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

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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-

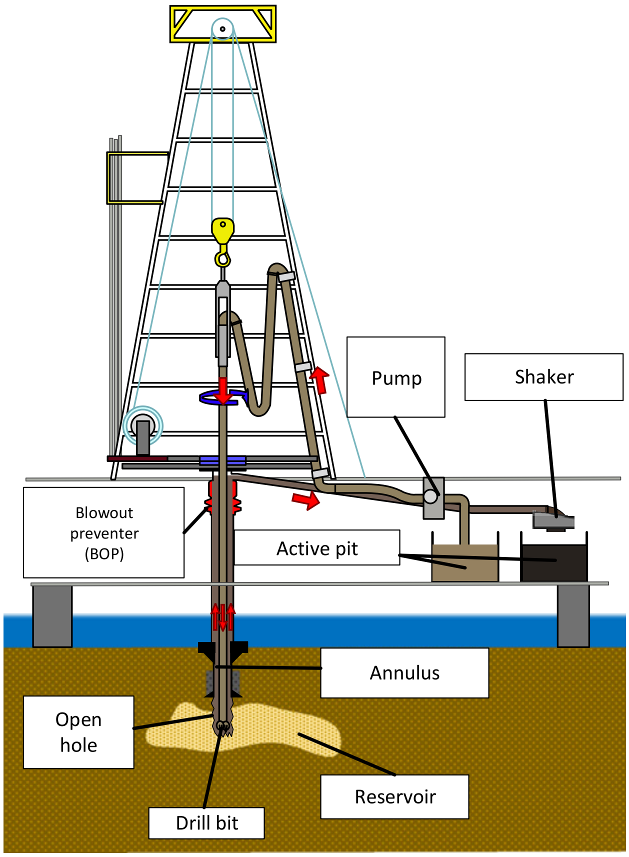

Figure 1: Overview of drilling operation, with emphasis on the system for drilling fluid circulation. The fluid is pumped along the circulation system as shown by the red arrows, down into the well through the drillpipe, returning through the annulus. It then enters a gravity drained return channel which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

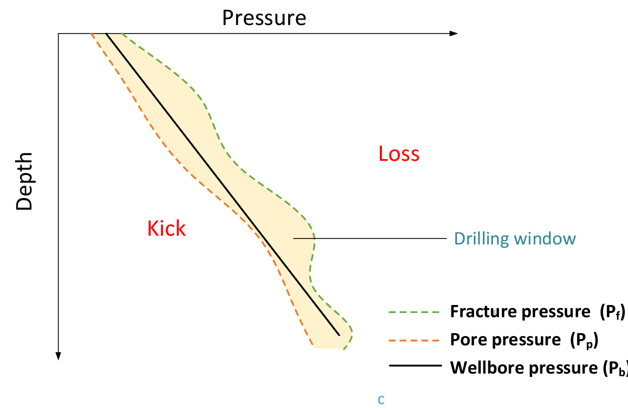

Figure 2: Drilling window. Pore pressure, Pp, represents the lower bound for the wellbore pressure, Pb. The fracture pressure, Pf represents the upper bound. If Pb exceeds either of these, a kick/loss situation will most likely occur, as indicated in the figure.

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 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

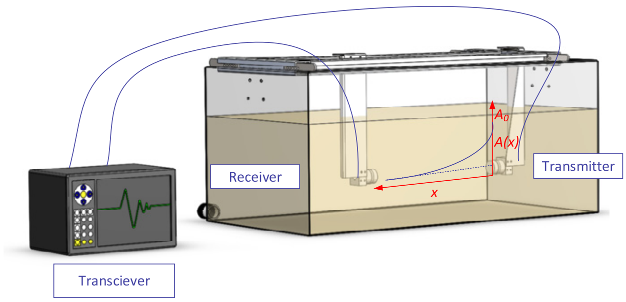

Figure 3: Ultrasonic measurements setup. x is the linear distance between transmitter and receiver. $A(x)$ is the amplitude as a function of the linear distance, relative to the reference amplitude A_0 measured at $x = 3$ cm.

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

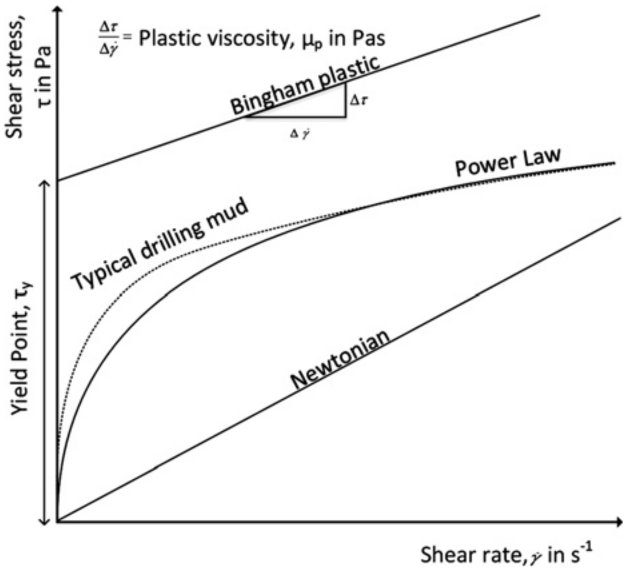

Figure 4: Sketch of rheological models for non-Newtonian fluids. Emphasis on Bingham plastic model and the plastic viscosity given as the slope of the line. The idea of the API standard is that the Bingham Plastic model may satisfactorily describe the approximately linear portion of the curve for typical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

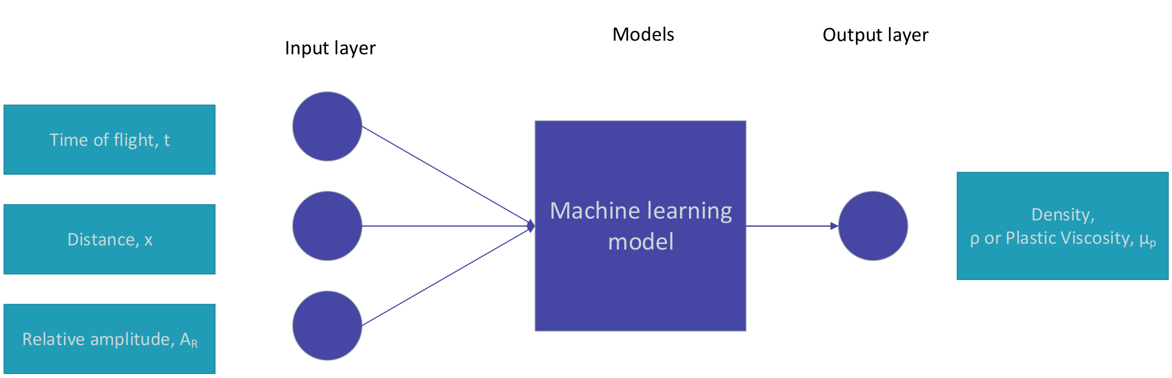

Figure 5: General model overview of inputs and outputs.

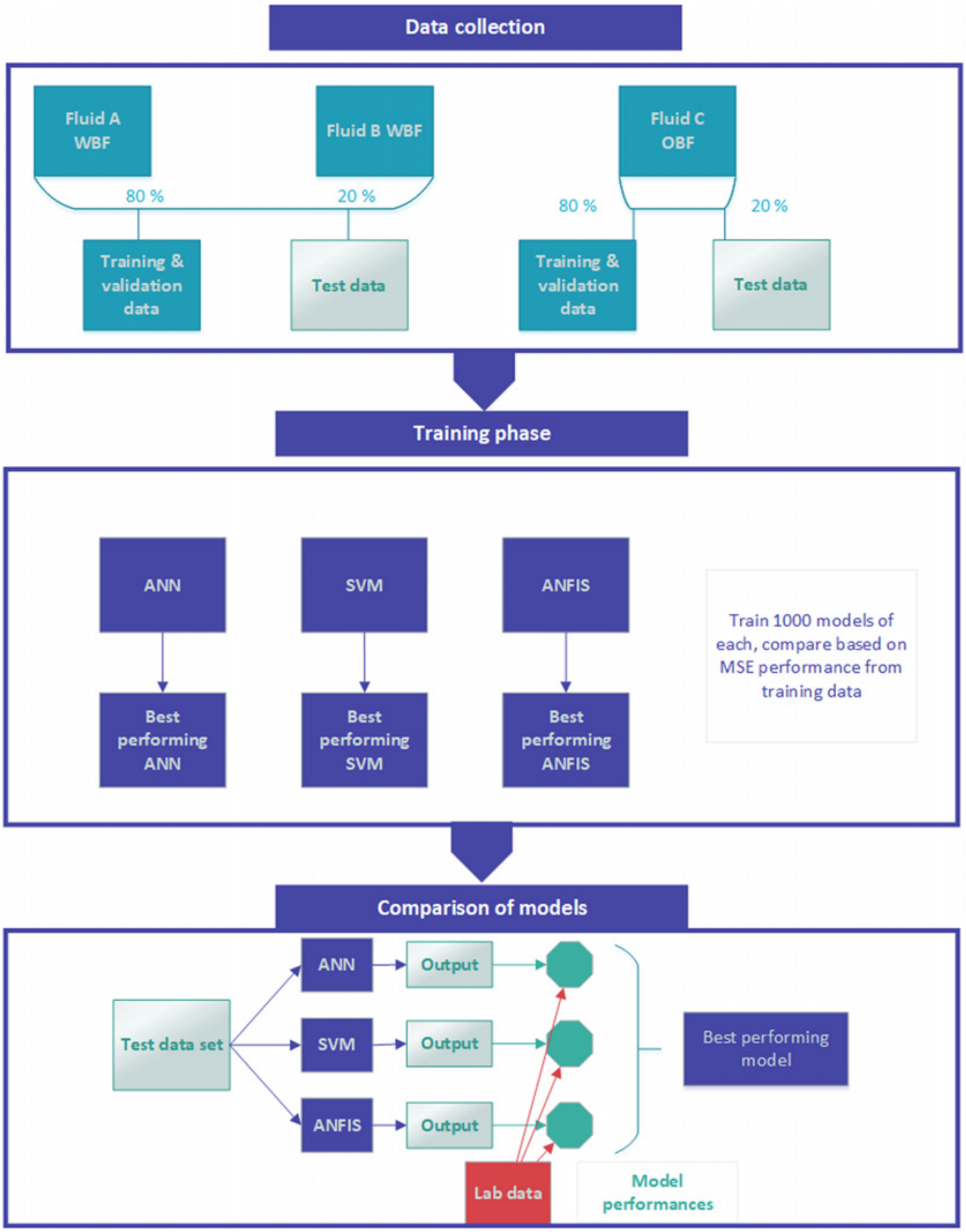

Figure 6: Machine learning model training and selection flowchart. In the first phase, the ultrasonic data is collected and organized in the training phase. The three models are trained repeatedly to find the best meta parameters for each model type. The models are compared against each other using mean 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].

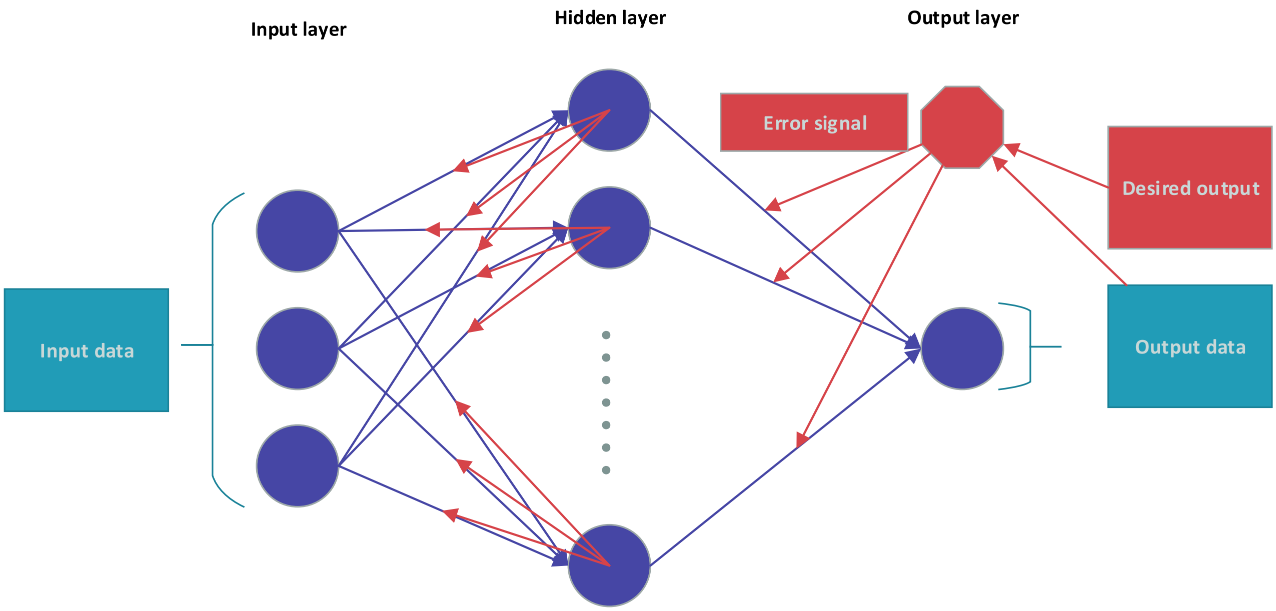

Figure 7: ANN general overview. ANN with one hidden layer, three input neurons and one output neuron. The circles represent the neurons, the purple arrows show the forward connection between the neurons. The error signals (red arrows) are generated by comparing the desired output (if known) to the network 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

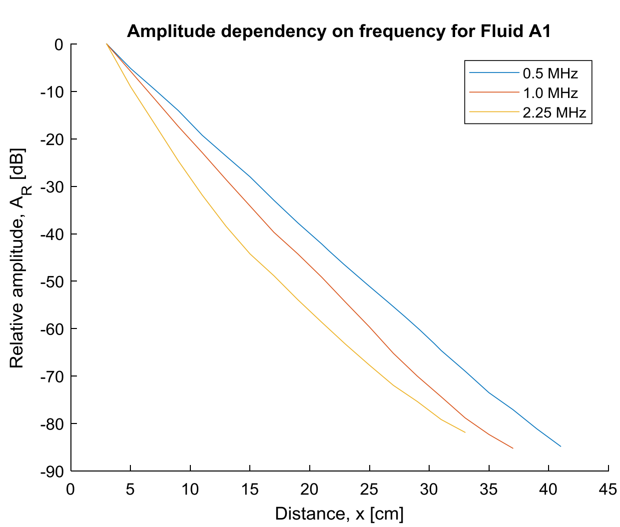

Figure 8: Attenuation dependency on frequency, fluid system A.

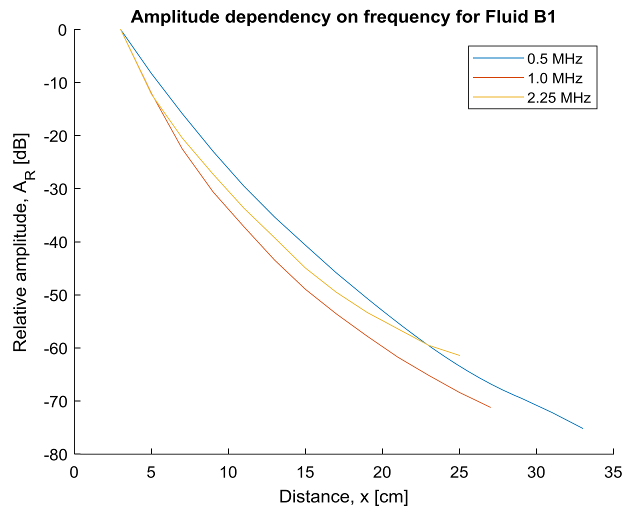

Figure 9: Attenuation dependency on frequency, fluid system B.

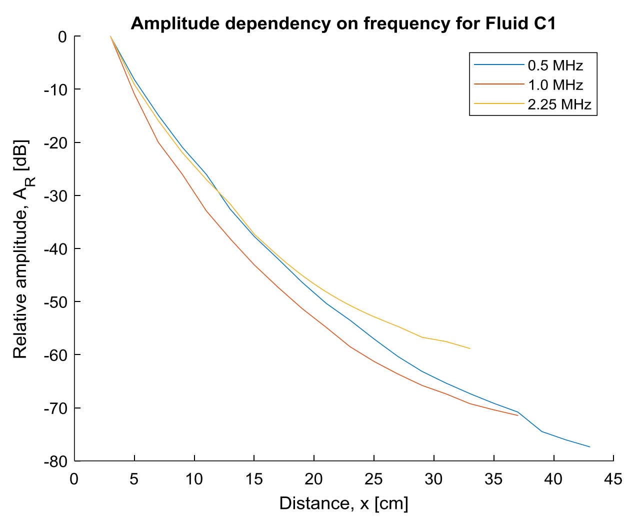

Figure 10: Attenuation dependency on frequency, fluid system C.

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

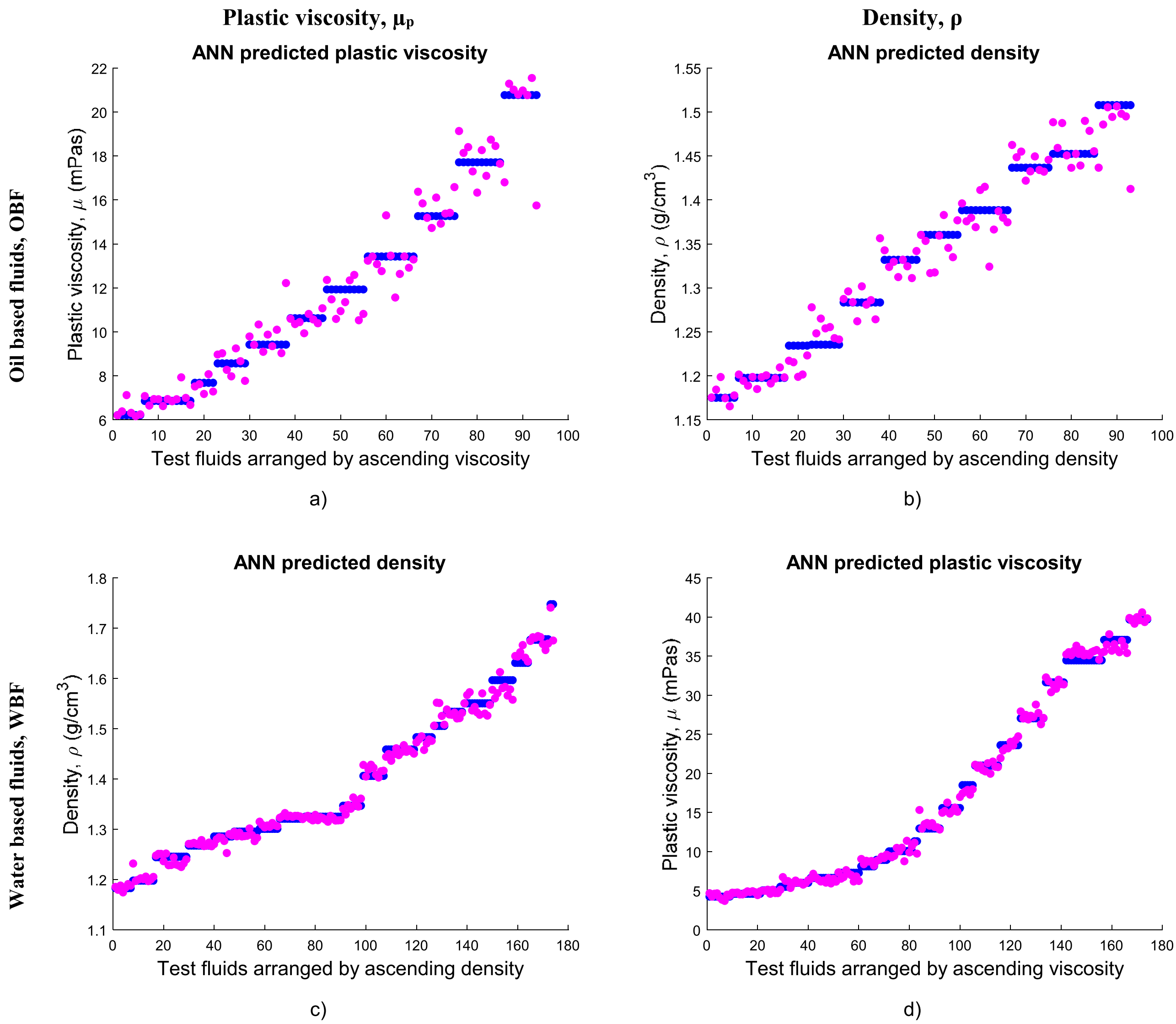

Figure 11: Results from the chosen models on test data sets. a) shows ANN predicted plastic viscosity for the OBF test data set (C4,C8, from left to right). Pink circles are the predictions, and blue are the known values from the lab analysis. b) shows ANN predicted density on the same test data set.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

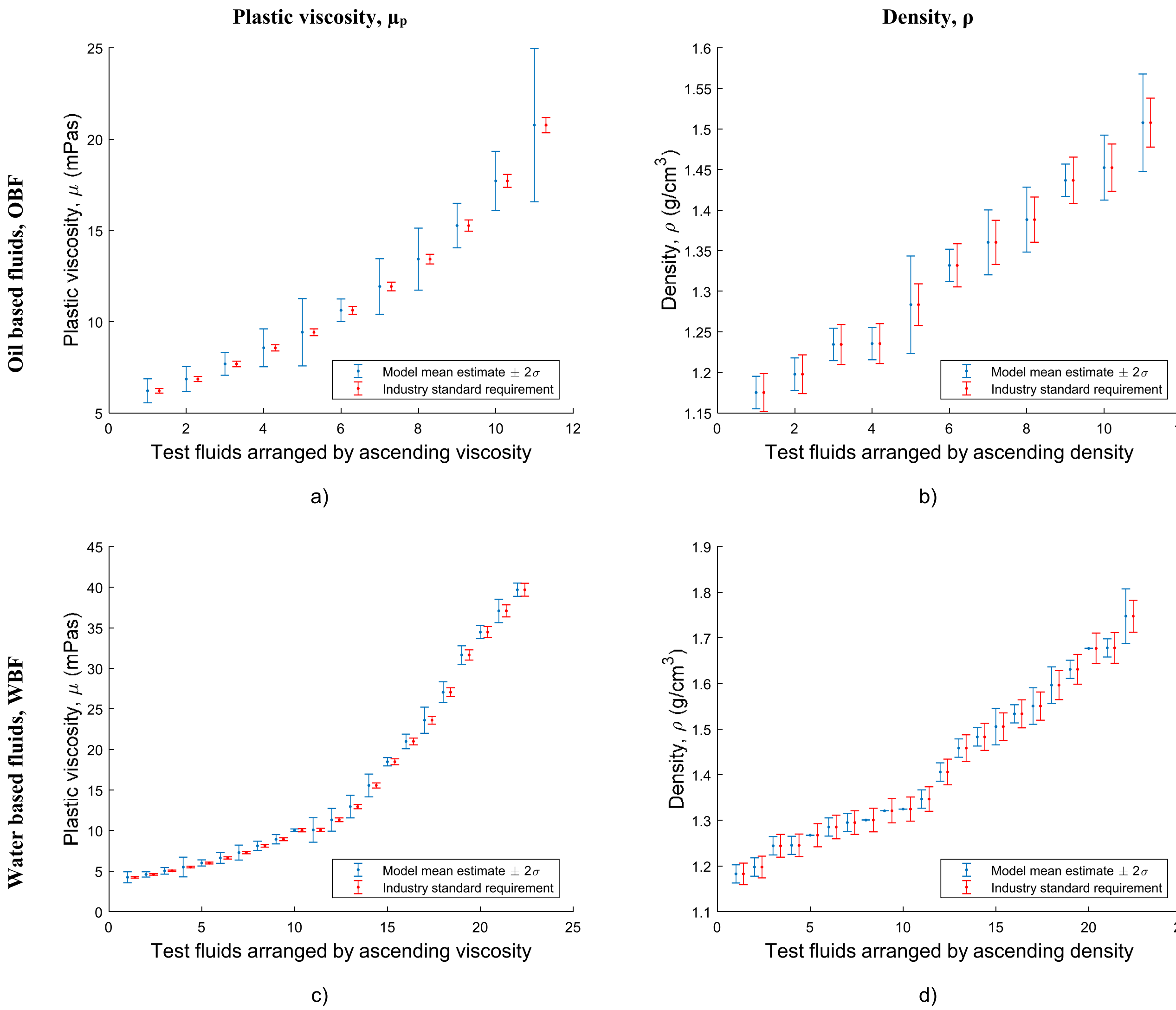

Figure 12: Errorbars showing the mean calculated output for each of the test fluids. The number of measurements for each fluid varies, as they were picked at random from the whole set. The red bars and points represent the lab measurement of density and viscosity, with ± 2 % as per the specifications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

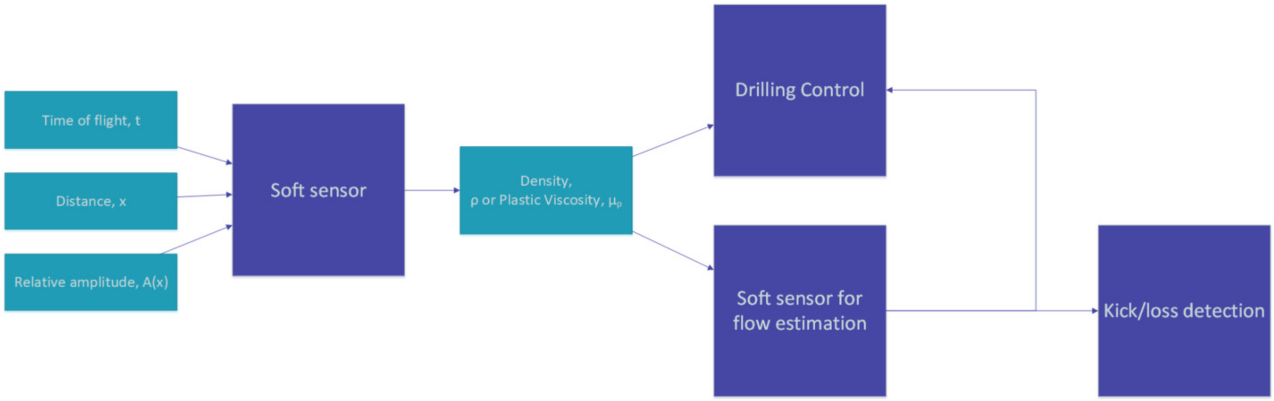

Figure 13: Model application overview. Inputs to the left, the soft sensor discussed in the paper outputting either density or plastic viscosity. This may then be used either directly as measurements in the general drilling process control, or as inputs into soft sensors for flow estimation, which again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