12 shows the top view of an open channel, where CFD simulations show the effect of an inlet volume fraction of 0.055 m cuttings on channel flow. The colour scale shows the build-up of cuttings along the channel edges.

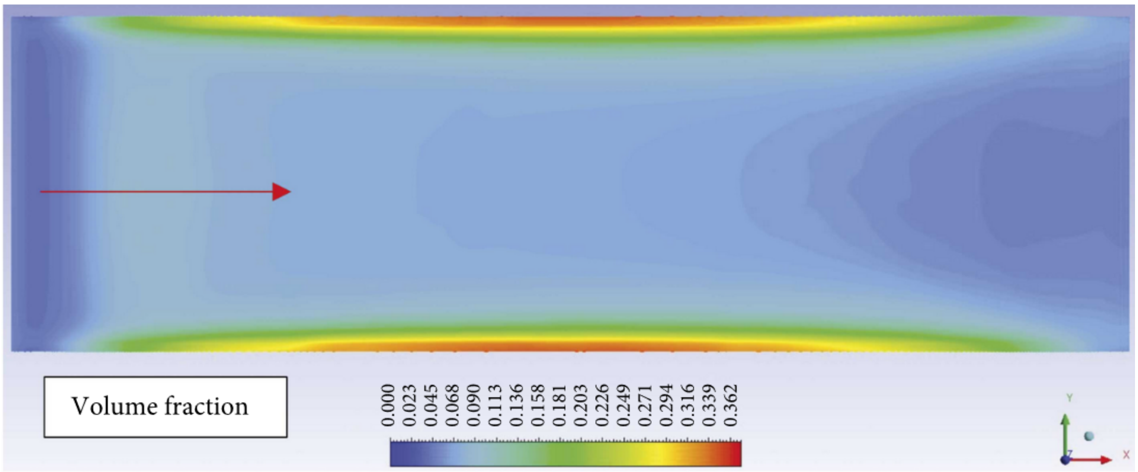

Figure 12. CFD Simulation showing the effect of drill cuttings in open channel flow. The volume fraction is indicated locally in the simulation by the color faded scale shown. The flow is steady state, with inlet volume fraction of 0.05 cuttings, and the size is 5 mm. Flow direction as indicated by the arrow. Adapted by the author from Welahettige et al. [62], published under the CC BY 4.0 [83] license.

In addition to implementation with the goal of performing inline measurements of the properties of the returning fluid for kick/loss detection and handling, the system can be applied elsewhere in the drilling process. On a drilling rig the drilling fluids are stored in several tanks, or pits, and there can be several drilling fluid types present on the rig, in storage but not in use in the current drilling operation. These are held in reserve, or for emergency purposes, to quickly mix with the current fluid, or for future use. The process of mixing these fluids, checking them against specifications and general control involves a lot of testing. An automatic system as we propose can be of great value here, increasing the quality of the mud mixing process, and enabling other automation technologies.

Considering the application of the proposed systems to offshore drilling operations, one major challenge related to floating rigs is in large part not addressed, i.e. the movement of the rig and the open channel. The effect this movement has on fluid flow characteristics, and the level measurements used to estimate the fluid flow has not been studied in detail. In [81] the effect of pitch motion, i.e. movement due to heave and waves on the rig are studied with simulations. This pitch is considered as happening along the flow direction axis in the channel, and thus the inclination of the gravity driven flow channel is a function of time and angular frequency of the rig movement. It concludes that this movement has severe effect on the flow regimes in the open channel flow, and states that it might be challenging for the flow estimation models. There are other measurement systems on a floating drilling rig that also has to account for the rig movement, such as the depth tracking system [84]. However, the effect on this measurement is limited compared to the effect rig movement has on the fluid flow in the channel. It could be possible to envision a solution where the rig movement is measured and coupled with simulations or models of the effect this has on the model, and thus the fluid channel level measurements can be compensated for the rig movement. This is a solution that would require additional studies.

6 Conclusions

The main contribution of my work has been to prove the potential of the measurement principle combining ultrasonic characterization and data driven models by lab experiments. This is the basis for developing a non-invasive in-line rheological fluid property measurement system. Furthermore, I have contributed to show that data driven models perform satisfactory in a lab scale for estimation of fluid flow rate in an open channel with Venturi constriction. Both efforts have foundations in the literature in their respective fields, but the experimentation on non-Newtonian fluids, and especially the drilling fluid ultrasonic characterization is novel and represent scientific progress.

By the combined efforts of the Semi-Kidd group a few steps towards improving methods for effective and early detection of kicks/losses in the drilling fluid circulation have been taken. Mechanistic models and data driven models to estimate fluid flow have comparable results within industry standard accuracies. These models and their experimental verified results along with CFD simulations prove the value of the Semi-kidd technology idea. This is an important contribution to a technology that will enable automation and improved process control of the drilling process. If applied in the industry, this technology will reduce risks and increase efficiency. The extension of their influence on drilling process automation can also be significant.

As outlined above, when the next step is considered, there are some challenges to handle for the open channel and sensor system proposed by the Semi-Kidd group, in addition to the limitations of the models developed. Most important are the scale and dimensions that are needed in the field. This will change the flow regimes, surface waves and consequent noise in level measurements. In addition, the drilling fluid used in the field can vary greatly over different wells and sections, compared to the model drilling fluids used. This can be mitigated once the models can be trained and tuned to experiments on field scale with drilling fluids used in the field. Then the models and algorithms can be developed to adjust to the specific channel dimensions and the actual fluid used. The misting and steaming of a hot return drilling fluid, as well as splashes and dirt can further diminish the quality of the level measurements. These may be treated by engineering cleaning or screening solutions to protect the sensors.

The effect of rig movement should be studied in suitable experimental setups. The simulations in [81] indicate a challenge, but it should be studied in more detail. Then the potential for the system to floating rigs may be found, and a possible limitation to fixed platforms may be addressed.

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Paper 1

Upstream Ultrasonic Level Based Soft Sensing of Volumetric Flow of Non-Newtonian Fluids in Open Venturi Channels

Upstream Ultrasonic Level Based Soft Sensing of Volumetric Flow of non-Newtonian Fluids in Open Venturi Channels

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Abstract—Reliable flow measurements of drilling fluid entering and returning from the wellbore can improve safety of people and assets by avoiding kicks (blowouts) and fluid loss. The return flow with cuttings and entrained gas in the drilling fluid pose a big challenge to the rig operators. An indirect way of measuring the volumetric flow is by measuring the flow level in an already existing open channel in the flow loop, as this level changes with changing volumetric flow. In this paper, different mechanistic and machine learning models, based on one to three fluid levels at specific locations along the custom designed open Venturi channel, are presented. The mechanistic models involve tuning of different correction factors, related to fluid rheology. As rheological properties vary with time, and real-time rheological measurements are not available, these models are valid only for fluids with known rheology. With real-time density as an extra input, fluid specific machine learning models for mass flow, can be applied to any fluids. In contrast, the proposed machine learning models for volumetric flow are robust and not dependent on the rheological properties of the fluids. These models have mean absolute percentage error between 2.05% and 4.76%. Soft sensing of volumetric flow based on non-invasive level measurements presented here has an additional advantage for applications in harsh environments.

Index Terms—Drilling operations, Open channel, Venturi constriction, Non-Newtonian fluids, Volumetric flow rates, Machine learning.

I. Introduction

A. Background on Drilling Operations

While drilling an oil or gas well, pressure control is important for several reasons, but primarily for safety. The drilling system includes a drilling fluid (also called drilling mud) circulation system, which ensures the circulation of the drilling fluid down the wellbore through the drill pipe and then back to the surface via the annulus with minimal loss of drilling fluid under normal operational conditions. At the surface, the drilling fluid goes through a treatment system consisting of various stages, where the fluid will be treated and made ready to be pumped back into the well [1]. This treatment at the topside of the drilling platform consists of removal of rock cuttings, sand and wellbore fluids (oil and/or gas), a check of the drilling fluid's rheological properties and adding additives if necessary. This circulation system and the properties of the drilling fluid is crucial in controlling the pressure in the well. For a well that may be anywhere from 2000 [m] to 10 000 [m] long, the task of measuring and controlling the pressure can be a challenge. Typically, drilling operations in oil & gas wells have real-time data of the pressure in the well close to the drilling bit [2]. In addition, the pressure is monitored in the drilling fluid circulation system on the platform. However, the pressures of the formation being drilled are challenging to estimate and harder still to measure. Hence, good measurements of the volumetric flow going into and coming out of a well can be a good estimator for the pressure relationships in the wellbore. The pore pressure (P_p) is the pressure of the fluid in the formation, fracture pressure (P_f) is the pressure integrity of the formation, i.e. the pressure the formation can withstand before fracturing. The pressure of the wellbore (P_b) is limited by these for normal drilling operations. Should P_b fall below P_p formation fluids will flow into the well (influx). On the opposite side is P_f limiting the maximum P_b, as a fractured formation will cause loss of drilling fluids into the well and a loss of pressure control. By comparing the inflow to the return flow kick/loss situations may be detected and treated, this method is referred to as the delta flow method first proposed by [3] and further discussed by [4]–[6]. There are also other kick and loss detection methods as described in [7] requiring other measurements in addition to return flow, other sensors are hence necessary. As proposed in [8], a downhole sensor may be able to detect changes in flow to indicate kick and loss situations. This solution although elegant, faces challenges due to high pressure, temperature and associated stresses in downhole equipment. These problems are circumvented by using delta flow method in open Venturi channels located on the topside of the drilling platforms.

A flow loop system for drilling fluid comprising an open channel with sieves for filtering out cuttings has been

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existing almost a century with very few modification in the sensors for monitoring the in- and outflows of drilling fluid from the drilling fluid tank after its flow downhole and back to the tank.

There has been a dire need for a monitoring system to supervise the in- and outflow of the drilling mud. The drilling mud flowing downhole is processed and at a lower temperature, whereas the drilling mud flowing back to the topside of the drilling platform, is hot and has cuttings and multiphase. Any intrusive and invasive assembly of modules in the drilling mud will not last long in such a hostile environment. Al-Naamany et al. [9] describe a laboratory arrangement for measuring liquid levels in the presence of emulsions and report some success in their efforts. This system described in [9] uses the measurement data in a feed forward neural network with good estimates of the heights involved in the laboratory scale bath used in the experiments. Such an assembly will not be possible due to the stipulations from the operators of drilling platforms and firms handling drilling mud. Ultrasonic wave propagation studies for drilling fluid characterization have been done previously with limited success, [10]. Intrusive ultrasonic instrumentation in the environment of drilling fluid is prone to many problems due to the presence of cuttings, vibration of the open channel, high temperatures etc. During offshore boring operations, the drilling mud returning to the open channel has temperatures in the range of 30-92 [$°C$]. As there is no monitoring system currently, the operators prefer a system capable of functioning at least some of the time, giving process information. The current non-invasive design was designed to meet some of the specifications of the operators due to ease of handling of the non-invasive sensor system and the reduced maintenance costs. Any housing or stand as proposed in Al-Naamany et al. [9] will not survive the harsh and erosive flow in the drilling fluid loop. The operators came with the requirements of non-intrusive and non-invasive measurement system for monitoring the flow and rheological parameters of the drilling fluid. In addition, there are established procedures to limit emulsion and foam formation by using additives, commonly practised in the drilling industries. The motivation for the current study is to have a monitoring system able to provide reliable data on the flow of drilling mud most of the time, even though such a system may malfunction at times, but not always. In fact, there have been efforts to use gamma radiation to monitor drilling fluid flow and some studies are still going on to test this modality, again in a non-intrusive and non-invasive manner, [11].

A mechanistic volumetric flowrate model based on the fundamental Bernoulli equation is limited by the need for the tuning of correction factors, which among others depend on the drilling fluid density. However, experimental results show that the majority of these models are hampered in their performance due to changes in fluid density. Generalized models with densitometers synchronized to other sensors are possible, but in some applications as in the measurement of drilling fluid flow in the petroleum industry, density measurement is not a prevailing standard, due to costs associated with their procurement and maintenance.

B. Background on Fluid Flow Measurement

Multiphase flowmeters (MFM) are frequently found in the oil & gas industries involving different techniques [12]. In the oil & gas industries, three-phase flow of water, oil and gas is frequently encountered. In multiphase flow involving three phases, the fraction of each phase in addition to its flow rate is also needed. As noted in [12] MFM is a highly competitive area, where business interests may overshadow scientific interests, as reflected in the available literature. Nonetheless, there are several types of MFMs. In [13] a multimodal approach using capacitance and gamma-rays is presented. Capacitance and acoustic sensors are used in [14] to measure the three-phase flow of oil, gas and water with discussions on their applicability to other industrial sectors. Additional information for users of multiphase flowmeters can be found in [15].

Measurement of the volumetric flow rate of the return flow from an oil/gas well is especially challenging, as the multiphase drilling fluid also contains large amounts of abrasive rock cuttings, with very varying particle size distribution. Contrary to the applications mentioned above, a fractional determination of the different phases is not needed in this case. Selected flowmeters used in the oil and gas industries are described in detail in [4]–[6] and these include pump stroke counter, rotary pump speed counter, magnetic flow meter, ultrasonic Doppler flow meter and Coriolis mass flow meter for inflow. For return flow, the literature lists standard paddlemeter, ultrasonic level meter, prototype rolling float meter, magnetic flow meter and Venturi flow meter. Due to the challenges with measuring the return flow, the paddlemeter is still the industry standard [16]. As mentioned by Schafer in [6], this sensor only gives a qualitative measurement, and human interpretation is necessary. The delta flow method needs precise inputs of both inflow and return flow as discussed in [7]. Thus, there is a need for better volumetric flow meters for measuring the return flow.

Artificial neural network (ANN) has earlier been used in flow estimation, [17] to estimate and interpolate velocity profiles. In another study related to multipath ultrasonic flow metering, a three-layer ANN was used with flow velocities on individual sound paths as inputs and the averaged flow velocity over the cross-section of the pipe as output. The estimated mean velocity with ANN had a measurement uncertainty of $\pm 0.3\%$ within Reynolds numbers from 3.25×10^3 to 3.25×10^5 without the use of any flow conditioner [18]. Another approach of enhancing multipath ultrasonic flow meter performance used genetic algorithm (GA) for optimizing the performance of the ANN used. The GAs were used in determining the ANN architecture, weights and biases in the ANN without getting stuck with local minimum [19]. Both methods indicated the versatility of using inferential soft sensing techniques to estimate volume flow velocities using time of flight (ToF). Indirect, or what is now known as soft sensing of volumetric flow rate estimation has been described by Godley [20], based on ToF Doppler and cross correlation of echo signals from particles/bubbles in the flow. Yang et al. [21] describe in detail a system using a Parshall-flume. Furthermore, Lynnworth and Liu [22] describe different types of ultrasonic flow meters developed over the last 50 years. The current technologies based on ultrasonic flowmetering can yield accuracies close to 0.5% and in fiscal metering applications even down to 0.25%. The techniques based on ultrasonics are limited to closed circulation systems. Based on these earlier works, different methods of soft sensing of volumetric flow in open channels are presented. Additional information for users of ultrasonic flowmeters for oil, gas and oil with water droplets can be found in [15].

The presented measurement strategies use transit times from arrays of transducers as well as density from Coriolis meters for estimating volume and mass flow velocities. Using ISO 4359:2013, [23] as the basis and their performances are compared starting from an array consisting of three ultrasonic transducers, another configuration using density from Coriolis meter as an additional input and finally a single ultrasonic transducer for estimating volume flow velocity in open channels.

Estimation of volumetric flow rate of the drilling fluid using the Delta Flow method can facilitate early detection of kick and loss in drilling operation. Through this non-invasive approach, the problems associated with the composition of the non-Newtonian drilling fluids and the inclusions in them are circumvented. Furthermore, the non-invasive approach will have no effect on the flow or pressure in the circulation system.

This study focuses on the use of Venturi constriction in an open channel to measure the return flow of circulating drilling fluid. For the study, a test flow loop is available at University College of Southeast Norway (USN), Porsgrunn Campus.

II. Materials and methods

A. Test Flow Loop at USN

The test flow loop at USN consists of a fluid tank (with a blender on the top), a pump, an open channel with Venturi constriction, different types of sensors along the pipelines. A schematic of the flow loop is shown in Figure 1a, including some of the sensors. The fluid in the tank is pumped through the pipelines along the open channel and back to the tank. For the flow measurement through the pipe, a Coriolis mass flow meter is used. For the flow measurement through the open channel, there is a Venturi constriction and three different ultrasonic level sensors as shown in Figure 1b.

For the flow studies, different types of model-drilling fluids are available. The fluids are prepared by mixing water with potassium carbonate (as densifier) and xanthan gum (as viscosifier). In this study, five different fluids with varying densities and viscosities are used. Table I shows details of the chemical composition of the fluids. All the fluids are non-Newtonian and shear thinning in nature as shown in Figure 2.

B. Flow Measurement Systems

Different flow measurement systems are introduced and evaluated in this section.

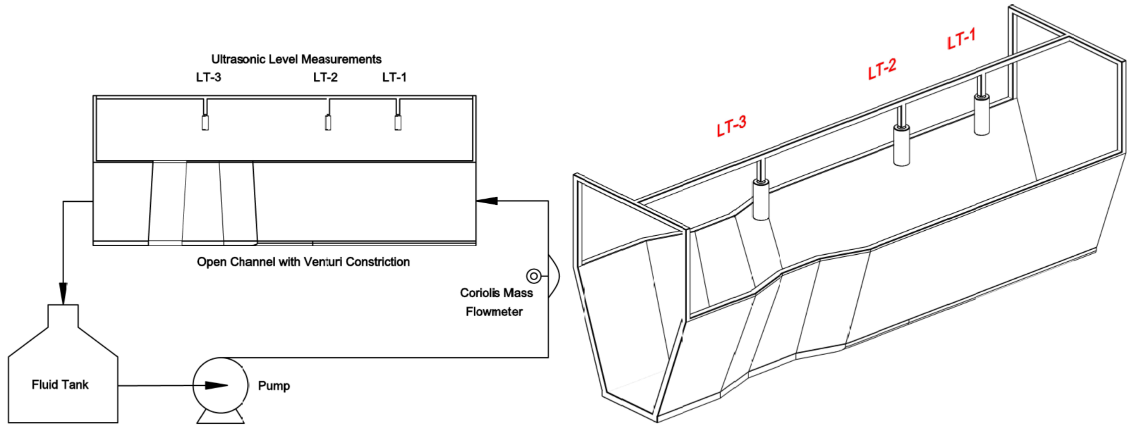
1) Coriolis Mass Flow Meter: For this study, a Coriolis mass flow meter (Vendor: Endress + Hauser, Model: Promass 63F, Range: 0-1000 [l/min], Uncertainty: ±0.10%) is used. It is an accurate flow meter for a pipe flow. However, the current study shows that the Coriolis mass flow readings are not reliable for the fluids flowing with excessive air bubbles. Figure 3 shows how the mass flow measurements of the Coriolis meter are affected by the introduction of air bubbles. Measurements performed with Fluid 2 are shown here, but the effect is similar with all fluids used in this study. The drilling fluid in the inflow section of the circulation loop while drilling is a single phase fluid flowing into the wellbore and Coriolis mass flow meter can be preferably used. The scenario is completely different in the return flow section of the circulation loop. The fluid is contaminated with rock cuttings, formation gasses, and formation fluids. To analyze the effect of gas/air bubbles on Coriolis readings in our flow loop, additional air bubbles are created by running a blender at 235 rpm. The rotating blades of blender generate extra air bubbles and turbulence in the circulating fluid. The model-drilling fluids used in this work consist of air bubbles due to the presence of xanthan gum. Figure 3b shows that the Coriolis mass flow readings in the presence of excessive air bubbles are not reliable. Hence, it seems that Coriolis mass flow meter is not appropriate to use in the return flow section of the circulation loop while drilling. However, this has to be verified using more extensive tests.

2) Mechanistic Flow Models using Uniform Geometry Open Channel: In 1889, Robert Manning presented a flow model for an uniform geometry open channel, which is given in Eq. 1, [24].

$$V = \frac{1}{n_{Manning}} (R_h)^{2/3} \sqrt{\sin \Theta} \tag{1}$$

where V is average velocity of the fluid, $n_{Manning}$ is a coefficient dependent on the roughness of the channel, R_h is the hydraulic radius, and Θ is the channel slope. The applications of these models are limited as they need proper tuning of the coefficients and are applicable only for Newtonian fluids [25]. Other models for Newtonian fluids are discussed in [25].

Haldenwang et al. have developed a model suitable for flow of non-Newtonian fluids in open channels with

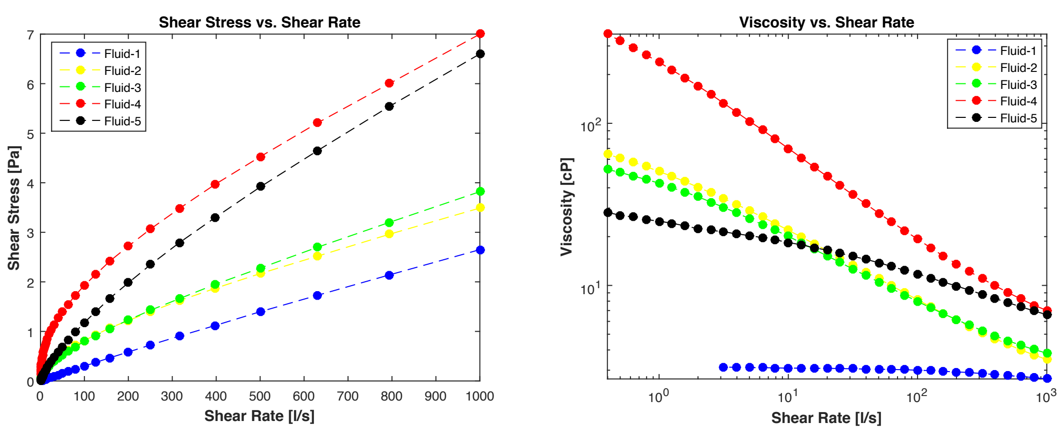


(a) (b)

Fig. 1: a) Simplified schematic of the measurement system with the array of ultrasonic level sensors. b) Open channel with an array of Venturi constriction and three ultrasonic level sensors scanning the upper surface of drilling fluid exposed to air.

TABLE I: Different fluids used in the study along with the corresponding chemical compositions. Fluid 1 is a mixture of water with residual fluids in the tank during the process of changing drilling fluid in the flow loop.

Fluids	Potassium Carbonate [%weight]	Xanthan Gum [%weight]	Density [kg/m^3]
Fluid-1	0	0	1015
Fluid-2	18	0.07	1145
Fluid-3	21	0.07	1190
Fluid-4	29	0.21	1240
Fluid-5	73	0.22	1340

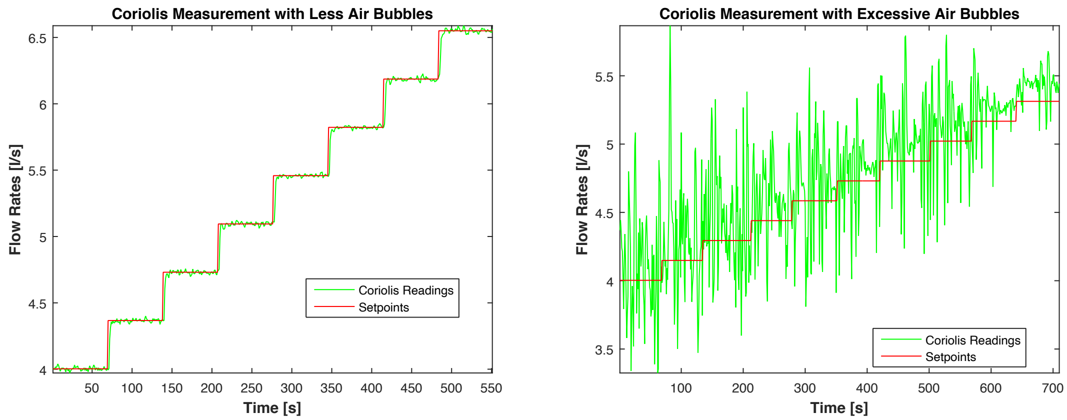


(a) (b)

Fig. 2: a) Shear stress vs. shear rate curves for all the types of non-Newtonian fluids used in the study. b) Viscosity curves at different values of shear rates for the all the fluids. Rheological parameters measured using Anton Paar Viscosmeter in STATOIL laboratory.

uniform cross-section, [26], [27]. Other different flow models for non-Newtonian fluid flow through a uniform geometry open channel are discussed in [25]. In [27], open channel flow models applicable for all types of non-Newtonian fluids (Bingham-plastic, power-law, or Herschel-Bulkley fluid) are presented. Eq. 2 and Eq. 3 are the models used to estimate average velocity of the fluid in laminar and turbulent flow respectively.

$$V = \frac{R_h}{2}\left[\frac{(16/K)\tau_w - \tau_y}{k}\right]^{1/n} \text{ for laminar flow} \qquad (2)$$



(a) (b)

Fig. 3: The performance of Coriolis mass flow meter (flow rate vs. time) in the presence of air bubbles. (a) The Coriolis mass flow readings are stable and reliable in the absence of air bubbles. (b) The Coriolis mass flow readings with numerous spikes are not reliable with excessive air bubbles and high turbulence.

$$V = \sqrt{\frac{2\tau_w}{\rho c_1 (R_H)^{c_2}}} \quad \text{for turbulent flow} \tag{3}$$

$$\text{where,} \quad R_H = \frac{8\rho V^2}{\tau_y + K\left(\frac{2V}{R_h}\right)^n} \tag{4}$$

where K is a constant dependent on the geometry of the open channel (for example: K is 17.6 for a trapezoidal channel, which is experimentally found in [28]). τ_w is average wall shear stress, τ_y is yield stress, k is consistency index, n is flow index, ρ is density, c_1 and c_2 are empirical constants based on the geometry of the channel (for example: $c_1 = 0.0851$ and $c_2 = -0.2655$ for a trapezoidal channel, [28]), and R_H is Haldenwang's Reynolds number.

The flow models given in Eq. 2 and Eq. 3 depend on the rheological properties of the fluid. In drilling fluid circulations, the returning fluids have different rheological properties in each circulation and it is a challenge to perform real-time rheology measurements. Hence, these models are not applicable for measuring the return volume or mass flow rates of drilling fluids.

3) Mechanistic Flow Models using Open Channel with Venturi Constriction: The volumetric flow of an incompressible non-Newtonian fluid through an open channel with a Venturi constriction can be estimated using the fundamental Bernoulli equation defined by Eq. 5.

$$\frac{P_1}{\rho g} + \frac{\alpha_1 V_1^2}{2g} + z_1 = \frac{P_2}{\rho g} + \frac{\alpha_2 V_2^2}{2g} + z_2 \tag{5}$$

where P is fluid pressure, g is gravitational acceleration, α is kinetic energy correction factor, z is the elevation with respect to the datum, and the labels 1 and 2 represent the upstream and the throat sections respectively.

Two standard forms of the energy equations are used in the study. The first form is given in Eq. 6, which is derived by rearranging Eq. 5 and implementing continuity equation, $V_1 \times A_1 = V_2 \times A_2$ [29].

$$Q_v = C_d A_1 A_2 \left\{ 2g \left\{ \frac{(h_2 - h_1) + (z_2 - z_1)}{\alpha_2 A_1^2 - \alpha_1 A_2^2} \right\} \right\}^{1/2} \tag{6}$$

where Q_v is volumetric flow rate, A is cross-sectional area, h is fluid level, and C_d is the coefficient of discharge. This flow model estimates the volumetric flow based on the upstream and throat level measurements, henceforth referred to as upstream-throat based model.

The Bernoulli energy equation defined by Eq. 5 can be modified to specific energy equation as in Eq. 7.

$$E_s = h + \frac{V^2}{2g} \tag{7}$$

where, E_s is a specific energy. Implementing the concept of minimum specific energy at critical level (i.e. $dE_s/dh = 0$ for $h = h_c$), the second standard form of the flow model as given by Eq. 8 is obtained. Detailed mathematical derivation is given in ISO-4359 [23].

$$Q_v = C_d C_s C_v \left(\frac{2}{3}\right)^{3/2} \left(\frac{g}{\alpha_1}\right)^{1/2} b_2 h_1^{3/2} \tag{8}$$

where C_s is the shape coefficient, C_v is the coefficient of velocity, and b is the bottom width of the channel. This flow model estimates the volumetric flow based on a single upstream level measurement, henceforth referred to as upstream based model.

Figure 4 shows the estimations of these standard flow models based on the level measurements of Fluid-2. The estimations show that the problem of measuring the flow rates in the presence of excessive air bubbles is solved. Hence, these models are considered as standard flow models for the open channel with Venturi constriction. However, there are several limitations with these models. One of the main issues is tuning the kinetic energy correction factor (α) for different types of fluids. The correction factor is dependent on the flow regime (normally $\alpha = 1$ for turbulent flow and $\alpha = 2$ for laminar flow) and the flow regime is dependent on fluid rheology. Thus, the correction factor is different for different fluids and for different flow rates of the same fluid. In Figure 4, the kinetic energy correction factor is tuned to $\alpha = 1.3$ for this particular fluid.

In Figure 5 the mechanistic models are used to estimate flow rates of different fluids with $\alpha_1 = 1.3$ and $\alpha_2 = 1$. The estimates are accurate for fluids with low density and viscosity (Fluid-1 and Fluid-2), whereas the estimates are over-estimated for fluids with higher density and viscosity (Fluid-3 and Fluid-5). It is because the kinetic energy correction factor is tuned based on low-density fluid (Fluid-2). The variations in Mean Absolute Percentage Error (MAPE) for different fluids show that there is a need for proper tuning of kinetic energy correction factor. The turbulence in the flow profile reduces with increased density and viscosity. Hence, the correction factor should be chosen higher than 1.3 (closer to 2) for high density and high viscosity fluids.

4) Machine Learning based Flow Models: Due to the limitations in Coriolis mass flow meter and flow measurement systems and models presented above, this study focuses on machine learning models. In our previous study [30], [31], different machine learning models are developed to estimate the mass flow rate based on three ultrasonic level measurements in the open channel. The selection of three ultrasonic level sensors as inputs is based on loading weights plot in multivariate data analysis [30]. Further study showed that these mass flow models are limited to a single fluid, i.e. a data model based on single fluid is not generalized to other fluids. Figure 6 shows mass flow rates vs. upstream levels at different flow rates for different fluids. The plot shows that fluids with different densities flow with different upstream levels to get the same mass flow rate. For example, to get 300 [kg/min] flow, a low-density fluid (Fluid-1) has around 80-85 [mm] upstream level and a high-density fluid (Fluid-5) has around 65-70 [mm] upstream level. A low density fluid needs high volumetric flow and a high density fluid needs low volumetric flow to have a same mass flow rate. Hence, the mass flow rate model based on level measurements is not generalized to different fluids.

One possible way to generalize mass flow rate model is by including density as another input variable along with three ultrasonic levels. Figure 7 shows the estimations of artificial neural network based generalized mass flow model with four different fluids (Fluid-1, Fluid-2, Fluid-3, and Fluid-5). MAPE calculated for each estimation show that the trained ANN mass flow model is highly accurate and can generalize different fluids.

It is possible to implement such a generalized mass flow model in the flow loop at USN, as the density of the fluid is measured using Coriolis mass flow meter. However, in current drilling operations most of the work is performed manually, including density measurement (done on samples taken from the flow loop). With the increase of autonomous solutions/operations in drilling, the need for real-time measurements will increase, but they are not standard yet [32].

Hence, the focus of this study is on developing new machine learning models (simple linear regression, polynomial linear regression, support vector regression, and artificial neural network) for estimating volumetric flow rates using a single upstream level measurement. The single upstream level is measured using LT-2 level sensor and the position of the sensor is shown in Figure 16a in Appendix C. Further details of all the proposed models are given in Appendix B.

III. Results and discussions

A. Data Pre-processing

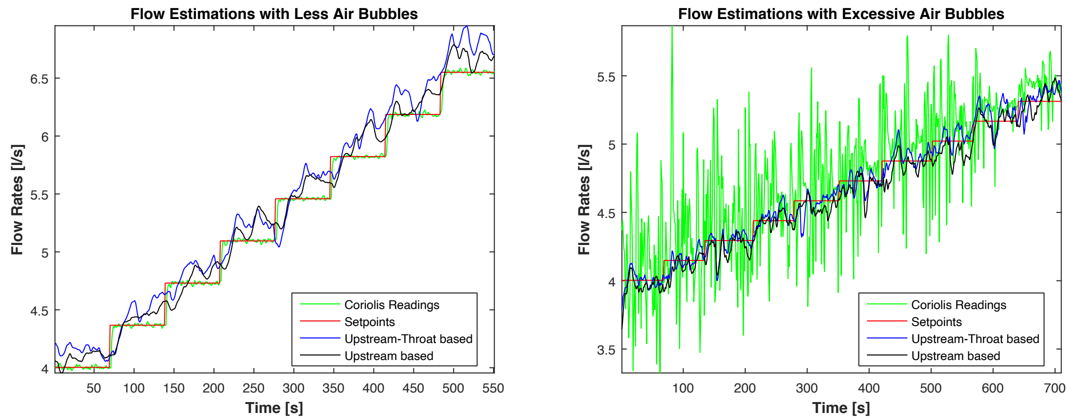
All the fluids are circulated in the test flow loop at USN. The reference volumetric flow rate and corresponding upstream level data are logged. Figure 8a shows the logged raw data. The ultrasonic level measurements have some random uncertainties in measurements. Therefore averaged values of upstream levels are computed for each volumetric flow rate. Figure 8b shows the averaged volumetric flow rates vs. averaged upstream levels for different fluids. This averaged data is used to train the machine learning models.

B. Performance Evaluation of Proposed Models

Four different types of machine learning models are used to fit the averaged data. Figure 9 shows the averaged data plot with fitted models using simple linear regression (SLR), polynomial linear regression (PLR), support vector regression (SVR), and artificial neural network (ANN).

The polynomial linear regression is of second degree. The SVR with radial basis function is used. The model hyperparameters of the SVR model are tuned based on the grid search method. The ANN model with two hidden neurons in one single layer is used. For comparison purposes, two different ANN models (one with three inputs $\rightarrow$ three ultrasonic level sensors; another with four inputs $\rightarrow$ three ultrasonic level sensors + density; for both ANN models output $\rightarrow$ mass flow rates) are trained. For learning ANN models, Bayesian regularization training algorithm available in MATLAB Neural Network Toolbox is used. Further details on all the proposed models are given in Appendix B.

Figure 10 shows the performance of the proposed machine learning models used on the randomly varying experimental data of Fluid-5. Table II shows the comparison of the performance of different proposed models based on MAPE and Root Mean Squared Error (RMSE). All of the models are capable of estimating randomly varying volumetric flow rates. The SLR model has the largest error and the proposed ANN model has the lowest error in the estimations.



(a) (b)

Fig. 4: The mechanistic flow models are capable of estimating reliable flow rates in the case of both less and excessive presence of air bubbles. Flow rates vs. time shown with the kinetic energy correction factor tuned to $\alpha = 1.3$.

TABLE II: The comparison of the performance of different machine learning models used for estimating the volumetric flow rates based on Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE).

Machine Learning Models	MAPE [%]	RMSE [l/s]
Simple Linear Regression	4.76	0.24
Polynomial Linear Regression	2.09	0.16
Support Vector Regression	2.37	0.17
Proposed Artificial Neural Network (with Input = single ultrasonic level)	2.05	0.16
ANN (with Inputs = three ultrasonic levels and density)	2.44	0.16
ANN (with Inputs = three ultrasonic levels)	2.25	0.16

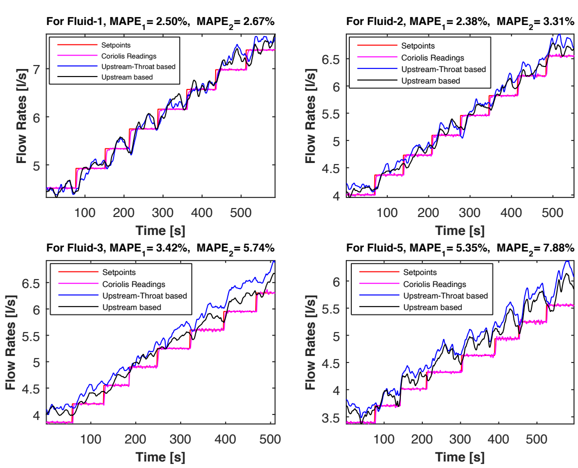


Fig. 5: Results from mechanistic models using the fluids (Fluid-1, Fluid-2, Fluid-3, and Fluid-5) shown in all figures as flow rate vs time. The performance of the models are evaluated based on Mean Absolute Percentage Error (MAPE). MAPE_1 and MAPE_2 given for estimates for upstream based and upstream-throat bases respectively.

C. Extrapolating the Proposed Models to Higher Flow Rates

The results show that the proposed models are reliable to use for the considered flow range ($3 - 7.5$ [l/s]). But the objective of the study is to develop a generalized

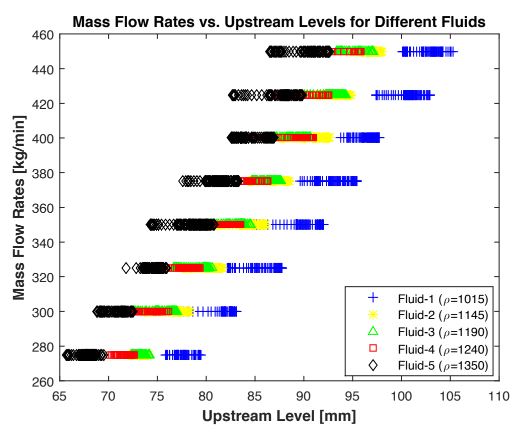


Fig. 6: The reference mass flow rates with the corresponding upstream levels for fluids with different densities (or rheological parameters).

volumetric flow model that is reliable over a wide range. Based on an earlier paper [5], a suitable flow meter should have the following features:

- an accuracy of $1.5 - 3$ [l/s] for flow rates up to 75 [l/s] in normal drilling operational environment.
- reliability and accuracy of measurements over the full range of flow.
- the accuracy should be maintained on any type of drilling fluids (water and oil based) in the viscosity range $1 - 200$ [cP], and density range of $1000 - 2160$

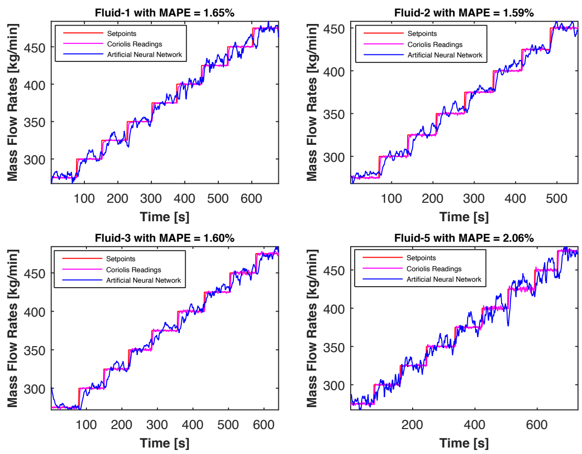


Fig. 7: Artificial neural network (ANN) trained with the three ultrasonic levels and density as inputs and mass flow rate as output. ANN model is used to estimate mass flow rates of four different fluids (Fluid-1, Fluid-2, Fluid-3, and Fluid-5) with high accuracy. Mass flow rates vs. time at varying setpoints, in all plots.

$[kg/m^3]$.

Therefore the proposed models should be tested by extrapolating to 75 [l/s]. To compare the extrapolation fittings of the proposed models, we need a standard reference. In this study, the standard upstream based model (defined by Eq. 8) is tuned for the averaged data values and considered as a reference for extrapolation. Figure 11 shows the tuning of kinetic energy correction factor of the upstream based flow model to fit the averaged data. Based on the RMSE calculation for each correction factor, the upstream based flow model with $\alpha = 1.4$ fits the averaged data with minimum error.

Figure 12 shows the comparison of the standard upstream based model with the proposed machine learning models in the wide range of flow. The volumetric flow estimates of the PLR model and the SVR model are very close to the estimates of the standard model. The volumetric flow estimates of the SLR model and the ANN model are limited to data range used in the study. Despite being the best model in the given data range, the ANN model cannot generalize the wide range. The calibration of a neural network with back propagation learning algorithm needs scaled data, which depends on the activation function used in the hidden neurons. In this work, sigmoid activation function is used in the hidden neurons. Therefore, for any upstream level below or above the data range, the ANN model will estimate minimum or maximum volumetric flow rates of the data range as shown in Figure 12d.

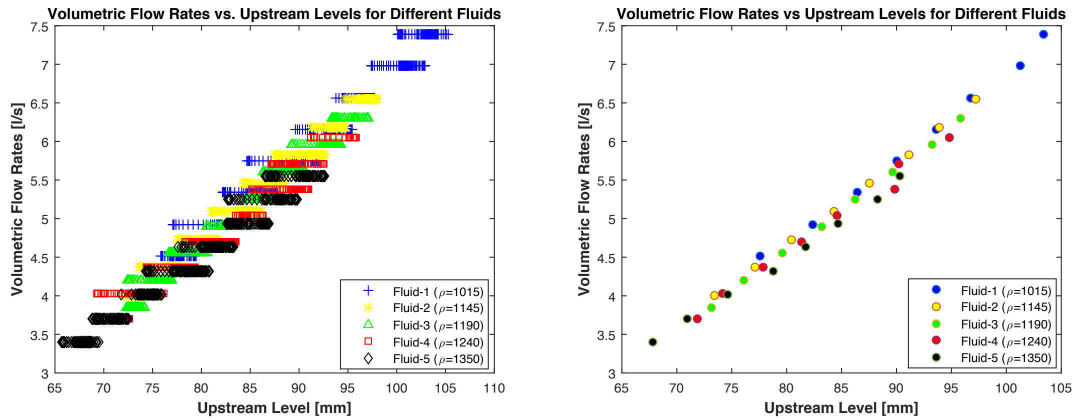
IV. Conclusions

In this study, different machine learning models are proposed to estimate volumetric flow rates using upstream level measurements in an open channel with Venturi constriction. These models are meant for the volumetric flow estimations of non-Newtonian drilling fluids while drilling an oil or gas well. In drilling operations, pressure control is important for several reasons, but primarily for safety. These models can be used to estimate return flow of drilling muds, which can be further used to monitor the pressure in the wellbore. To develop machine learning models, a test flow loop available at USN is used. Different types of non-Newtonian model-drilling fluids are circulated in the flow loop to generate data for training and validating models.

The study shows that the flow measurements using a standard Coriolis mass flow meter are not reliable in the presence of excessive air bubbles. Two different standard mechanistic flow models seem to overcome the effect of excessive air bubbles. But the need of tuning a kinetic energy correction factor for different flow conditions limits the reliability of these models. Machine learning models developed to estimate mass flow rates in our previous study appear to be reliable in any flow conditions but are limited to a single fluid. By using density as an additional input to the existing mass flow rate models, the models developed can be generalized for different fluids. However, the current study focuses on using generalized volumetric flow models based on single upstream level measurements. The proposed machine learning models (SLR, PLR, SVR, and ANN) are accurate and reliable in any flow conditions and for different types of fluids. The experimental study shows that all the proposed models are capable of tracking randomly varying setpoints. The ANN model gives the best estimations with MAPE of 2.05% and SLR model gives the worst estimations with MAPE of 4.76%. However, all the estimations are within the acceptable accuracy limits as needed for a new flow meter as given in [5].

Based on the requirements given in [5], a new flow meter should have a measuring range up to 75 $[l/s]$. Therefore, all the developed models are extended to cover the whole range of flow. As a reference, the upstream based mechanistic flow model with a tuned correction factor is used. The extrapolation results show that PLR and SVR models are capable of estimating wider range, whereas SLR and ANN models are limited to the range of training data.

As a possible way of further improvement of these models, ultrasonic level sensors can be replaced by radar level sensors for upstream level measurements. Experimental data show that the ultrasonic level measurements are affected by air bubbles present in a fluid. By reducing the random uncertainties in the level measurements, the accuracy in the flow estimations can be improved. The uncertainty analysis of ultrasonic level measurements and machine learning based flow estimations is performed in Appendix B-E.



(a) (b)

Fig. 8: (a) The reference volumetric flow rates with the corresponding upstream levels for different fluids. (b) The averaged volumetric flow rates with the corresponding averaged upstream levels for different fluids.

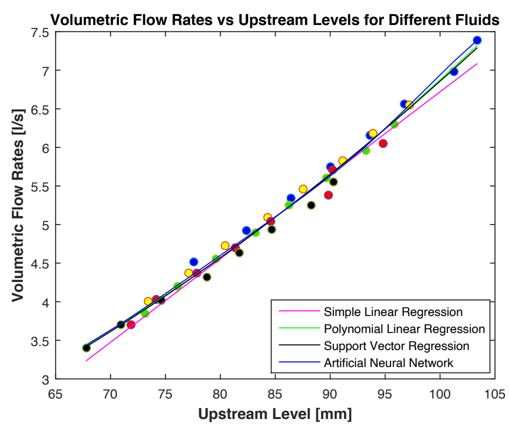


Fig. 9: The averaged data are fitted with the different models discussed in the paper. Models used given in the inset for flow rate vs. upstream level.

Appendix A
Data used for Modelling

The averaged data are sorted based on the upstream level. The averaged upstream level is input (in $[mm]$), which is denoted by 'x' as,
x={0.0678, 0.0709, 0.0719, 0.0732, 0.0734, 0.0742, 0.0747, 0.0761, 0.0771, 0.0776, 0.0779, 0.0788, 0.0796, 0.0804, 0.0814, 0.0817, 0.0823, 0.0832, 0.0843, 0.0846, 0.0846, 0.0863, 0.0865, 0.0876, 0.0883, 0.0896, 0.0899, 0.0900, 0.0902, 0.0903, 0.0911, 0.0933, 0.0936, 0.0939, 0.0948, 0.0958, 0.0968, 0.0972, 0.1012, 0.1034 }
The averaged reference volumetric flow is output (in $[m^3/s]$), which is denoted by 'y' as,
y={0.0034, 0.0037, 0.0037, 0.0039, 0.004, 0.004, 0.004, 0.0042, 0.0044, 0.0045, 0.0044, 0.0043, 0.0046, 0.0047, 0.0047, 0.0046, 0.0049, 0.0049, 0.0051, 0.005, 0.0049, 0.0053, 0.0053, 0.0055, 0.0052, 0.0056, 0.0054, 0.0057, 0.0057, 0.0056, 0.0058, 0.006, 0.0062, 0.0062, 0.006, 0.0063, 0.0066, 0.0066, 0.007, 0.0074 }

Appendix B
Machine Learning Models

A. Simple Linear Regression Model

A simple linear regression model is of form given by (Eq. 9), where $w_0 = -0.0041$ and $w_1 = 0.1082$ for the data under the study.

$$f(x) = w_0 + w_1 x \tag{9}$$

B. Polynomial Linear Regression Model

A polynomial linear regression model is of form given by (Eq. 10), where $w_0 = 0.001$, $w_1 = -0.0117$ and $w_2 = 0.7043$ for the data under the study.

$$f(x) = w_0 + w_1 x + w_2 x^2 \tag{10}$$

C. Support Vector Regression Model

A support vector regression model is of form given by (Eq. 11).

$$f(x) = \sum_{i=1}^{n_{SV}} (\lambda_i - \lambda_i^*) k(X_i^{SV}, x) + w_0 \tag{11}$$

For the data under the study, number of support vectors $n_{SV} = 37$ and bias term $w_0 = 0.2166$. Support vectors denoted by X^{SV} as,
X^{SV}={ 0.0709, 0.0719, 0.0732, 0.0734, 0.0742, 0.0747, 0.0761, 0.0771, 0.0776, 0.0779, 0.0788, 0.0796, 0.0804, 0.0817, 0.0823, 0.0832, 0.0843, 0.0846, 0.0863, 0.0865, 0.0876, 0.0883, 0.0896, 0.0899, 0.09, 0.0902, 0.0903, 0.0911, 0.0933, 0.0936, 0.0939, 0.0948, 0.0958, 0.0968, 0.0972, 0.1012, 0.1034}
The difference in the Lagrange multipliers is denoted by $(\lambda - \lambda^*)$ as,
$\lambda - \lambda^*$ = {5.00e-05, -0.000174389, -5.49e-05, 0.000957214, 0.000110989, -2.12e-05, 7.10e-05, 470.3760786, 499.9998988, 5.09e-05, -499.9994899, 5.29e-05, 499.9997232, -499.9999591, 499.999593, 1.45e-05,

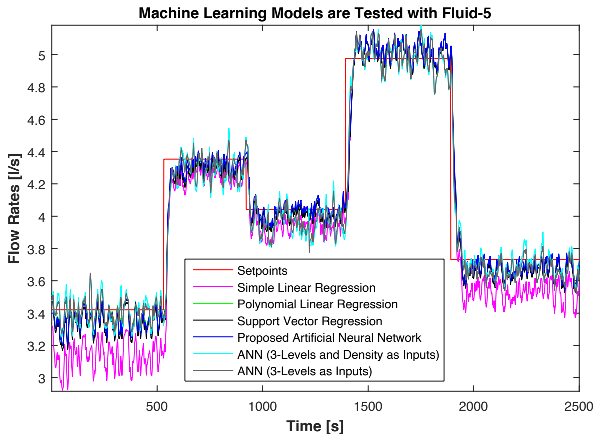


Fig. 10: The performance of fitted machine learning models are tested with randomly varying flow rates (for Fluid-5, flow rates vs. time).

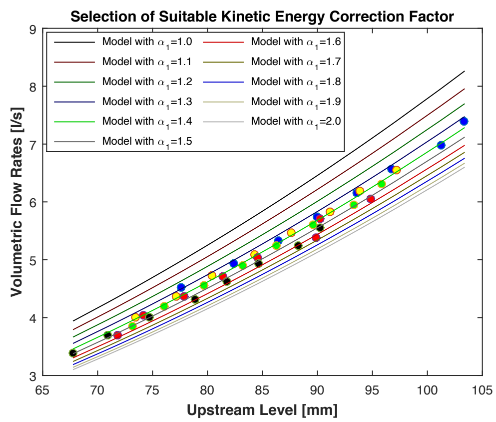


Fig. 11: Tuning kinetic energy correction factor (α_1) for fitting the standard upstream based flow model to the averaged data. Volume flow rate vs. upstream level.

0.000220111, -499.9970822, 3.27e-05, 0.001997597, 0.000728455, -499.9999113, -1.45e-05, -499.9999324, 499.9983046, 4.26e-05, -499.9997141, 3.81e-05, -0.000306798, 29.61633402, 0.003657766, -499.9999413, -7.12e-05, 499.9993156, -1.06e-05, -8.43e-05,499.9994947} $k(X_i^{SV}, x)$ is a Mercer kernel and radial basis function is used as the kernel in this study. The values of hyperparamters (regularizing parameter (C) = 500, spread (σ) = 0.7, and error tolerance (ϵ) = 0.0001) are selected based on grid search method. The value of Lagrange multipliers depends on these hyperparameters. The detail mathematics on support vector regression is found in [33].

D. Artificial Neural Network Model

In this study, the proposed artificial neural network consist of 2 hidden neurons as shown in Figure 13. A sigmoid activation function is used in hidden neurons and a linear activation function is used in the output neuron. The neural network model is of form given by (Eq. 12), where $w_{20} = -1.28$, $w_{21} = 1.60$, $w_{30} = 0.51$, $w_{31} = 0.84$, $w_{40} = -0.05$, $w_{42} = 0.62$, $w_{43} = 0.98$, and $\phi(.)$ is hyperbolic tangent sigmoid function.

$$f(x) = \phi(w_{20} + w_{21}x) * w_{42} + \phi(w_{30} + w_{31}x) * w_{43} + w_{40} \tag{12}$$

The architecture of two different mass flow rate ANN models used in the study are shown in Figure 14. The number of neurons in these networks are selected based on the grid search method with an objective of lowest mean squared error.

E. Uncertainty Analysis of Volume Flow Rate Estimates based Fluid Height

For mathematical simplicity, the PLR model is chosen for uncertainty analysis. The systematic uncertainty of the ultrasonic level sensor used in this study is ±0.0025 [m] for measured distance of less than one meter [34]. As the proposed models for flow rate are based on single ultrasonic level measurement, the systematic uncertainty of the level sensor is propagated to the proposed PLR model based on Eq. 13 given in [29].

$$u_{f(x)} = \frac{\partial f(x)}{\partial x} \times u_x \tag{13}$$

where u represents systematic uncertainty.

The differential term in Eq. 13 is computed by differentiating Eq. 10 with respect to level (i.e. 'x') and using an average value of level. Average level at 4 $[l/s]$ is considered in this calculation (i.e. $\mathrm{x}_{\mathrm{average}}$ at 4 $[l/s]$ is 0.0742 $[m]$). The systematic uncertainty estimate based on the PLR model is ±0.23 $[l/s]$.

The random uncertainties are analysed based on box plots. Figure 15 shows the box plots of upstream ultrasonic level measurements and flow rate estimations of the PLR model at different flow rates. The box plots show that the uncertainty in the flow estimations is directly dependent on uncertainty of level measurements.

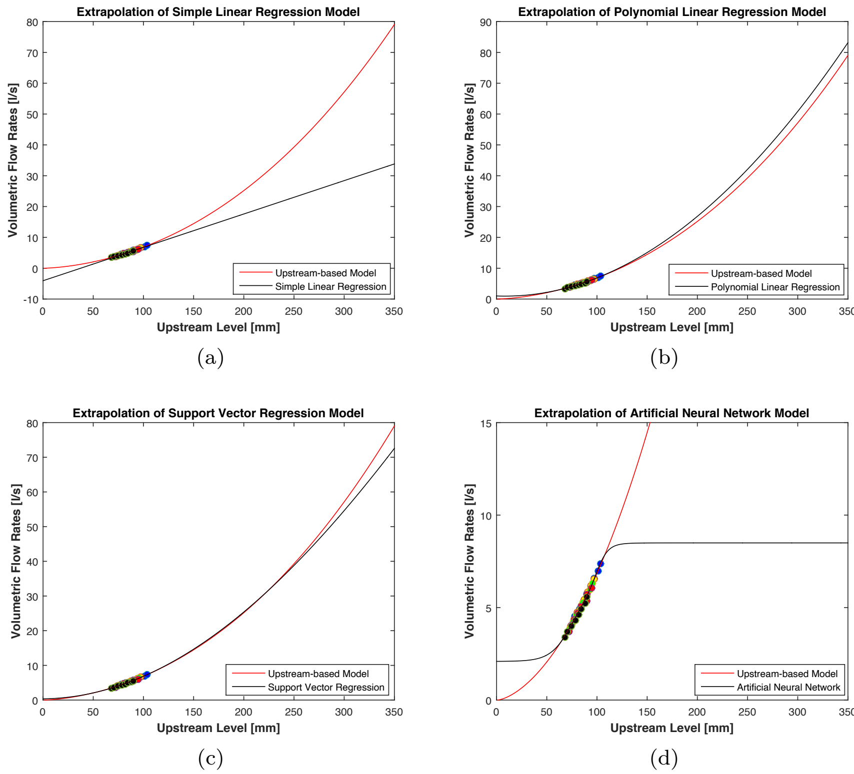


Fig. 12: All the proposed machine learning models are extrapolated to wider range and compared with the standard upstream based flow model. The neural network model uses sigmoid activation function. Volumetric flow rate vs. upstream level.

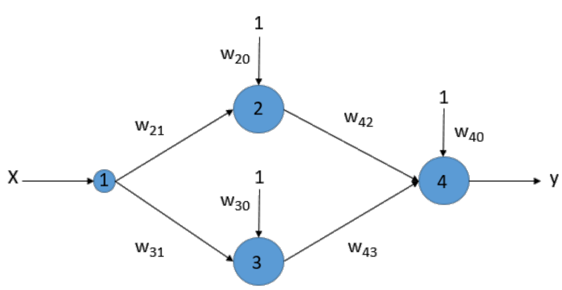


Fig. 13: The artificial neural network architecture with single upstream ultrasonic level measurement as input and volumetric flow rate as output. The hidden layer consists of a single layer with 2 hidden neurons.

Appendix C
Geometry of the Open Channel

The channel geometry of the open Venturi channel used in the study is shown in Figure 16. The positions of three ultrasonic level sensors used in this study are shown in Figure 16a. For the standard flow models given in Section II-B3, h_1 is measured using LT-2 level sensor and h_2 is measured using LT-3 level sensor. For the proposed single level based machine learning models, the level is measured using LT-2 in the position shown in Figure 16a.

Acknowledgment

The Ministry of Education and Research of the Norwegian Government is funding Khim Chhantyal's Ph.D. studies at University College of Southeast Norway (USN). Morten Hansen Jondahl is doing his Ph.D. in USN within the project Semi-kidd funded by the Royal Norwegian Council and the industries. The authors at USN appreciate the collaboration with and support from STATOIL for providing and commissioning open channel Venturi rig with various types of sensors and control systems dedicated for flow studies of different Newtonian and non-Newtonian fluids. The economic support from The Research Council of Norway and Statoil ASA through project no. 255348/E30 "Sensors and models for improved kick/loss detection in drilling (Semi-kidd)" is gratefully acknowledged. We appreciate the expert advice on drilling operations by Dr. Geir Elseth of STATOIL. We acknowledge all the practical works done by various groups of bachelor and master students of USN in conjunction with this work.

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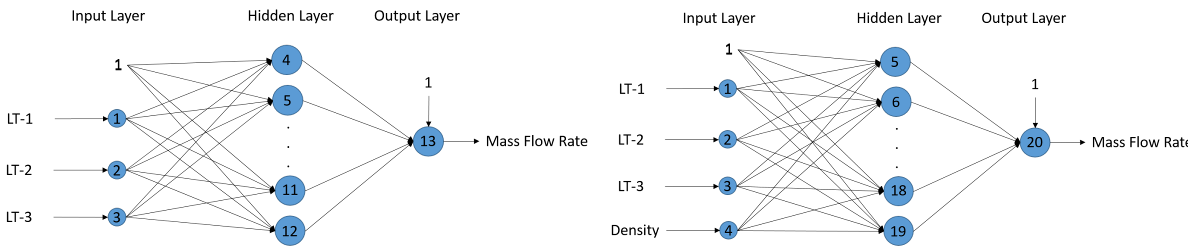
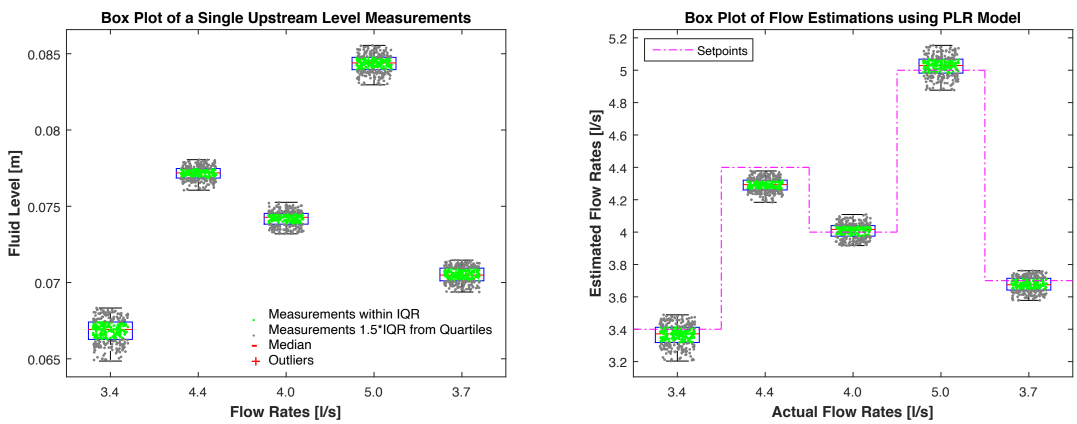


(a) (b)

Fig. 14: (a) The artificial neural network architecture with three ultrasonic level measurements as inputs and mass flow rate as output. The hidden layer consist of a single layer with 9 hidden neurons. (b) The artificial neural network architecture with three ultrasonic level measurements and density as inputs and mass flow rate as output. The hidden layer consists of a single layer with 15 hidden neurons.



(a) (b)

Fig. 15: Box plots showing the spread of the ultrasonic level measurements and PLR model-based flow estimates at different flow rates. Green dots, black dots, and the red plus sign represent measurements/estimates within the Interquartile Range (IQR), within the upper and lower bounds, but out of IQR, and outliers, respectively. (a) Box plots for the upstream ultrasonic level measurement. (b) Box plots for flow rate estimations of the proposed PLR model.

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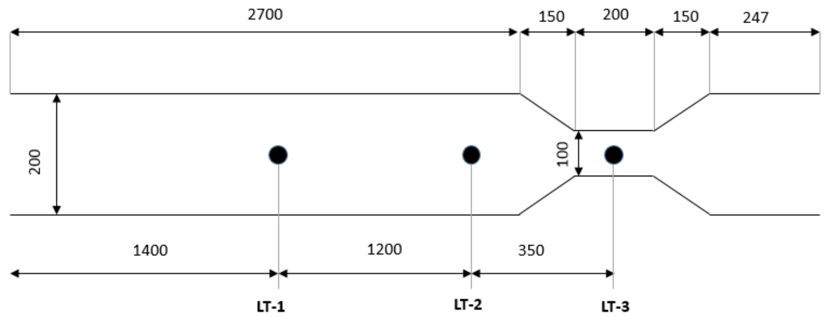
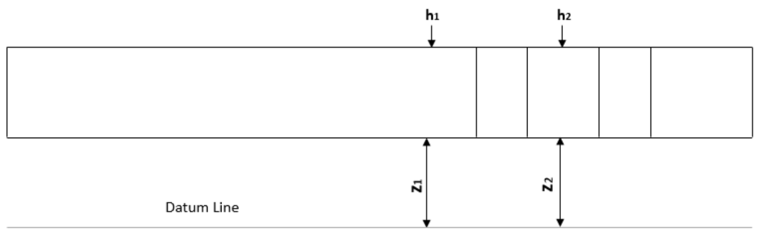
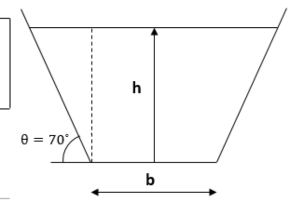


(a) Top View Sketch



(b) Side View Sketch



(c) Cross-sectional View Sketch

Fig. 16: Geometry of the open channel with Venturi constriction available at University College of Southeast Norway. (a) Top view sketch, (b) Side view sketch, and (c) Cross-sectional view sketch of the channel tiltable to angle $\Theta = \pm 2$ degrees to the horizontal. All the dimensions are in [mm]. Three black dots in the top view sketch represent the positions of three ultrasonic level sensors used in the study.

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Paper 2

Rheological characterization of non-Newtonian drilling fluids with non-invasive ultrasonic interrogation

Rheological Characterization of non-Newtonian Drilling Fluids with non-invasive Ultrasonic Interrogation

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Abstract*—The drilling process is generally costly and time consuming and prone to serious hazards. Cost-efficiency and enhanced safety measures are vital for any drilling operation. Recent studies indicate that poor reliability in the drilling process resulted in as much as 30% loss of production time. Improved sensor technology with process automation can improve process performance and safety. During drilling operations, along with the drillstring, a drilling fluid, commonly very dense and viscous fluid, is circulated in a closed flow-loop. The drilling fluid, non-Newtonian in its rheological behavior, serves three main objectives: keeping the bottom-hole pressure at an acceptable level, lubricating the drill bit and facilitating the removal of cuttings and debris from downhole. These three goals have to be kept in balance and are achieved by adjusting the density (ρ), viscosity (μ) and the flow-rate (q_v) of the drilling fluid. These three drilling process parameters need to be continuously monitored for optimizing process performance and securing safety. The cuttings in the drilling fluids make it especially challenging when conventional in-line sensor systems are used due to the unavoidable erosion and maintenance costs. Non-invasive ultrasonic measurement techniques can be part of a robust and easily implementable control and monitoring system. In this work ultrasonic properties of different drilling fluids are studied. Propagational properties of different samples of drilling fluids are studied with focus on attenuation and frequency characteristics in transmission mode. Experimental results using different sets of ultrasonic transducers with different frequencies, confirm the high attenuation of ultrasonic pulses. A model is proposed to estimate the attenuation and viscosity of the drilling fluid based on ultrasonic and rheological parameters. This study presents results from ultrasonic interrogation of non-Newtonian fluids with focus on their rheological properties.

Keywords*— Ultrasonic attenuation; Drilling fluid; Drilling fluid viscosity, Drilling fluid density, non-Newtonian fluid

I. INTRODUCTION

The process of drilling oil & gas wells either on land or offshore, uses a special drilling fluid for several purposes. The drilling fluid is circulated through a flow loop which extends from the surface equipment down to the drill bit in the bore hole. Some of the more important purposes of the drilling fluids are: Controlling the bottomhole pressure (BHP); cool, lubricate and clean the drill bit; and remove rock cuttings from the well [1], [2].

These and other characteristics of drilling fluids require them to possess conflicting chemical and physical properties. These conflicting requirements lead to challenges to the engineers involved in their production. The drilling fluid can be either water based mud (WBM) or oil based mud (OBM), satisfying environmental regulations and possessing specific rheological properties. Several additives are used to tune the drilling fluid to achieve the set of desired properties necessary for a particular application. Drilling fluids with their high viscosities and high densities are non-Newtonian in their rheological behavior and help to carry the cuttings from the borehole to the surface.

Online access to the rheological parameters of the drilling fluid and its behavior during its circulation in the flow loop is useful for the optimal operation of the rig. The drilling fluid is designed, mixed and checked before being fed into the circulation. During the drilling operation, properties of the drilling fluid changes continuously. The drilling engineer has to rely on various measurements based on samples taken at specific locations in the circulation system, including intermittent lab-analysis. Hence, dedicated non-invasive online measurement techniques would improve the monitoring of rheological properties. Monitoring the drilling fluid properties is important for safety reasons, but also for maintaining and improving the drilling efficiency.

In this study, we have investigated the relationship between ultrasonic and rheological properties of the drilling fluid. By combining empirical models with ultrasonic measurements of the mud returning from the wellbore, we can better understand the behavior of the drilling fluid. This will ensure that the drilling fluid keeps its properties as desired, and thus performs according to expectations.

Ultrasonic measurements are one of the measurement principles to be applied to the drilling fluid during its return flow. This is a non-intrusive measurement of selected characteristics on the drilling fluid, and measurements of ultrasonic properties of drilling fluid have been shown to be correlated to fluid properties such as density and viscosity[3]–[5].Ultrasonic measurement techniques are already used in flow-metering of various oil, gas and multiphase streams in the petroleum industries. Flow meters using transit-time difference and Doppler frequency-shift are already in use in the field [6]. We wanted to explore further the possible uses of ultrasonic measurement principles to determine the rheological properties of drilling fluids. A similar study [7] in the food industries has shown very good results in characterizing another complex fluid, the well-known tomato ketchup, which is also non-

Economic support from The Research Council of Norway and Statoil ASA through project no. 255348/E30 "Sensors and models for improved kick/loss detection in drilling (Semi-kidd)" is gratefully acknowledged.

Newtonian. Similar attempts have been made in characterizing slurries, another complex fluid found frequently in the process industries [8]. The aim of the current study is to model the rheological properties that are hard to measure online, by using the ultrasonic properties.

II. Experimental Methods

A. Ultrasonic measurements

Data for the developed models have been collected at University College of Southeast Norway (USN). The setup was developed and used as a part of a final year project at USN [9], and further developed for collecting data for this study. The measurements were taken in a tank, with capacity of 170 liters. Transmission mode of ultrasonic wave propagation was used in the tests with transmitter and receiver submerged in the drilling fluid, both mounted on a rack and guided using a rail above the tank, as shown in Fig. 1. This rack and rail arrangement is used to adjust the linear spacing x between the transmitter and receiver. The ultrasonic attenuation and transit-time were recorded at each location, as the spacing was stepwise increased.

We used three transducer couples in through transmission mode. All with the same dimensions, 2.54 cm (1 in) element diameter, and three frequencies; 0.5, 1.0 and 2.25 MHz. The attenuations measured at a 3 cm linear spacing were used as references (0 dB) for the three different transducer couples. The linear spacing was stepwise increased in 2 cm increments. The measurements were repeated to add to the data available for facilitating the development of a suitable model development.

B. Mud analysis

The drilling fluid used in these experiments was produced by MI Swaco, and supplied by Statoil for the purpose of these measurements. To relate the rheological and ultrasonic properties, it was decided to gradually dilute the supplied sample. We started out with the drilling fluid as it was supplied, and in steps diluted it five volume percentage 10 times with water. This gave us ultrasonic measurements on 11 different fluids, which then had the same components, but with different concentrations and therefore different rheological properties. The fluids will be referred to as Fluid 1 through Fluid 11. For Fluid 1 and 2, only two samples for mud analysis were collected, for the remaining fluids the results of the mud analysis are from 4 samples. Extensive fluid analysis on the sample fluids, with focus on rheological properties, was done at Statoil. The methods used in this analysis are comparable to, but are not exactly the same as those used in the field analysis of drilling fluid. This limits the comparability of the results from our analysis of the mud to the results from other drilling fluid analysis. For our purpose, they serve very well, as they allow us to compare the attenuation with the changes in specific rheological properties. The rheological properties analyzed are density, viscosity, gel strength and yield point. Since the sample fluids are non-Newtonian, the viscosity is dependent on the shear rate, and a single value will not describe the fluid. The established practice in drilling is then to use a Bingham-Plastic model to describe the viscosity, and the reference viscosity is known as plastic viscosity (PV) [1]. The initial yield stress needed to start the flow of fluid, known as the yield point, is one of the main characteristics of non-Newtonian fluids. The Bingham-Plastic model for non-Newtonian fluids are described by the equation,

$$\tau = \mu_p \dot{\gamma} + \tau_y \qquad (1)$$

where the parameters are: τ – shear stress [Pa]; μ_p – the plastic viscosity [Pas] ; $\dot{\gamma}$ – the shear rate [1/s]; τ_y – yield point [Pa].

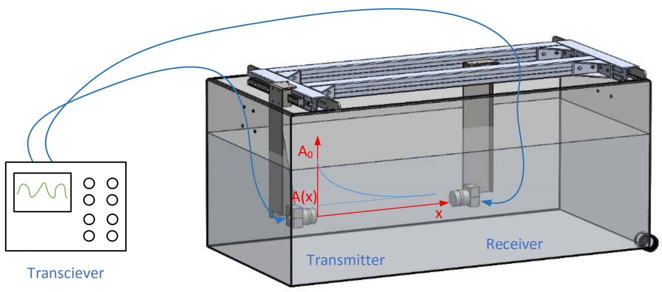

Fig. 1: Ultrasonic experimental setup with transmitter and receiver submerged in a tank containing the drilling fluid. x is the linear spacing between transmitter and receiver

III. Results and Discussion

A. Ultrasonic attenuation

For the ultrasonic data, we recorded the time of flight (ToF) and the received amplitude [dB]. Using these measurements, we calculated the relative amplitude. Fig. 2 shows the relative amplitude, *A(x)* [dB] against the distance, x [cm] between the transmitter and receiver for all 11 fluids used in this study, with the three different frequencies. We can observe two important characteristics for the fluids and the ultrasonic attenuation here. First, we see that the attenuation in dB for each fluid appears linearly dependent on the distance. Secondly, the order the curves stack on each other is the same order the fluids were diluted from fluid 1, as the slope of the curves is increasing with decreasing density, which implies positive correlation between density and attenuation coefficient. Furthermore, the spacing between them indicate there is a close relationship between the changing properties of the fluids, and the decreasing slope (attenuation) of the curves.

With this, we could anticipate that the diluting process had changed the fluid in such a way that the attenuation decreased as well. We used a linear least squares method on measurements in dB scale to determine α based on the model for reduced amplitude [10]–[12], as in

$$A(x) = A_0 e^{-\alpha x} \qquad (2)$$

where the parameters are: A – reduced amplitude [V]; A_0 – unattenuated amplitude [V] at $x = 0$; α – attenuation coefficient [Np/m]; x – propagation distance as shown in Fig. 1 [m].

Now, with the data shown in Fig. 2 we can develop the regression models as outlined in (2) for each fluid sample, for each frequency. This gives an estimate of α, which we can compare for all fluid samples, given the frequency.

B. Regression models

The ultrasonic measurements clearly indicated that there is a close relationship with the decreasing density of the fluid samples and the ultrasonic attenuation. With the rheological lab measurements, we can relate this change in attenuation to rheological properties. We used linear least squares methods on the lab measurements for density and viscosity together with the estimated attenuation coefficient. This gave some promising models for these rheological properties, based on the ultrasonic properties. Regression plots of the models are shown in Fig. 3, in total six models are presented. Table 1 shows the model coefficients as in (3) as well as R^2 and RMSE (Root Mean Square Error) for fit evaluation.

$$[\rho \quad \mu_p] = \begin{bmatrix} a_\rho & b_\rho \\ a_{\mu_p} & b_{\mu_p} \end{bmatrix} \begin{bmatrix} \alpha \\ 1 \end{bmatrix} \tag{3}$$

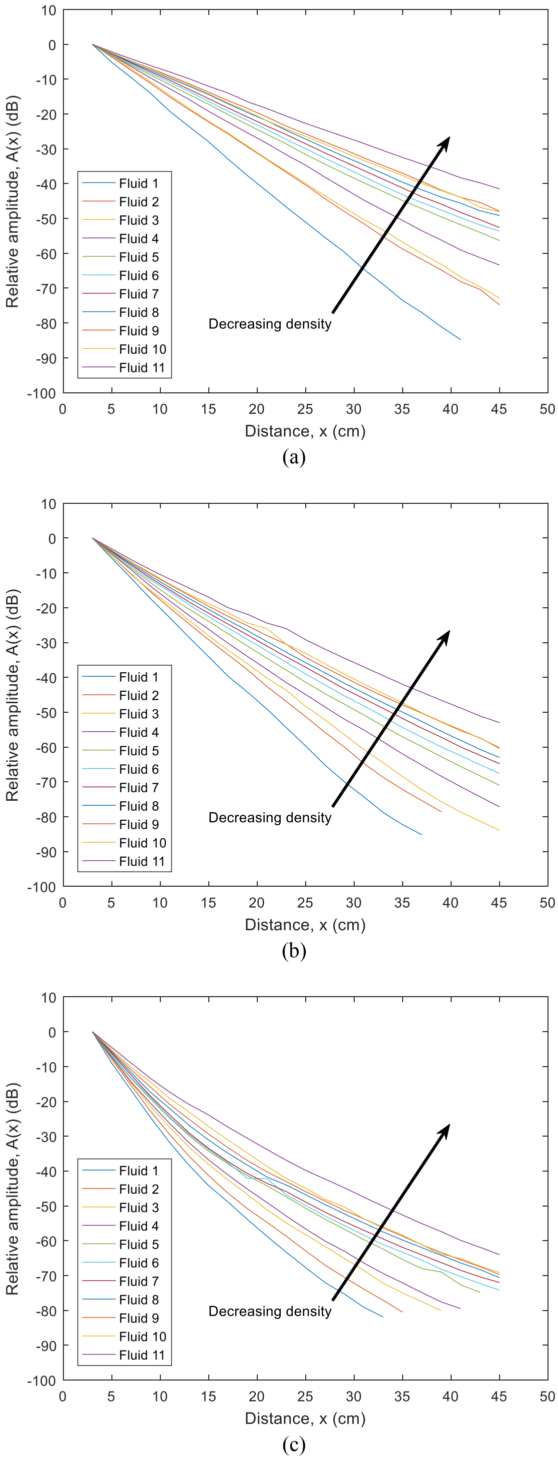

Fig. 2: Relative amplitude for 11 fluids plotted against linear spacing of the transmitter and receiver. Signal frequency is 0.5 MHz (a), 1.0 MHz (b) and 2.25 MHz (c).Where the curves end for shorter distances than 45 cm, attenuation resulted in an unrecognizable amplitude.

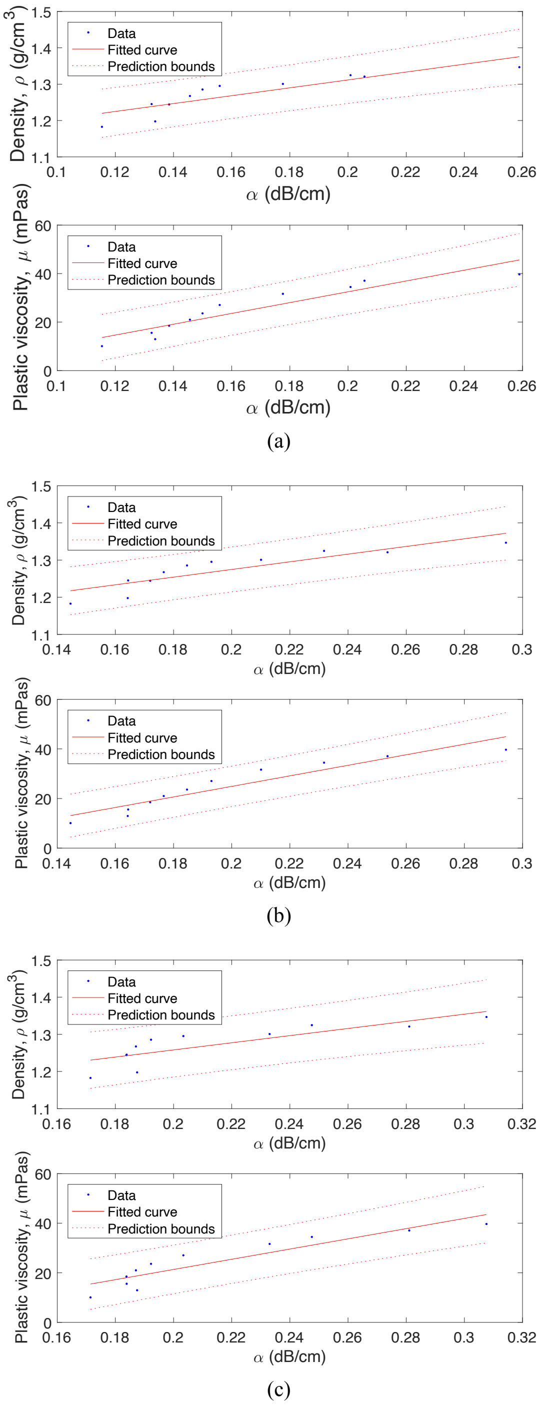

Fig. 3: Regression models for density and plastic viscosity. (a) for 0.5 MHz, (b) for 1.0 MHz and (c) for 2.25 MHz.

These results are varying in fit quality, and albeit showing potential, we believe that non-linear models, and combing more inputs will lead to improved models. One model may describe all available data for the different fluids. Both the lab measurements of the drilling fluid as well as the ultrasonic measurements are extensive and include more data than we could use for analysis in this paper. Preliminary studies looking into the development of non-linear empirical models with data fusion of measured sound velocity as well as measured attenuation indicate that such models can give reliable estimates of density or viscosity. A sketch for realizing such a data fusion scenario is shown in Fig. 4. Similar to the matrix equation (3) above, the model can fuse the times of flight yielding velocity of sound in real time thus enabling a continuation evaluation of the density and plastic viscosity in the process. Such a real time estimate will help to trace trends and alleviate extraordinary and dangerous process scenarios such as blowouts.

IV. CONCLUSION

In this study we have made extensive and numerous ultrasonic measurements on 11 samples of drilling fluid. Equally extensive lab measurements were made on the same 11 samples. This has provided large amounts of ultrasonic data and data on rheological properties to be analyzed for correlation. The first analyses are presented in this publication. Applying linear least squares method on the ultrasonic data yielded good results in estimating the attenuation coefficients for the different fluids, using three frequencies: 0.5 MHz, 1.0 MHz and 2.25 MHz. The linear trend was better with lower frequency.

TABLE 1: REGRESSION MODEL COEFFICIENTS AND FIT EVALUATION VALUES.

Model	Density, ρ [g/cm³]			Viscosity, μ_p [mPas]		
	0.5 MHz	***1.0 MHz***	***2.25 MHz***	***0.5 MHz***	***1.0 MHz***	***2.25 MHz***
a	1.08	1.03	0.96	223	213	206
b	*1.10*	1.07	1.1	-12	-18	-20
R²	0.77	0.78	0.69	0.87	0.89	0.85
RMSE	0.03	0.03	0.03	3.8	3.4	4.1

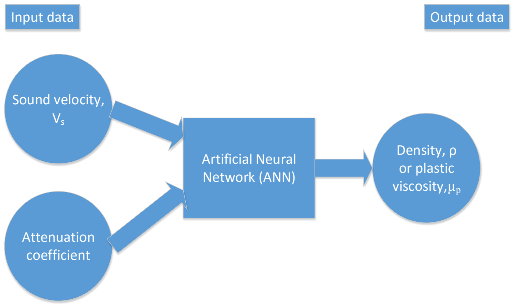

Fig. 4: Sketch of future planned empirical model with data fusion on input and rheological properties as output.

The experimental results show positive correlations between both attenuation and density, and between attenuation and plastic viscosity. However, the relationships are only fairly described by linear models, with R^2 values between 0.69-0.89. Further analyses will focus on more data fusion and non-linear empirical models, e.g. artificial neural networks.

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Paper 3

Estimating Rheological Properties of Non-Newtonian Drilling Fluids using Ultrasonic-Through-Transmission combined with Machine Learning Methods

Estimating Rheological Properties Of Non-Newtonian Drilling Fluids Using Ultrasonic-Through-Transmission Combined With Machine Learning Methods

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Abstract— During drilling an oil/gas well, situations where the pressure integrity of the well is lost are great risks to assets, humans, and the environment, and represent high costs to the drilling operation. The non-Newtonian drilling fluid that is circulated while drilling serves several purposes, and its properties are essential to fulfil them. The density (ρ) enables the drilling mud to maintain pressure integrity during drilling operations. The plastic viscosity (μ_p) enables the fluid to transport cuttings, while the gel strength (S) keeps the cuttings suspended when circulation is stopped. The industry standard is to perform manual drilling fluid checks every six hours to measure these three important rheological properties. To increase safety, efficiency and enable more automated drilling operations, sensor technology to perform these measurements in real-time is in high demand. Non-invasive ultrasonic measurement techniques in combination with machine learning represents one promising and easily implementable solution to meet these demands. In the presented work acoustic properties of different drilling fluids are studied. Three different pairs of ultrasonic transducers were utilized to evaluate the propagational properties of 22 different samples of water-based drilling fluids. The parameters measured in the ultrasonic experimental setup is received signal amplitude, time of flight and the lateral distance between receiver and transmitter. The trained machine learning models predicted density with a mean absolute percentage error (MAPE) in the range of 0.84% to 0.95%, plastic viscosity from 4.4% to 7%. The models for gel strength were not nearly as accurate, with MAPE ranging from 15% to 19%. This shows that the measurement principle has potential to develop a sensor system capable of meeting the demands regarding safety, efficiency and automation.

Keywords— Ultrasonic attenuation, Drilling fluid, non-Newtonian fluid rheology, machine learning, neural network

I. INTRODUCTION

A. Drilling operations

In oil & gas drilling, pressure control of the well is of great importance. For this purpose, among others, a drilling fluid is continuously pumped through the drilling equipment, down into the well through the drillstring and back to the surface via the space between the drillstring and the borehole wall, i.e. the annulus [1], [2]. The drilling fluid serves three main purposes: control the pressure in the wellbore, clean and lubricate the drillbit, and transport the cuttings to the surface [1], [3]. In Table 1 these purposes are shown together with their related fluid properties that are considered for real-time measurements in this study.

TABLE 1: DRILLING FLUID PURPOSES AND ASSOCIATED PROPERTIES

Drilling fluid purpose	Relevant properties
Pressure control	Density, viscosity, gel strength
Clean, lubricate	Lubricity (not in this study)
Transport cuttings	Viscosity, gel strength

B. Drilling fluid rheology

The properties, density (ρ), viscosity (μ_p) and gel strength (S) are some of the properties defining a drilling fluid's rheology. Measuring them during drilling operations follows an American Petroleum Institute (API) recommended practice (RP) [4]. This is a very generic procedure, and meant to be applicable to all drilling operations, either it is in a farm field, or offshore in the arctic circle. As these two examples of drilling locations are extremely different, many variances exists in the equipment used in drilling the wells, but the main principles behind the drilling remain the same. However, for both operations the measurements of the rheological properties are manually performed, typically four times a day during normal operations. The equipment and methods should be improved, to provide real-time, non-invasive measurements. This would increase safety in the operation, give more reliable measurements, and enable better system automation and control in the drilling process. Podio and Gregory [5] studied the ultrasonic properties related to drilling fluid rheology, and found that attenuation and drilling fluid density are highly correlated. Pope, Veirs and Claytor [6] developed a technique to relate density as a function of resonant peaks in a FFT spectrum. A densimeter operating on ultrasonic Doppler methods is also described for slurries, although it is not stated if these are non-Newtonian [7]. This is discussed in further detail, also measuring viscosity by Bamberger and Greenwood [8], [9]. Our study aims to

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investigate whether ultrasonic measurements may also be used to estimate rheological properties of the non-Newtonian drilling fluids, to lay the foundation for non-invasive non-destructive and inexpensive real-time measurements.

II. Methods

A. Ultrasonic measurements

The experimental setup for the ultrasonic through transmission measurements were the same as in our previous study [10] and is shown in Fig. 1. The system consists of a tank, holding approximately 82 litres of the fluid under study. Into the tank, transmitter and receiver were submerged, attached to a rack and rail system that allowed for the linear distance (x) between them to be varied. Three pairs of receiver/transmitter were used, all with the same element diameter (2.54 cm/1 in) but with different frequencies, 0.5, 1.0 and 2.25 MHz. From 3 cm to 45 cm the received signal strength and transit-time was recorded at 2 cm increments. The measurements were made in 11 different fluids, and for each fluid, each distance was measured twice. The attenuation was related to the 3 cm measurement as the reference.

B. Fluid analysis

For the experiments two water based drilling fluids (Fluid A and Fluid B) produced by MI Swaco and supplied by Equinor were used. To increase the spread of data collected, we diluted the original samples in 10 steps. For each step, the fluids were diluted by adding five volume percentage of water. The fluids referred to as Fluid B-1 through Fluid B-11, constitutes the measurement samples for this study. Fluids A-1 through Fluid A-11 were measured in the previous study, but the data is used in the models presented here. For each of the fluids, two samples were collected and used for fluid analysis by Equinor. In this lab analysis the rheological properties were measured using an Anton Paar Modular Compact Rheometer MCR 502. These measurements will be the reference to which the developed models will be compared, and also used for the supervised learning of machine learning models. The measurements are comparable, but not exactly the same as in the API RP. In fact, the accuracy is higher for these lab devices compared to prevailing equipment used in the drilling industry following the API RP [4]. The rheological properties in focus in our work are density, viscosity and gel strength. As the drilling fluids are non-Newtonian, the latter two are special cases. The viscosity cannot easily be given as a single number, as it is shear-rate dependent, and the gel strength refers to the fluid's resistance to flow [3], i.e. the pressure required to break (start) circulation after a period of settling (10 seconds or 10 min). For the viscosity, there are several models describing it for non-Newtonian fluids. Most commonly used to describe drilling fluids is the Bingham-Plastic model, and the related plastic viscosity (μ_p). The yield point is related to the shear stress at zero shear rate, and is thus just a model parameter, not a physical property like the gel strength. The Bingham-Plastic model is given as:

$$\tau = \mu_p \dot{\gamma} + \tau_y \tag{1}$$

where the parameters are: τ – shear stress [Pa]; μ_p – the plastic viscosity [Pas] ; $\dot{\gamma}$ – the shear rate [1/s]; τ_y – yield point [Pa].

C. Artificial neural network

Artificial neural networks (ANN) are machine learning models that are inspired by the connections between nodes, or neurons in the human brain. These neurons act as computation points in a larger network. Modelling such a network may enable efficient modelling of non-linear systems without complex and time-consuming computation. The neurons are organized in layers, typically three; one input layer, a hidden layer, and an output layer. In Fig. 2 this basic structure is shown, with the three layers and the hidden layer with more neurons than in both the input and output layers. The connections between the neurons in the different layers are called weights. Together with a non-linear activation function in each neuron in the hidden layer(s) these make up the computations effectively connecting the input data to the

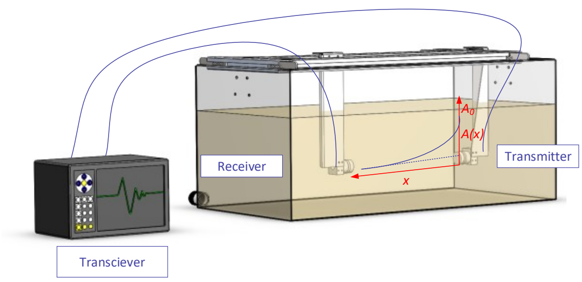

Fig. 1: Ultrasonic experimental setup with transmitter and receiver submerged in a tank containing the drilling fluid. x is the linear spacing between transmitter and receiver.

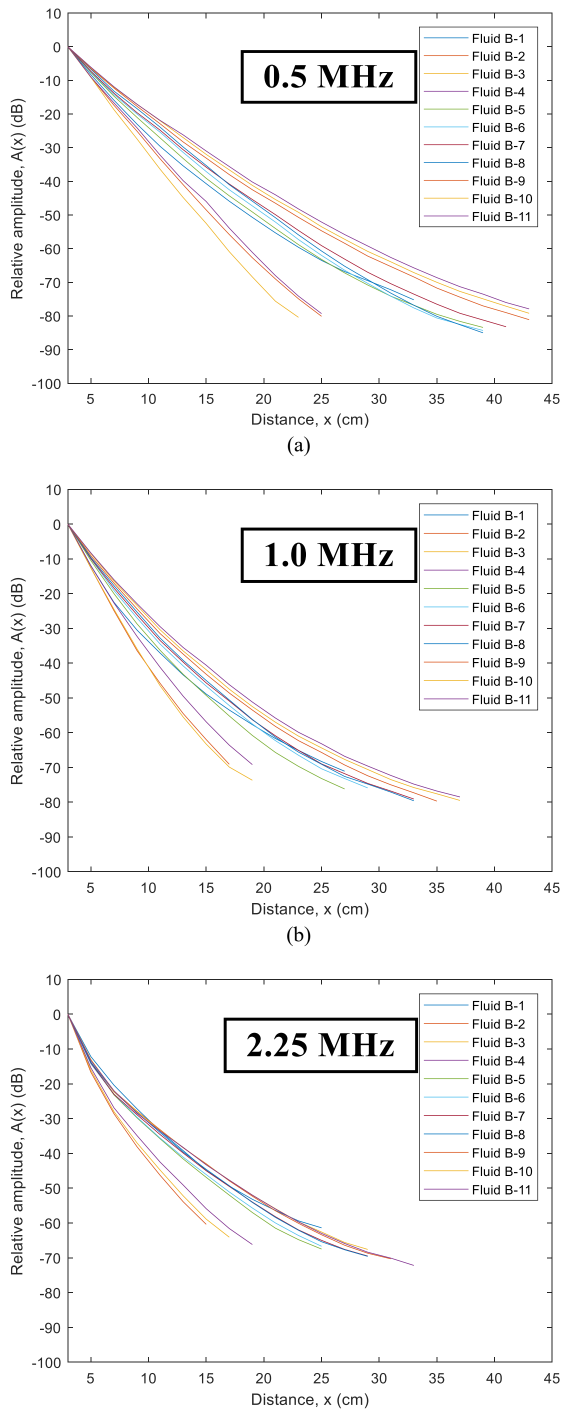

Fig. 3: Relative amplitude ($A(x)$) for Fluid B-1 through Fluid B-11 plotted against linear spacing (x) of the transmitter and receiver. Signal frequency is 0.5 MHz (a), 1.0 MHz (b) and 2.25 MHz (c).The curves ends at various distances according to the variation in attenuation, and signal not received.

output. Developing the network involves three phases: Training, validation and testing. In the training phase the network is shown input data with the correct output data. The output of the model is compared against this target output, and an error signal is generated. This error signal is used to adjust the values of the weights to improve the performance. To ensure the network will not just memorize the training data, validation data is used to stop training when the error signal has decreased beneath a predetermined level. In the test phase, new data is presented to the network, and the error signal from this data set will indicate the performance of the model. The trained network should may now be used to model the outputs for new input data. There are several options to be considered regarding the structure of the network, and in selecting a preferred training algorithm. Knowledge of the system to be modelled may speed up this process, especially if there are some known relations between inputs and outputs. The main concern is however data, preferably large amounts of high precision data, spanning the known or expected range of both input and output variables.

III. RESULTS AND DISCUSSION

A. Ultrasonic attenuation

The attenuated signals were plotted against the distance, x, in Fig. 3. The attenuated signals are represented as relative amplitude ($A(x)$ [dB]) to the 3 cm measured signal, as this is chosen as the first measurement point. This is according to Mozie's consideration of the near-field effects [6]. As expected the higher frequency couple have higher attenuation and the signal is lost at shorter distances. The curves follow in general a logic trend, where the attenuation to some extent correlate with the dilution of the fluid. Furthermore, the attenuation is non-linear for all

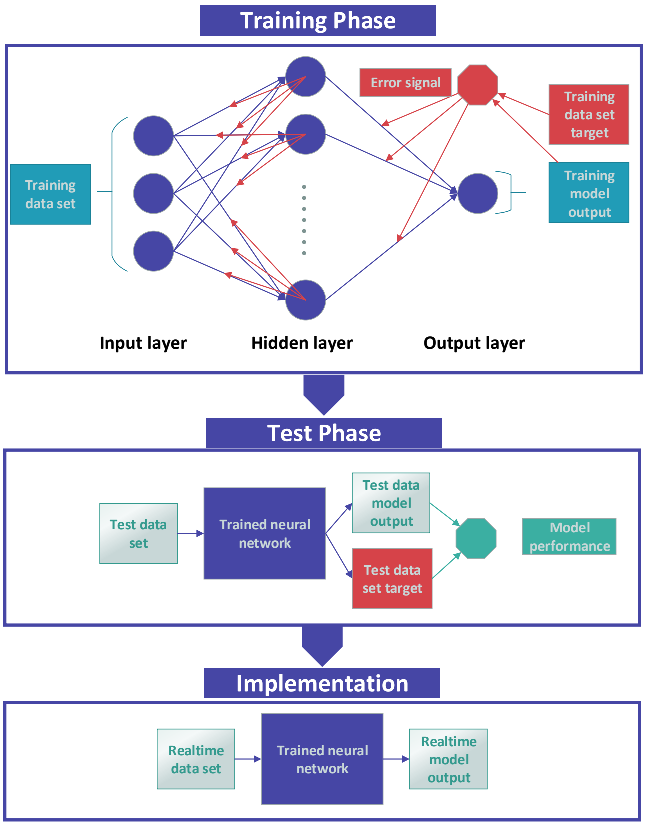

Fig. 2: ANN structure. The circles are the neurons, connected forward by the purple weights, and backwards with the red error signal adjustments to the weights. The training data is used to train the weights according to the error signal, where the model output is compared to the known output of the training set.

TABLE 2: ANN ARCHITECTURE(NUMBER OF HIDDEN NEURONS) AND PERFORMANCE (MAPE) RESULTS

Frequency	Network output	Architecture	MAPE
0.5 MHz	Density, ρ	17	0.94%
	Plastic Viscosity, μ_p	17	6.4%
	Gel strength, S	17	15%
1.0 MHz	Density, ρ	16	0.95%
	Plastic Viscosity, μ_p	15	7%
	Gel strength, S	18	19%
2.25 MHz	Density, ρ	11	0.84%
	Plastic viscosity, μ_p	18	4.4%
	Gel strength, S	9	16%

frequencies. The density of the fluids are ranging from 1.41 to 1.75 g/cm3 for Fluid B and from 1.17 to 1.33 g/cm3 for Fluid A. The plastic viscosity ranged from 4.23 to 11.13 cP and from 10.1 to 40.5 cP, for B and A, respectively. Thus, we have covered a wide range of values in our dataset. From a data analysis point of view, it is worth to notice that the dilution of the fluids results in correlation of changes in the fluid properties, i.e. the density, viscosity changes more or less equally. This is however close to the real application for the drilling fluids, and normal under drilling operations. The number of samples available for training/validation/testing during the network development was around 700-800 samples, depending on the frequency. As we concluded in our previous paper, the relationship between attenuation and density/plastic viscosity could only be fairly described using a linear regression model. Thus non-linear models, including additional inputs are considered here.

B. ANN models

ANNs were trained and tuned with various number of hidden neurons. The inputs to the networks were the distance, x, decay of received signal relative to 3 cm received amplitude, A_d, and time of flight, T. One model was created for each of the outputs, density (ρ), viscosity (μ_p) and gel strength (S). In these models we have chosen a simple structure with only three layers as described above. Training and tuning showed us that the optimal number of neurons in the hidden layer would usually be between 10 and 20. As the training regime used was Levenberg-Marquard [8] a randomness in the data selected, and also the starting points for the weights results in slightly different models each time they are trained, and each time a model was trained, the number of hidden neurons will differ slightly. Our networks were trained on datasets separate for each frequency couple set, and of each 70% were used for training, 15% for validation, and 15% for testing. The results from the models developed on the 1.0 MHz data (Both Fluid A and B) are presented in Fig. 4 and Table 2 and show that the three different networks perform very differently. It is clear that the performance of the density network is by far the better, while the network with gel strength as output is not very successful. The samples and mean absolute percentage error (MAPE) presented are samples that are from the test data set.

IV. CONCLUSION

The measurements show that the ultrasonic attenuation correlates non-linear with changes in the rheological properties. The non-linear effect is not entirely understood, but has now been observed in two separate fluid systems, and is assumed to be related to the non-Newtonian behavior of the fluids. The results shown in Table 2 show that the potential for using ANN is good for density, challenging for plastic viscosity, but unlikely for gel strength. We see this as a promising measurement principle, and a first step in developing a sensor system for non-invasive and realtime measurement of drilling fluid rheological properties. The results show that there is no significance in the different frequencies concerning the overall model performance. However, there is an uncertainty in that the inputs to the model have not been independently investigated, as the change has been correlated as the fluids were diluted. The next steps for this development is to continue collecting data from different drilling fluid systems, as well as developing a setup for use on a flowing system. Furthermore other machine learning models, e.g. support vector machines will be explored.

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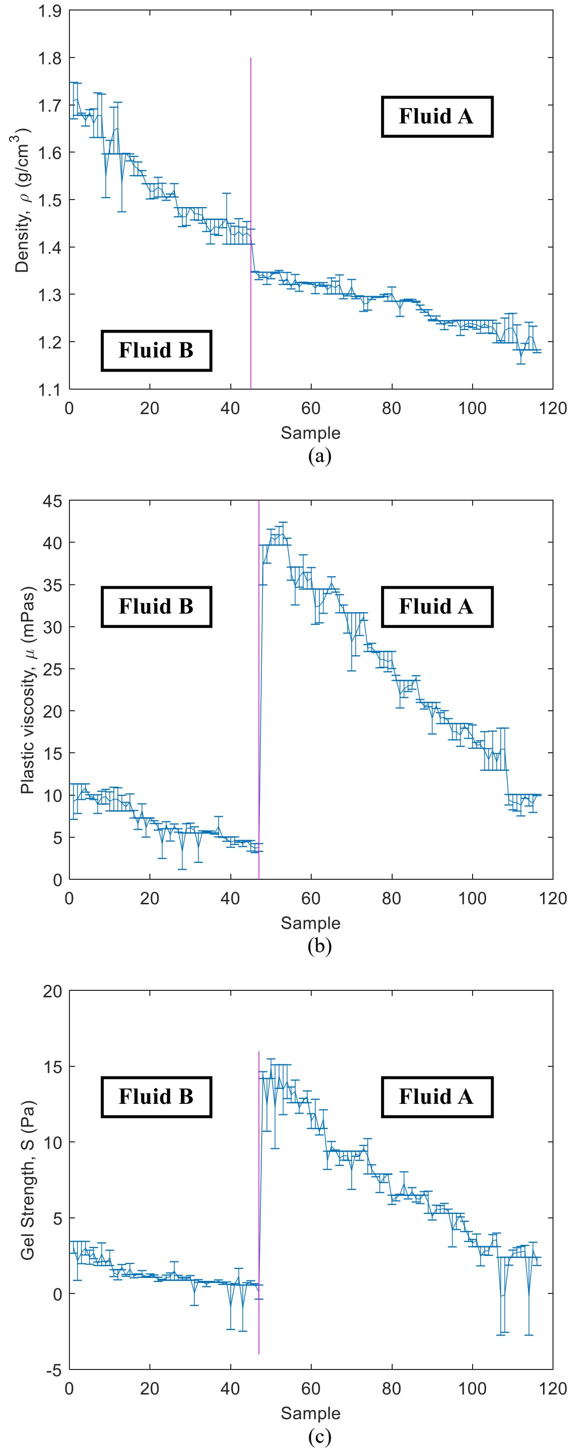

Fig. 4: Results from ANNs used on test data set containing 116 samples (15% of entire dataset). The ANNs are presented as three separate networks, with one output each: (a) density, ρ; (b) plastic viscosity (μ_p) and (c) gel strength, S. The bars indicate the error relative of the ANN prediction to the target value determined by lab analysis. The data was sampled from the 1.0 MHz measurements. The line and text box indicates from which of the fluids the samples are retrieved.

Paper 4

Developing ultrasonic soft sensors to measure rheological properties of non-Newtonian drilling fluids

Morten Hansen Jondahl* and Håkon Viumdal

Developing ultrasonic soft sensors to measure rheological properties of non-Newtonian drilling fluids

Ultraschall-Sensoren zur Charakterisierung der rheologischen Eigenschaften von nicht-newtonschen Bohrspülungen

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Abstract: Surveillance of the rheological properties of drilling fluids is crucial when drilling oil wells. The prevailing standard is lab analysis. The need for automated real-time measurements is, however, clear.

Ultrasonic measurements in non-Newtonian fluids have been shown to exhibit a non-linear relationship between the acoustic attenuation and rheological properties of the fluids. In this paper, three different fluid systems are examined. They are diluted to give a total of 33 fluid sets and their ultrasonic and rheological properties are measured. Machine learning models are applied to develop soft sensors that are capable of estimating the rheological properties based on the ultrasonic measurements. This study explores three different machine learning model types and, extensive training and tuning of the models is carried out. The best model types that show good results and the potential to develop a real-time sensor system suitable for use in oil & gas drilling process automation are selected.

Keywords: Ultrasonic measurement, non-Newtonian fluids, rheology, machine learning, artificialneural network, drilling.

Zusammenfassung: Die Überwachung der rheologischen Eigenschaften von Bohrflüssigkeiten ist bei der Erdölexploration von entscheidender Bedeutung. Der derzeit vorherrschende Standard ist die chemische Laboranalyse. Es besteht aber der Bedarf nach einer automatisierter Echtzeitmessung. In nicht-Newtonschen Flüssigkeiten besteht eine nicht-lineare Beziehung zwischen der Schallabsorption und den rheologischen Eigenschaften der Flüssigkeit. In dieser Arbeit werden drei verschiedene Systeme von Bohrflüssigkeiten, aus denen 33 unterschiedlich zusammengesetzte Mischungen hergestellt wurden, hinsichtlich ihre Ultraschall- und rheologischen Eigenschaften untersucht. Mithilfe von Modellen für maschinelles Lernen werden virtuelle Sensoren entwickelt, mit denen die rheologischen Eigenschaften auf der Grundlage von Ultraschallmessungen abgeschätzt werden können. Diese Studie vergleicht drei verschiedene Methoden des maschinellen Lernens hinsichtlich ihrer Eignung in einem Echtzeit-Sensorsystem bei der Automatisierung von Öl- und Gasbohrprozessen eingesetzt zu werden.

Schlagwörter: Ultraschallmessung, nicht-Newtonsche Flüssigkeiten, Rheologie, maschinelles Lernen, künstliches neuronales Netz, Bohrtechnik.

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1 Introduction

When drilling an oil well, the drilling fluid is circulated in a closed loop. Figure 1 shows a typical drilling operation, the focus of the illustration being on the drilling fluid circulation system. Drilling fluid is continuously pumped down the wellbore through the drill pipe and is circulated through the annulus back to the surface. The returning fluid also contains drill cuttings, formation fluids and possibly gas from the formation. The drilling fluid then enters the treatment system, which handles the gas and removes drill cuttings, the drilling fluid running through a storage tank (active pit) before being pumped back into the well. This completes one circulation of the system. The returning fluid is pumped back into the well. It is therefore important to monitor the rheological properties and ensure they remain within certain specifications. Intermittent manual lab analysis of the drilling fluid is the measuring method used today. The focus of our work has, however, been on the automation of this process by developing methods and sensor technology to measure in-

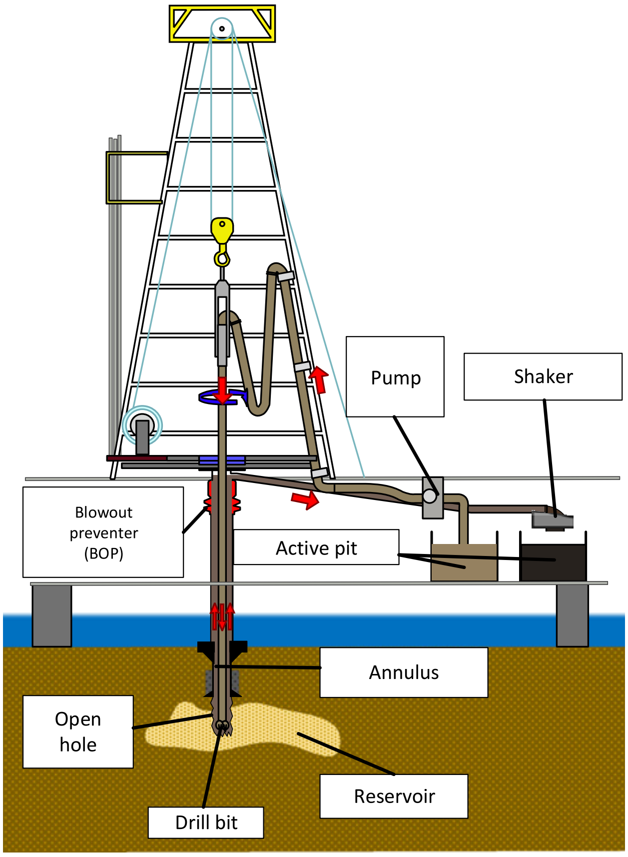

Figure 1: Overview of drilling operation, with emphasis on the system for drilling fluid circulation. The fluid is pumped along the circulation system as shown by the red arrows, down into the well through the drillpipe, returning through the annulus. It then enters a gravity drained return channel which leads to the shaker and pits, where it is treated before being pumped back into the well.

line rheological properties of the drilling fluid based on time of flight measurements, using ultrasonic through-transmission measurement principles, measuring attenuation and sound of speed [1].

Drilling fluid design uses additives to achieve the properties required by the particular drilling operation. Three main drilling fluid objectives are: (1) bottom hole pressure control, (2) the cooling, lubrication and cleaning of the drill bit and (3) removal of rock cuttings from the well [2]. In this work, the main focus is on pressure control. A safe and stable drilling operation requires bottomhole pressure (Pb) to be controlled very closely. The upper bound is the formation fracture pressure (P_f), the point at which the formation will break down. If the wellbore pressure exceeds this limit, severe loss of drilling fluid and subsequent loss of pressure in the wellbore may result. The lower bound is the formation pore pressure (P_p) which is the pressure of the formation fluids. If Pb

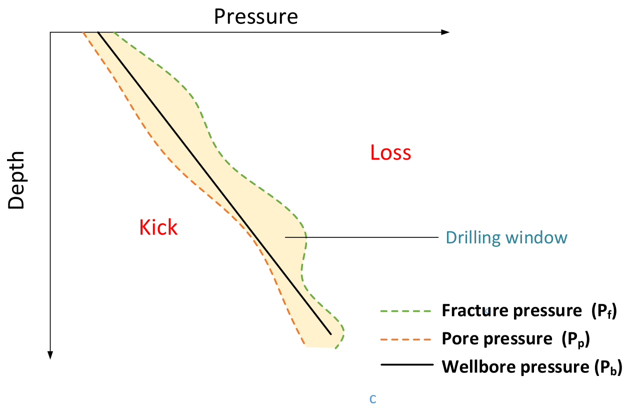

Figure 2: Drilling window. Pore pressure, Pp, represents the lower bound for the wellbore pressure, Pb. The fracture pressure, Pf represents the upper bound. If Pb exceeds either of these, a kick/loss situation will most likely occur, as indicated in the figure.

falls below P_p, then an influx of formation fluids into the wellbore will occur. This influx, called kick, is a common scenario when drilling oil & gas wells. Detected in a timely manner, at a moderate volume, the kick can be handled using normal procedures. It does, however, represent a severe risk if not detected at an early stage, or if the influx volume is too great, the Deepwater Horizon incident [3] being an extreme case. It furthermore results in non-productive time in an already costly drilling operation. The pressure span between P_p and P_f is commonly named the drilling window and is illustrated in Fig. 2.

Early detection of these two events, kick and loss, is therefore essential for safe and efficient drilling operations. A crucial role of the equipment and systems used to log data during drilling, both downhole and topside (the drilling system at the surface), is therefore the early detection of kick and loss. The varied environments, equipment and companies involved in drilling operations worldwide, however, mean that common practices for detecting kick and loss are not well developed. Pit level monitoring, and trendbased measurements of the flow out of the well, through the use of a paddle meter, are the standard indications of kick and loss [4]. A proposed method for more precise detection of kick/loss situations during drilling is monitoring the difference between fluid flow into and out of the well. This is referred to as the delta flow method [5].

The delta flow kick and loss detection method proposed by Speers and Gherig [5] relies on an accurately measured return flow and comparison to an equally (but more commonly) accurately measured inflow. The prevailing standard instrument for measuring volumetric flow in the return flow is the paddle meter, which has poor accuracy and reliability. This instrument is therefore not good enough to facilitate this method. The fluid level in the active pit (the fluid pit that is part of the circulation system) is also monitored. Any difference between the inflow rate and the return flow rate will result in a level change in the pit. Any drilling progress will result in a loss of pit level, as the well is drilled ahead and the effective volume of the well and circulation system is increased. Pit level response may, however, be slow and incremental, depending on the total volume of the wellbore, surface pipes and pit volume. Furthermore, the effect of drilling progress and the consequent loss of pit level may mask kick/loss effects. The response times and accuracies currently available show that there is a need for improved sensor technology. One approach that could be applied is improvements in the measurement of return flow, which would allow the delta flow method to be used. Although, as pointed out by Schafer et al. [6], several flowmeters were in development as early as in 1992, but the industry standard instrument is still the flow paddle to the best of our knowledge. Other flowmeters maybe be available, but are used only as redundancy [7]. Improving return flow measurements in some instances, however, requires good knowledge of fluid rheological properties, as pointed out by Chhantyal et al. [8]. Improved sensor technology for early kick and loss detection may furthermore increase the degree of automation in drilling operations. In-line sensor technology in such applications is an important prerequisite, as the rheological measurements made today are manual, intermittent, offline measurements performed around 4 times every 24 hours. For these reasons, we chose to focus on developing an automated measurement principle capable of non-invasive and non-intrusive measurement of fluid rheological properties. The variation of the acoustic properties of fluids with rheological properties makes ultrasonic through-transmission measurements a very interesting measurement principle to explore. Podio and Gregory [9] found a non-linear relationship between attenuation and frequency for any fluid density, and found that the non-linear effect is increasing with density. Pope, Veirs and Claytor [10] developed technology that estimates drilling fluid density using a function of resonant peaks in a FFT spectrum. These developments were made in the early 90's, but do not seem to have been further developed in later years, or resulted in applied sensor technology. Pappas, Bamberger, et al. [11] and Greenwood and Bamberger [12], [13] have described a densimeter that is operating by measuring ultrasonic impedance, and velocity of sound, which is also able to estimate viscosity in slurries based on shear wave velocity. The published works do not specify whether these slurries are non-Newtonian, or show us whether the technique is relevant to our application. Non-Newtonian fluids behave very differently from Newtonian fluids, the viscosity of non-Newtonian fluids being shear-rate dependent. This means that viscosity will change with flow or any other agitation of the fluid. This property is a vital part of the design of any drilling fluid. In practice this means that the drilling fluid is designed to behave like shear-thinning, such that it can keep pressure integrity when stationary, but is still able to be pumped at high flow rates. Thus, the rheological properties of these fluids are challenging to measure, and so is further defining good models that can relate rheological properties to propagation of ultrasonic longitudinal waves in the fluid. Shear waves are not considered as they do not propagate well in fluids. Scattering effects are known to be apparent in drilling fluids, as they are made up from particulates in base fluid [14], [15]. In addition, cuttings from the drilling process will further add to this effect in field applications. We have chosen not to quantify this effect, as we focus on the acoustic measurements and the mathematical models which will be affected by this.It was therefore decided that the first step of the development process would explore the relationship between ultrasonic waves and fluid rheological properties. This began as a MSc project [16], exploring Newtonian fluids (tap water), and later also non-Newtonian drilling fluids, a water based fluid (WBF) [17]. The latest development of this work reported here includes a new type of non-Newtonian drilling fluid system, an oil-based fluid (OBF) and the further development of machine learning (ML) models, support vector machines (SVM) and fuzzy-neural systems.

2 Methods

2.1 Ultrasonic measurements

The setup used to perform the measurements consists of a fluid tank, a transmitter a receiver, and a supporting frame to submerge and move the transmitter/receiver, see Fig. 3. An ultrasonic through-transmission principle was utilized by including one transmitter and one receiver, which measured the received signal amplitude and time of flight (ToF). The tank held around 82 litres of the fluid under study. Three pairs of transducers, Olympus Videoscan Large Diameter [18], were used, all with the element diameter of 25.4 mm but using different frequencies: 0.5, 1.0 and 2.25 MHz. The linear distance (x) between transmitter and receiver was adjusted during the experiments from 3 cm

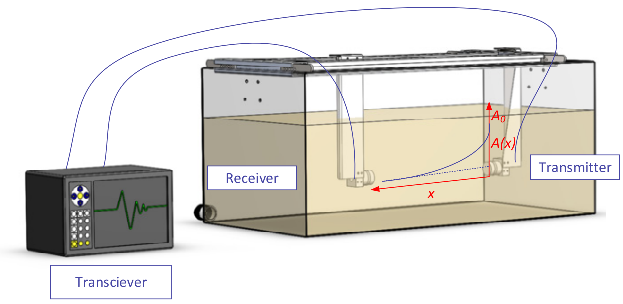

Figure 3: Ultrasonic measurements setup. x is the linear distance between transmitter and receiver. $A(x)$ is the amplitude as a function of the linear distance, relative to the reference amplitude A_0 measured at $x = 3$ cm.

up to 45 cm. Investigation in our preceding work [16], [17] showed that the submersion of the transmitter/receiver resulted in negligible noise, and that near-field effects were negligible from a linear distance of 3 cm between transmitter and receiver for the chosen frequencies. The measurement at 3 cm has been used as the reference for all experiments to calculate attenuation, and a stepwise increase in linear distance of 2 cm has been used in all measurement series. The Olympus Epoch 1000i instrument [19] was used to transmit and receive the ultrasonic square waves. Pulse voltage was set to 300 V and the gain was adjusted during measurements to ensure detection at the receiver end.

Three different drilling fluids were used, two WBFs (fluids A and B) and one OBF (fluid C). The range of the fluid rheology properties are representative for fluids in normal offshore operations. We, after consulting with the manufacturer, designed a process in which we diluted each of the three samples, this resulting in 33 fluids. Each fluid was diluted by its base (water or oil-premix) stepwise by adding 5 volume-percentage of base fluid of the initial volume, until each had been diluted 10 times. We could therefore collect ultrasonic measurements in fluids with a very wide range of rheological properties. Table 1 shows an overview of the fluids, the numbers indicating the diluted samples (1 designates the original fluid).

2.2 Fluid analysis

The fluids used in the study were sampled and then were analysed at Equinor's lab facilities, where the rheological properties were determined. These were used as the reference for our developed models. The properties of greatest interest in this study are given in Table 1. The measurements were performed with an Anton Paar Modular Compact Rheometer MCR 502, which gives highly reliable and accurate data. The values given as references are based on the analysis of two, or in some cases four, samples of the actual fluid.

In this study we have chosen to focus on drilling fluid density, ρ, and plastic viscosity, μ_p. The term plastic viscosity refers to the commonly used rheological model to describe a non-Newtonian drilling fluid, the Bingham-Plastic model [20]. Non-Newtonian fluids have shear-dependent viscosity. Plastic viscosity can therefore be used to characterize and distinguish different fluids with shear thinning non-Newtonian behaviour. This is therefore not the exact viscosity, as this can not be quantified for non-Newtonian fluids. The fluids were also analysed for gel strength (S). This property is the shear strength, force required to initate flow of the fluid after a period of time without any stirring or flow, for 10 seconds or 10 minutes. This must not be confused with the yield point of the Bingham-Plastic model, which has a similar physical interpretation. This

Table 1: Measured fluid properties. Density in kg/m^3 and plastic viscosity in Pa·s.

Fluid	Density	Viscosity	Fluid	Density	Viscosity	Fluid	Density	Viscosity
A1	1350	0.0397	B1	1750	0.0111	C1	1510	0.0208
A2	1320	0.0371	B2	1680	0.01	C2	1450	0.0177
A3	1320	0.0345	B3	1680	0.0089	C3	1440	0.0153
A4	1300	0.0316	B4	1630	0.0081	C4	1390	0.0134
A5	1300	0.027	B5	1600	0.0072	C5	1360	0.0119
A6	1290	0.0236	B6	1550	0.0066	C6	1330	0.0106
A7	1270	0.021	B7	1530	0.006	C7	1280	0.0094
A8	1240	0.0185	B8	1510	0.0055	C8	1240	0.0086
A9	1250	0.0156	B9	1480	0.005	C9	1230	0.0077
A10	1200	0.0129	B10	1460	0.0046	C10	1200	0.0069
A11	1180	0.0101	B11	1410	0.0042	C11	1180	0.0062

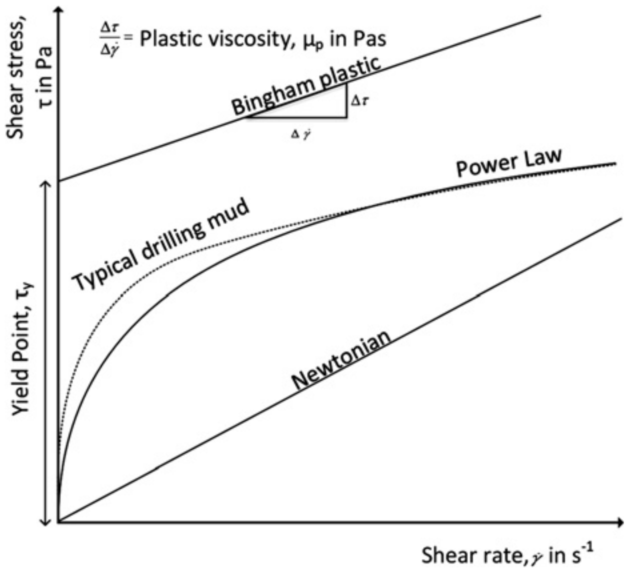

Figure 4: Sketch of rheological models for non-Newtonian fluids. Emphasis on Bingham plastic model and the plastic viscosity given as the slope of the line. The idea of the API standard is that the Bingham Plastic model may satisfactorily describe the approximately linear portion of the curve for typical drilling mud shown.

yield point is, however, a model parameter, and not a measured value. The Bingham-plastic model is defined as

$$\tau = \mu_p \dot{\gamma} + \tau_y$$

the parameters being: τ – shear stress in Pa; μ_p – plastic viscosity in Pa·s; $\dot{\gamma}$ – shear rate in s^{-1}; τ_y – yield point in Pa. The model is shown in Fig. 4, where it is compared to a Newtonian model for viscosity, and Power Law. The Power Law closely describes the whole curve of viscosity, but according to the API [21] standard, the Bingham-Plastic model is chosen as it represents the fluid properties well enough for the typical shear rates that applies during drilling.

Models for estimating gel strength were developed in earlier studies, but with poor results. We include these measurements in this project, for parameter analysis, to see whether this could provide answers to the poor performance of the models that estimate this property. No new models to estimate gel strength are developed.

2.3 Machine learning models

The different ML models used in this study are defined and described in this section. Our previous work [16], [17], [22], [23] has explored simple regression methods, and artificial neural networks (ANNs). Here, however, we present two more advanced ML models to further accommodate nonlinearity in the relationship between inputs and outputs of the models, and to relate more than two variables. Common to all of the models analysed here, and to previous models, are the inputs and outputs, see Fig. 5: The division into training data and validation data in the algorithms for training the models differs somewhat, i. e. the dataset is the same, but the subsets used for training and validation are randomly selected each time. All models use validation to counter the problem of overfitting. The randomly selected validation data was used in the supervised training algorithm, so training is ended before overfitting occurs. Furthermore, 20 % of the total dataset was set aside in a test dataset before running the training algorithms, such that the performance of all models can be comparable through using an identical dataset. This test data set has not been used during training, and is presented as new measurements to the models. An overview of the phases included in collecting data, training models and a comparison of them are shown in Fig. 6. The training and selecting model process is carried out separately for density and viscosity measurements. All models are trained using MATLAB, Neural Networks Toolbox 11.0 and Statistics and

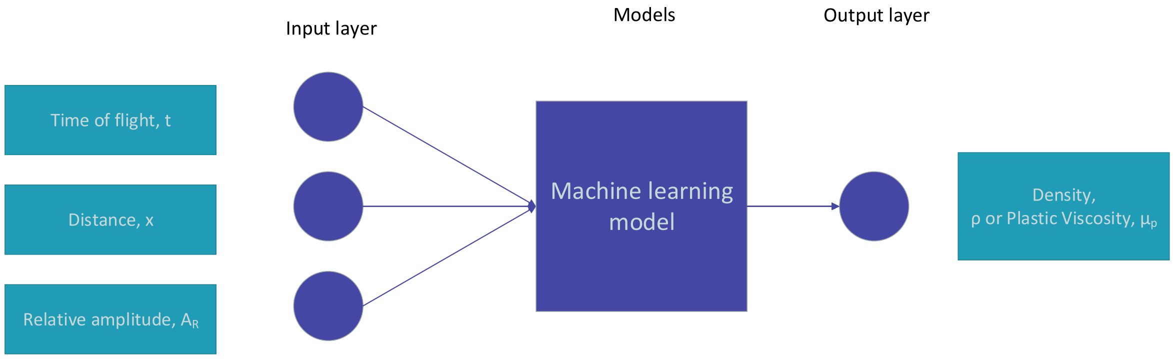

Figure 5: General model overview of inputs and outputs.

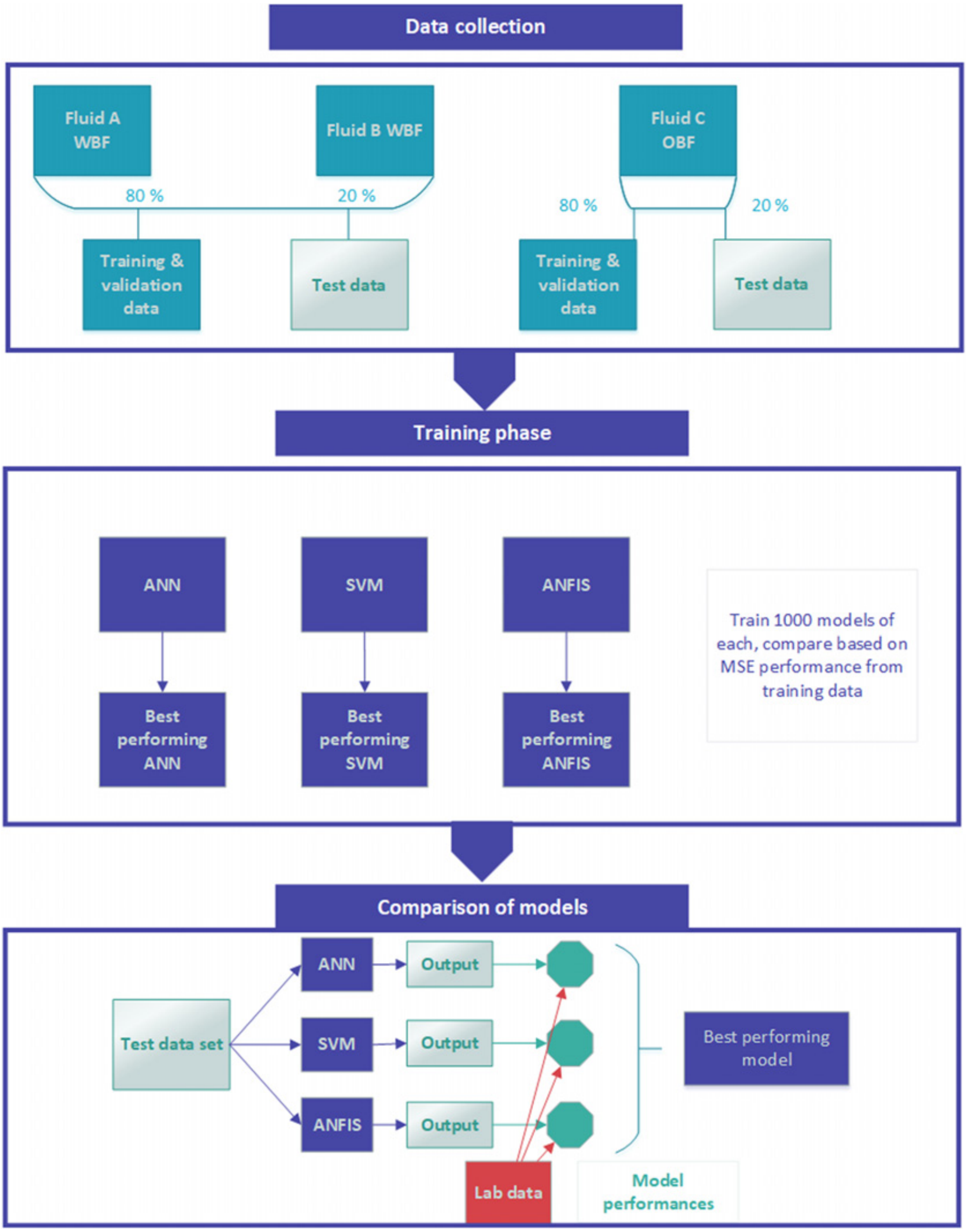

Figure 6: Machine learning model training and selection flowchart. In the first phase, the ultrasonic data is collected and organized in the training phase. The three models are trained repeatedly to find the best meta parameters for each model type. The models are compared against each other using mean square error (MSE), as this is the default performance value for the training algorithms used. The best model of each type is then used in the last phase, these being compared. This is carried out using the test data set extracted in the data collection phase, which has not been used for any of the models during training. The output from the models using this data set is compared to the lab measurements of the rheological properties. This is, in turn, used to calculate the model performances and finally select the best performing model, these two phases being carried out separately using density or viscosity as model output and target.

Machine Learning Toolbox 11.2. The training data and validation data are presented to the training algorithm as one set. The validation procedure in the algorithm handles the separation of the set into training and validation samples.

In search of a best possible model, the machine learning models were trained in a number of steps. Some learning points were taken from the exploratory analysis work, the choice being to focus on the 0.5 MHz data as input for all the models developed. Two classes of models, one for water based drilling fluids, and one for oil based were developed. This choice was made to reflect the ultimate application of the models in a drilling environment. The fluid in a drilling process is either oil based or water based. The fluid base is not changed during the drilling process and there is therefore no need for models that generalize this parameter. Then models were developed for these two fluid types that predict drilling fluid density, ρ, or plastic viscosity, μ_p. This resulted in four models for each of the three types of machine learning models described above, in total 12 models to be evaluated.

Extensive and repetitive training was carried out in the development and search for the optimal machine learning model for each of the twelve cases. The model types were trained in total 1000 times for each type, using the same training data. The best model for each type in each case, based on model performance with the validation data set. The best of each type were compared with each other in each case, so allowing the ultimate best model to be chosen.

The mean square error (MSE) of the training process was used to choose the best model of each type from the trained models. This is the default performance output from the training algorithms, and well suited to a comparison of the models. The test data was then used to evaluate the model types against each other. The mean absolute percentage error (MAPE) was used to choose the best model type in each case. MAPE was chosen as it gives clear and easily interpreted performance information while still being comparable to industry specifications [24].

$$MSE_{val} = \frac{1}{q}\sum_{i=1}^{q}\left(Y_i - \hat{Y}_i\right)$$

$$MAPE_{test} = \frac{100}{p}\sum_{i=1}^{p}\frac{(Y_i - \hat{Y}_i)}{Y_i}$$

Where q denotes the number of elements in the validation set. Y is the observed value of either ρ or μ_p as measured in the lab analysis. $\hat{Y}$ is the model predicted value of Y. p is the number of elements in the subset for testing, where the different model types are compared according to their MAPE values.

2.3.1 Artificial neural networks

Artificial neural networks (ANN) are models that imitate the structure of parts of the human brain [25], [26]. The neurons are represented as computation points organized in layers. The neurons in the different layers are connected by weights representing the synapses of the human brain. These weights are adjusted during training of the network. Figure 7 shows such a general network with three input neurons and one output neuron. This represents the general structure of the network used in this study. As described above, three inputs are used in developing our models, and one output is selected. These are in the input and output layers, as shown. The inputs and outputs are normalized and the default in the *fitnet* function in MATLAB ANN is to normalize the data such that the mean is 0 and the range is $[-1, 1]$ using the *mapminmax* function [27].

The number of neurons in the hidden layer varies, the number being dependent on the results of meta-parameter tuning. The architecture of the network is decided in this process. The number of hidden layers and the number of neurons in these layers are selected manually to maximize model performance.

The problem we want to solve, with just three inputs and one output, is relatively simple. Previous studies have furthermore shown that the relationship between inputs and output can to a certain degree be described by linear regression. We therefore chose a simple network architecture. Choosing only one hidden layer, we trained the network repeatedly with hidden neurons ranging from 3 to 50. This process showed us that the networks could be trained with 3 to 20 hidden neurons, this securing both performance and computational efficiency. Neural networks with larger numbers of neurons may result in overfitted models, and should be avoided. Based on the experiments, the lowest number of neurons that did not result in any significant reduction of performance was 15. Hence, this became the selected number of hidden neurons in our models.

The training was performed using the Levenberg-Marquardt backpropagation algorithm. This algorithm was chosen as it is a fast backpropagation algorithm that converges well. It does, however, require more memory than some of the other training algorithms implemented in the MATLAB *fitnet* function. We chose not to take into consideration the memory requirement, as the time available for training the models would not be an issue in this project, due to the relatively small dataset and a quite simple artificial neural network [28].

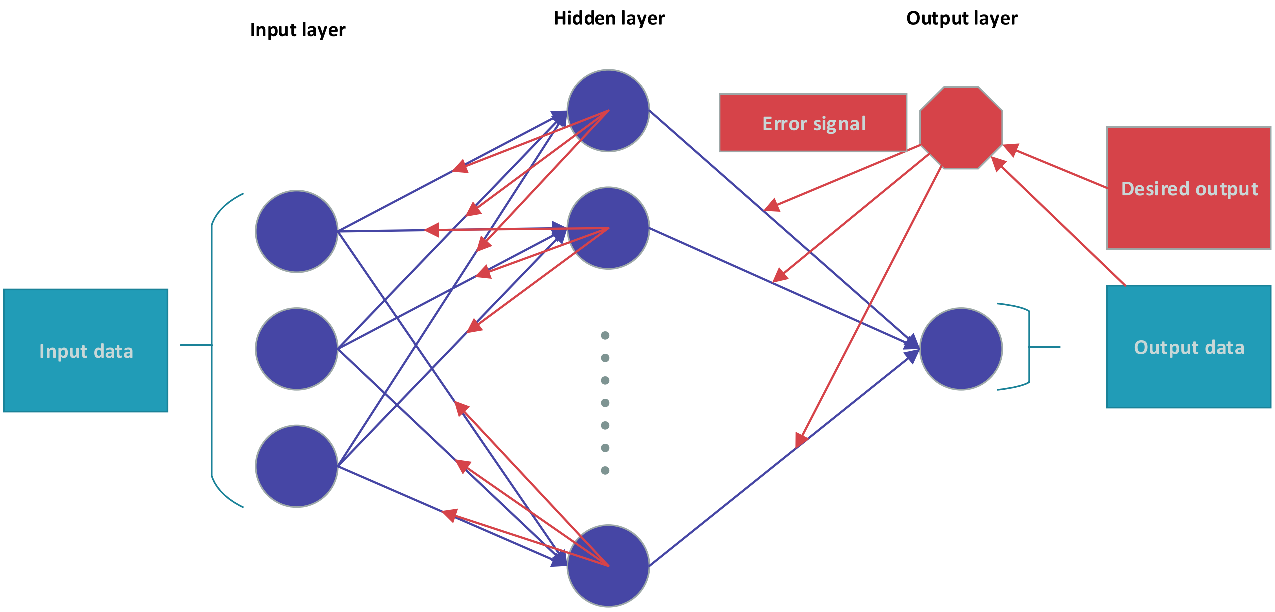

Figure 7: ANN general overview. ANN with one hidden layer, three input neurons and one output neuron. The circles represent the neurons, the purple arrows show the forward connection between the neurons. The error signals (red arrows) are generated by comparing the desired output (if known) to the network output. This error can then be used to adjust the weights between the neurons, to train the network and increase performance. The distribution of the error signal to the weights depends on the training scheme.

2.3.2 Support vector machines

Support vector machines (SVMs) is a branch of ML models that is capable of solving both regression problems and classification problems. The basic principle of a SVM is to solve a non-linear problem, either a non-linear classification problem, or a non-linear curve fitting problem, by mapping the original dataset into a new space of higher dimensionality. In this higher dimensional space, the dataset may be linearly separable by a hyperplane in case of a classification problem, or in case of a curve fitting problem linear regression may be used. This is explained concisely and to the point by Noble [29], using classification as the case. For further details and full details of mathematical descriptions, the reader is recommended to review Haykin [25]. The practical approach for a SVM is to find as few data points as possible to support a regression function that describes the data in a satisfactory manner. This involves choosing an acceptable error range for the function, and to train the function and find these data points that typically are referred to as support vectors. SVMs, which use the data points to describe the function, may therefore be more efficient than an ANN model, which uses a large network of weights and layers. The SVM algorithm we used is part of the MATLAB toolbox Statistics and Machine Learning Toolbox™ and is described in detail in the documentation [30]. We also used the Regression Learner App, which is part of this toolbox. The toolbox can be used to explore several regression models with the same dataset, and to give an overview of the models and methods best suited to our needs. We chose, based on analysing the different models in this app, to develop a SVM regression model with a Gaussian kernel function, as this gave the best results based on the models tested. The kernel scale gives the three differently named Gaussian SVM (fine, medium and coarse). The adjective refers to the value of the kernel scale that all inputs are divided by, fine scale being a value closer to 0, effectively influencing the Gram matrix and the kernel functions [31].

The Gaussian kernel function means the model is capable of treating non-linearity in the mapping of input data to output data, something earlier works shows exists in our dataset. The SVM was trained using the same training dataset as the ANN models. The MATLAB *fitrsvm* function for training SVM calls normalization standardization and uses an algorithm in which the values are standardized using the weighted means and weighted standard deviations [31].

2.3.3 Adaptive neuro-fuzzy inference system

An adaptive neuro-fuzzy inference system (ANFIS) is a type of machine learning model that combines the approach of two different systems into a hybrid. A neural network approach is taken to adjust membership functions, parameters and rules of a fuzzy logic inference system [32]. A fuzzy logic system may therefore be used without analysing the input data. It furthermore constructs the fuzzy logic system using user-defined membership functions. In this work, the fuzzy logic parameters are adjusted according to the training data set, which means the system learns from data, i. e. machine learning.

The ANFIS of this study was created using the MATLAB toolbox Neuro-fuzzy designer. The same training set as used by the other models was used here. Cost function optimization for training the model was a hybrid method and used both back propagation and the least squares method [33]. The data was grid-portioned to create a fuzzy system structure with Gaussian membership functions. The hybrid learning algorithm, as described by Jang et al. [32], was chosen. Least squares estimate ensures the backpropagation algorithm is not stuck in local minima, and increases the chance of convergence to a well performing model.

3 Results

3.1 Machine learning model results

We also investigated how the attenuation of the ultrasonic signals was affected by frequency in the three drilling fluid systems. This is shown in Figs 8–10, attenuation being represented as relative amplitude A_R in dB as a function of the distance, x [cm]. Attenuation is shown for the water

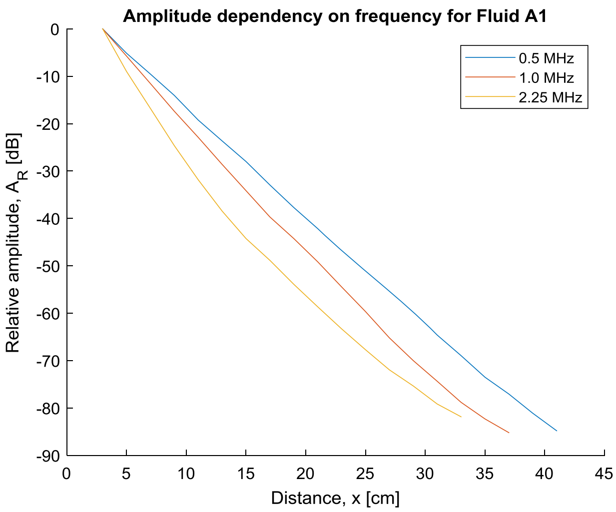

Figure 8: Attenuation dependency on frequency, fluid system A.

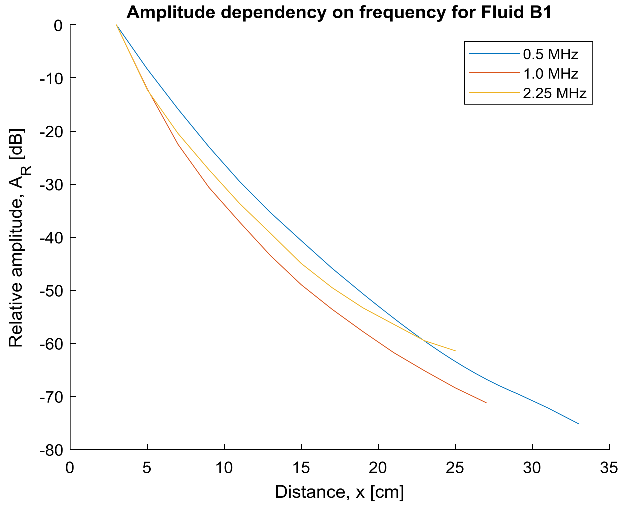

Figure 9: Attenuation dependency on frequency, fluid system B.

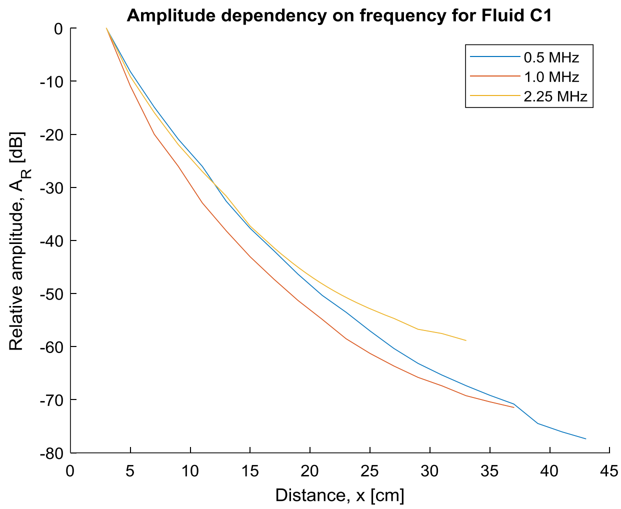

Figure 10: Attenuation dependency on frequency, fluid system C.

based fluid systems (A and B) and for the oil based fluid system (C). These show that the 0.5 MHz data sets yield the largest range of distances, as attenuation is in general less at this frequency. We, for this reason, chose 0.5 MHz as the most optimal frequency for our purposes. Our findings furthermore agree well with Podio and Gregory's findings, in which we see that the attenuation/frequency relationship is non-linear, and increases with density.

The model performances for oil based fluids (OBF) and for water based fluids (WBF) are shown in Table 2. This shows that when applied to the test data sets, the ANN models outperform the other model types in all four cases. Although only marginal for the water based fluid density case. The performance of the selected models used on the test data sets are shown in Fig. 11. The plots show

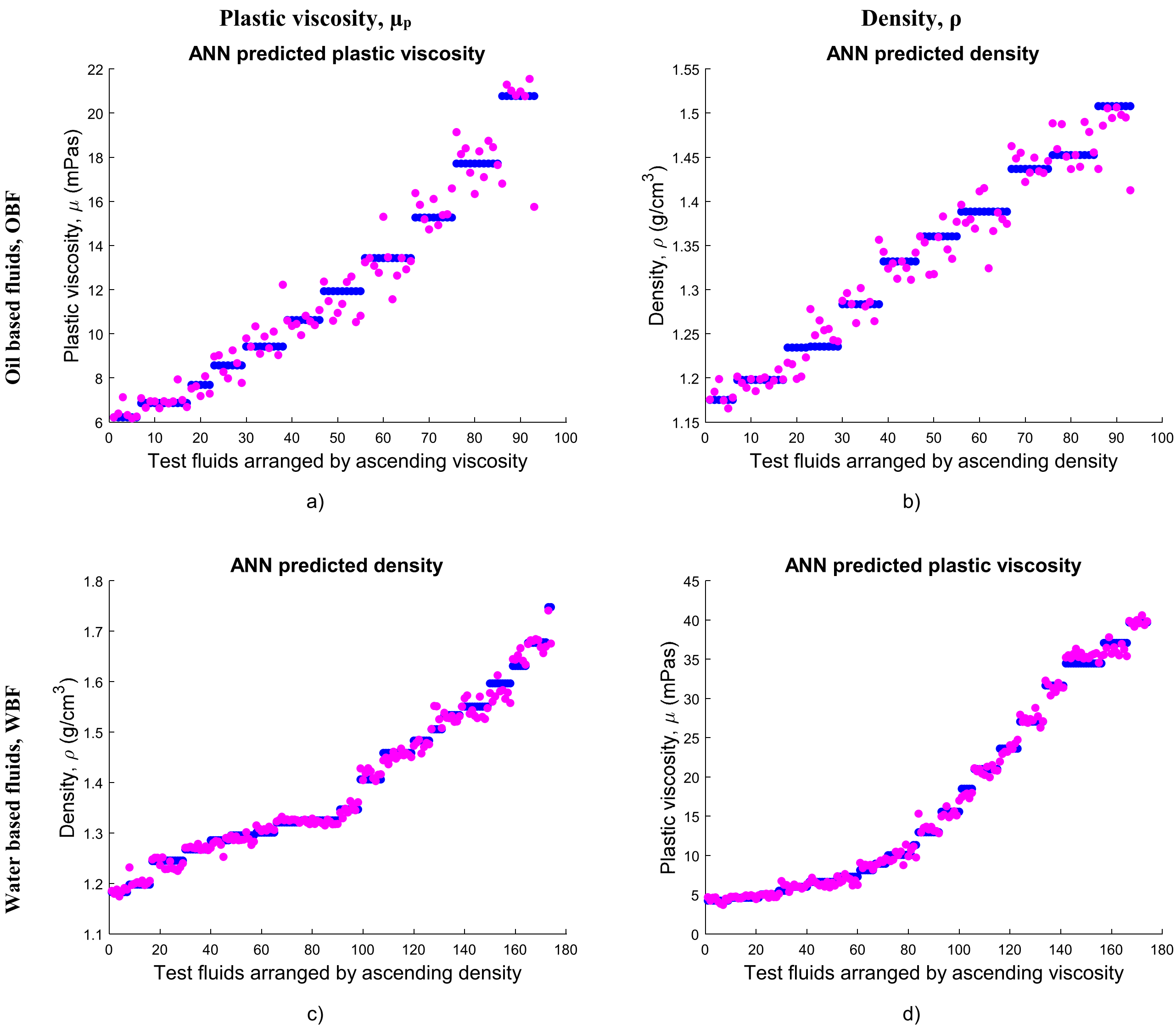

Figure 11: Results from the chosen models on test data sets. a) shows ANN predicted plastic viscosity for the OBF test data set (C4,C8, from left to right). Pink circles are the predictions, and blue are the known values from the lab analysis. b) shows ANN predicted density on the same test data set. c) the ANN predicted plastic viscosity for the WBF test data set (B4, B8, A4,A8 (from left to right)). d) shows the ANN predicted density for the same test data set.

Table 2: Model performances. Mean absolute percentage error (MAPE) in %, for all best models of each type for two fluid systems.

Model	**OBF**	**WBF**
ANN Density, ρ	1.17	0.69
ANN Viscosity, μ_p	4.66	4.07
SVM Density, ρ	2.87	1.27
SVM Viscosity, μ_p	13.6	22.2
ANFIS Density, ρ	1.79	1.52
ANFIS Viscosity, μ_p	10.60	19.5

the model performance compared to measurements from the rheological lab analysis. The estimated plastic viscosity (pink dots) is compared on the left side with the lab measurements (blue dots). The industry standard for measuring drilling fluid density using a mud balance, as specified by API [21], gives a typical uncertainty of 10 kg/m^3, which would be 0.01SG, and 0.6–0.8 % for the fluids used in this study. However, the Norwegian standard NORSOK D-001 [24] requirement for an online drilling fluid density meter is a maximum uncertainty of 2.0 %. The plastic viscosity of drilling fluid is not specified, and neither is the offline manual measurement. According to Table 2

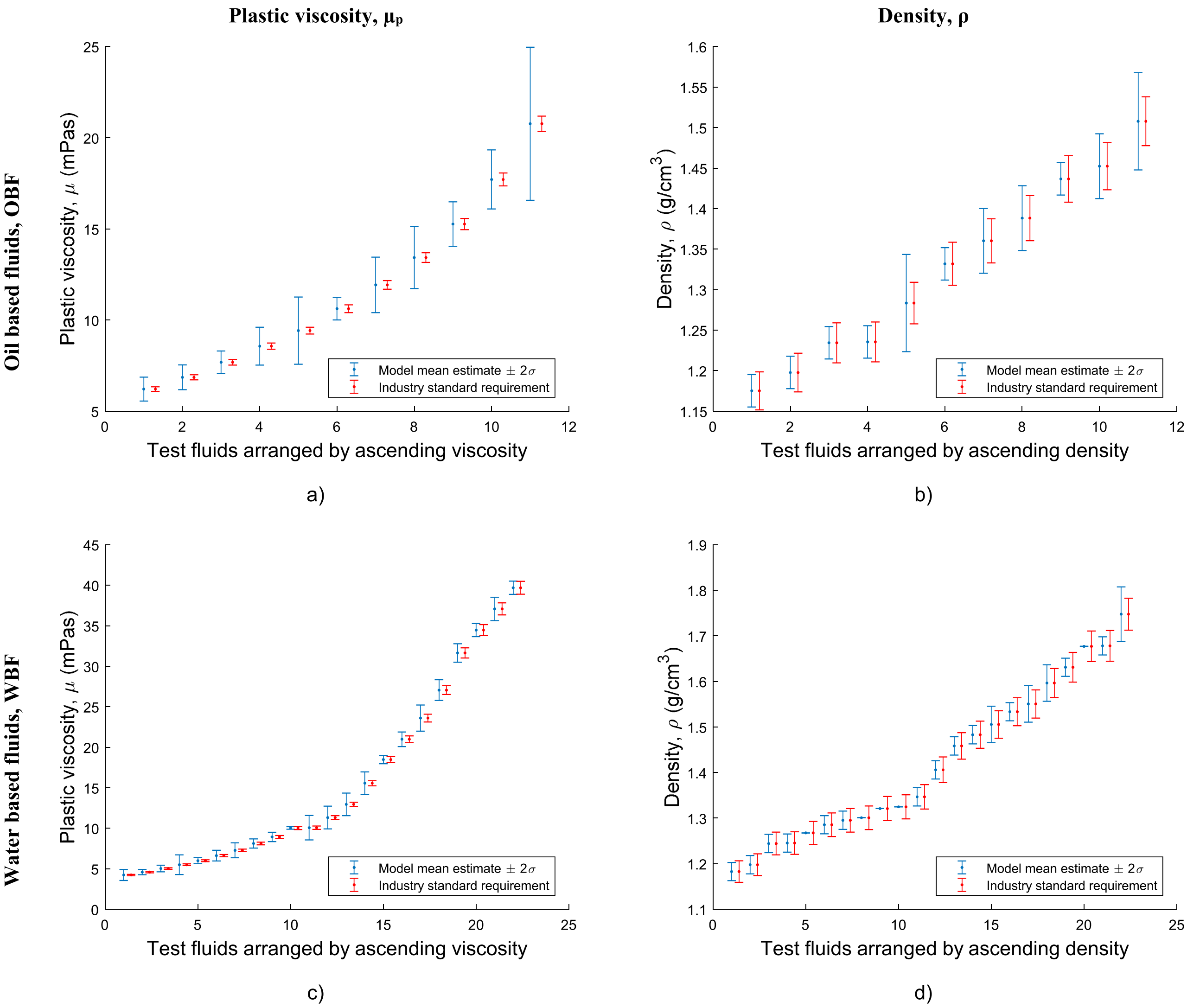

Figure 12: Errorbars showing the mean calculated output for each of the test fluids. The number of measurements for each fluid varies, as they were picked at random from the whole set. The red bars and points represent the lab measurement of density and viscosity, with ± 2 % as per the specifications mentioned above. The blue bars and points represent the mean of the model outputs and the 95 % confidence interval.

the WBF-models provide the best statistical results. The viscosity range for the WBF is larger than for the OBF, as the WBF is based on two different original drill fluids. The reason for the impaired WBF might therefore be related to the two different WBFs included in the dataset that are used to train the ML models. When estimating values in the upper end of the viscosity range, larger errors are therefore introduced. On the other side, the WBF-model is likely to be a more generalized model compared to the OBF-model. To further address the uncertainties of the models, we looked at the confidence interval of the model outputs. The results shown were averaged, and the standard deviation within each test fluid set was calculated. These are shown in Fig. 12 which also indicates the 95 % confidence intervals compared to the measurements specification of maximum 2 % uncertainty. No specification for maximum uncertainity in viscosity was given in the references. We therefore also show this with the 2 % intervals. The overall MAPE values for the models were good. Figure 12 however shows that model performance varies, being within the specification for some of the test fluid densities, but outside the specification for most of the viscosity outputs. It should, however, be pointed out that confidence interval calculation success varied, as test samples for each of the test fluids were drawn at random from the complete fluid type set, and the number therefore is varying.

The results show that developing a sensor system based on these principles is possible. The application of

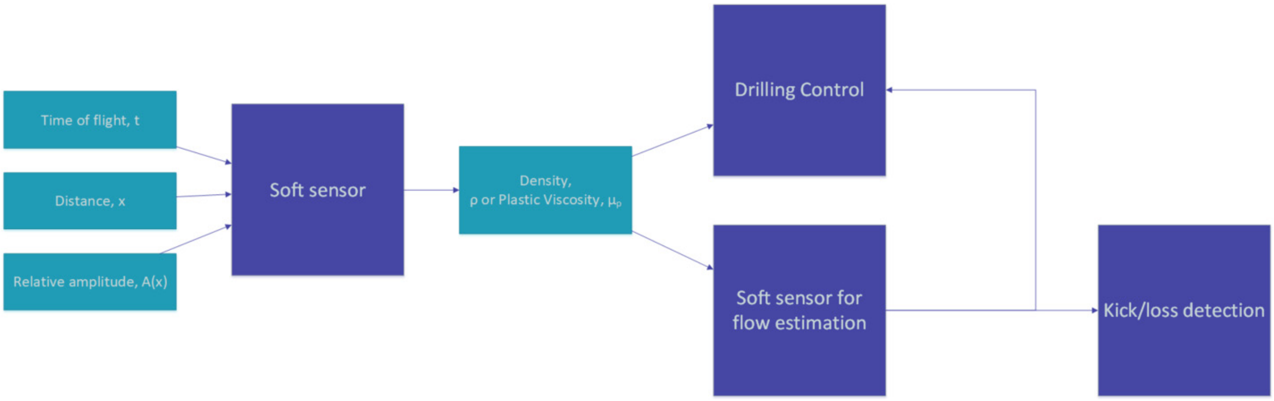

Figure 13: Model application overview. Inputs to the left, the soft sensor discussed in the paper outputting either density or plastic viscosity. This may then be used either directly as measurements in the general drilling process control, or as inputs into soft sensors for flow estimation, which again can be used in either drilling process control or kick/loss detection.

the measurements is twofold: to improve measurements of the rheological properties compared to 6 hour interval manual measurements and to enable soft sensor systems for flow estimation using reliable rheological inputs. Figure 13 shows the principle for such an application. The output of the sensor system that we aim to develop will be used as a measurement in the general drilling process control to monitor the rheological properties of the drilling fluid used. It may also be used to enable soft sensor systems to estimate the drilling fluid return flow. As pointed out by Chhantyal et al. [5], knowledge of fluid rheology is essential for many flow estimators. The placement of the sensor would be along the fluid return flowline, indicated as between the blowout preventer (BOP) and the shaker indicated in Fig. 1. An important point is that the sensor should be placed as close to the well as possible, but still on the surface, as this will give the shortest time delay to downhole conditions, which is particularly important for kick/loss detection. This placement will, however, present two challenges that we have not had the opportunity to evaluate so far in our study. The sensor system needs to function also in a partially filled pipe, as the flow here is gravity-driven, and full pipe conditions can not be ensured. It furthermore needs to measure correctly for contaminated fluid, as the placement before the shaker will mean the fluid is not treated in any way. A natural next step would then be to build a suitable measurement system to test these two challenges, flowing fluid and contaminated fluid. One option is to add a by-pass-pipe with sieves, which can be opened and closed with valves, so ensuring steady conditions and the filtering out of contaminations in the fluid. The drawback is a semi-in-line sensor system, with potential interruptions due to mechanical failures.

4 Conclusions

It is apparent from reviewing the results shown in Fig. 13 and the performance values given in Tables 2 that machine learning models have great potential in the estimation of fluid density using ultrasonic measurements. The performance of the ANN models are furthermore slightly worse than previous models, as presented in earlier work [22]. The MAPE performance for the density models is particularly promising, and the measurement principle should apply to this application. This is also supported by the averaged errors for the test fluids, as shown in Fig. 12. The presented results are based on a large number of data points. The range in rheological properties is quite large, indicating that this should apply to a large range of different fluids, and also to the two types, OBF and WBF. The findings are also supported by a parameter analysis and PCA that show that the measurements made are precise, and that there is a relationship between the measurements and the rheological properties of the fluids.

Our proposed measurement principle has therefore been studied for stationary conditions, which can be used in storage tanks in current operations. Further research may result in a system that is applicable to flowing conditions. The measurement principle and models may result in an improvement in the monitoring and control of drilling operations, and increased safety. We can also conclude that there is room for improvement and fine tuning, as we see that the performance values vary between the different models, but are generally in the same range. The data used in this study was limited to the data from one frequency pair. The experiment setup did not allow for recording the waveforms or frequency spectra of the received signals. The frequency is therefore not applicable as an input to the models used, as it would be a constant for a whole dataset of ultrasonic measurements from each transmitter/receiver pair. Capturing the waveforms and frequency spectra in future experiments might result in measurements that can help improve the proposed models. Of the models used, it seems that the ANN models have greatest promise. The other models are also promising, but are outperformed by ANN marginally in some of the cases. It is in general easy to conclude that with the current experimental setup, the principles applied look to be promising as a measurement principle. However, to evaluate this, the design of a setup which would work on a flowing system would be a crucial next step.

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Håkon received his B.S in optometry from Buskerud University College (Norway) in 1999, and his M.Sc. in cybernetics from Telemark University College in 2007. In his master thesis system identification methods where utilized to estimate water level in oil-water-gas separators. Level estimation using empirical models was also the main topic in his PhD-work carried out in collaboration between Tel-Tek, Telemark University College, Norwegian University of Science and Technology and Hydro Aluminium, Årdal. In addition to level estimation in aluminium electrolysis cells, his R&D work focused on measuring the same level using ultrasonic measurement in combination with wave guiding buffer rods. He finished his PhD in 2015. Since 2011 he has given lectures in physics, mathematics and sensor technology at Telemark University College. Currently he is an Associate Professor at The University of South-Eastern Norway, where he is program administrator for the M.Sc programme “Industrial IT and Automation” as well as an assistant project leader for a project with the topic “Sensors and models for improved kick/loss detection in drilling (Semi-kidd, Project No. 255348/E30)”. The project involved four PhD-students, supported by National R esearch Council of Norway and Equinor.

Paper 5

An overview and outlook for drilling measurements, with focus on estimations of flowrate and rheological properties of return drilling fluid

Under review as; M. H. Jondahl, H. Viumdal and A. Jinasena "An overview and outlook for drilling measurements, with focus on estimations of flowrate and rheological properties of return drilling fluid," with Institute of Physics' (IOPs) journal Measurement Science and Technology (MST) in December 2019.

Paper 6

Disruptive Clamp-On Technology Tested for Mud Measurement

Doctoral dissertation no. 65

2020

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Data Driven Models for Estimation of Drilling Fluid Rheological Properties and Flow Rate

Dissertation for the degree of Ph.D

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Morten Hansen Jondahl

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