Modelling Drilling Mud Viscosity Behaviour at Downhole Conditions Using Multi-Gene Genetic Programming

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Abstract

This study developed a nature-inspired algorithm based on multigene genetic programming to predict downhole mud plastic viscosity for oil and water based muds, using data obtained from the field and from open literature. The initial mud plastic viscosity (IPV), downhole temperature (T) and downhole pressure (P) were used as the input parameters to the algorithm. To develop the model, 88 and 149 data points were used to develop downhole mud plastic viscosity models for oil based muds and water based muds respectively. To assess the performance of the models, four statistical error tools namely: the mean square error (MSE), mean absolute error (MAE), root mean square error (RMSE) and determination coefficient (R^2) were adopted. The results indicate that the model for the oil based mud had an R^2 value of 0.9499 and an MSE of 0.2507, MAE of 3.12 and RMSE of 0.5. For the water based mud downhole viscosity model, R^2 value of 0.8166 and an MSE of 0.1418, MAE of 2.25 and RMSE of 0.3766. In order to ascertain the parametric importance of the input variables used, the partial derivative sensitivity analysis was utilized. In this regard, the initial mud plastic viscosity had the highest influence for water based muds (70%) followed by the temperature (29.3%) while the pressure had the least effect (0.75%) on downhole mud plastic viscosity. For the oil based mud, down hole temperature had the highest influence (99.6%) followed by the initial mud plastic viscosity (0.3%) while downhole pressure had the least effect. In addition, the MGGP model was presented in an explicit form that makes it easy to be deployed in software applications, something rarely found in most machine learning studies. The study also assessed the computational speed of the developed models. This was necessary so as to know the efficiency of the model when deployed in software applications. With respect to execution speed, 18 and 16 floating point operations per second for OBM and WBMs were obtained. The characteristics of the proposed model for which novelty is claimed include the computational speed evaluation of the model, the explicit nature of the models and a proposal for field implementation. These results indicate the efficiency of the developed MGGP models for prediction of downhole mud plastic viscosity.

***Keywords**: Multigene; Genetic Programming; Downhole; Mud Viscosity*

1. Introduction

There has yet to be a well drilled without the use of drilling mud. It's no surprise that the drilling community regards it as the lifeline of the borehole drilling process (Agwu *et al.,* 2015). However, in order for drilling mud to perform functions such as maintaining hydrostatic pressure, transporting and suspending drill cuttings, and so on, the fluid properties must meet international standards. Mud rheology is one of these properties. Rheology is fundamentally the study of fluid flow and deformation (Orodu *et al.,* 2018). Gel strength, plastic viscosity, yield point, and apparent viscosity are all rheological properties of muds. Tracking mud rheological properties downhole is a critical factor in determining the success or failure of a wellbore drilling operation. This is because these properties deviate from their original values at subsurface conditions due to temperature and pressure variations (Shah *et al.,* 2010).

Global hydrocarbon demand is pushing the oil and gas industry to drill deeper reservoirs. Maintaining desirable rheological characteristics of drilling muds is one of the tasks in such conditions. For example, Herzhaft *et al.* (2001) submitted that a typical mud in a well will encounter temperatures ranging from 0 to 150 degrees Celsius and pressures of up to 5800 psi. Such a temperature and pressure range would undoubtedly affect mud rheology. However, when these properties are properly tracked and maintained, they help to reduce the occurrence of wellbore issues such as lost circulation, pipe sticking, hole cleaning, and well control. Mud rheological properties are primarily determined in the laboratory using a viscometer (Oguntade *et al.,* 2020). Many factors can influence and change the rheological properties of deep drilling wells. Increasing temperature and pressure are two of the most significant factors. There is no doubt that significant amounts of oil and gas are trapped within the deep formations. Higher-temperature operations appear to be the new normal in the oil and gas industry. Drilling into reservoirs with high temperatures and pressures necessitates the use of a fluid with stable rheological properties.

Elkatatny (2019) submitted that because the use of viscometers is time-consuming, tedious, and always requires a significant amount of energy to clean, they are only used once every 12 hours. However, situations on well sites always necessitate frequent measurements of mud rheological properties in order to assure the driller(s) of the mud's quality. The time required to complete these tests would not allow for rapid detection of deviations from optimal baseline mud properties. Therefore, Spelta *et al.* (2017) agrees that a quick test would allow for immediate corrective actions on the mud to be implemented before downhole problems escalate and pose a safety risk. As a result, Elkatatny (2019) strongly supports the pursuit of real-time mud rheology estimation. A marsh funnel is used in the field to make up for lost time and to make quick decisions. Mud viscosity is measured with a marsh funnel and is usually expressed in seconds per quartz rather than centipoise (Alsabaa *et al.,* 2020). As it stands, marsh funnel tests, despite being quick, inexpensive, and performed every 10-15 minutes, do not provide the driller with information on the viscosity of the mud (Elkatatny *et al.,* 2016). As a result, regular measurements are required to make effective use of the Marsh funnel viscosity. Finally, a trend analysis of the measured values indicates an impending mud problem.

The drilling process becomes more complex as the search for hydrocarbons moves to unforgiving drilling terrains such as deep, ultra-deep offshore waters and high temperature, high pressure environments. In such circumstances, providing erroneous information about the rheological properties of mud to the drilling crew would almost always have disastrous consequences in terms of drilling cost and time. Because determining mud rheology directly in the field is difficult, several viable approaches have been reported in the literature. Predictive models are one of these methods. Temperature and pressure, on the other hand, rise with depth, so producing from such conditions presents several challenges to petroleum engineers in terms of drilling, completion, and production. Changing the rheological properties of drilling fluid is one of them. Petroleum engineers must understand the rheological properties of drilling fluids at higher temperatures and pressures. Under these conditions, the success of any drilling operation is dependent on the proper selection and monitoring of the drilling fluid system. The ability of a fluid to perform a specific function is determined by its rheological properties. This necessitates the development of a reliable model that depicts how rheological properties change with temperature and pressure. Despite extensive laboratory studies and research over the past decades, there is still a lack of systematic understanding of how flow behavior changes with downhole conditions.

Drilling fluid literature has been saturated over the last two decades with a series of publications in key journals that project models for determining fluid rheological parameters. As a result, there is a deluge of models in the drilling mud rheology literature. These models have taken many forms, including empirical, theoretical, and artificial intelligence-based models, as well as ensembles of models. It was Wan (2011) who submitted that the benefit of drilling mud rheological modeling is that it predicts mud behavior under extreme conditions such as high stress, high temperature, and high pressure, where conducting experiments would be difficult.

Despite the abundance of models for estimating drilling mud rheological parameters, they lack portability because it is difficult to visualize and present the model derived from these techniques in a compact and explicit form that a non-technical audience can appreciate. Because these techniques share this flaw, a research gap exists in developing a robust model with good accuracy and generalization ability while allowing downhole mud viscosity to be measured quickly and unambiguously. The primary goal of this study is to develop a new correlation that can be used to predict the downhole viscosity of a drilling fluid using multi-gene genetic programming (MGGP). As input parameters, the new correlation would be dependent on downhole pressure, temperature, and initial mud viscosity. The MGGP technique was chosen from a variety of artificial intelligence techniques for this work because it can provide explicit mathematical equations with high accuracy. Furthermore, the MGGP technique does not require a large data set for modeling (Agwu *et al.,* 2021). To assess the effectiveness or otherwise of the developed models, they would be subjected to scrutiny of previously unseen or unfamiliar data that is essentially outside of their comfort zones.

i. The main methods that exist in literature for predicting mud plastic viscosity are the multiplicative factor method, linear regression method and relative dial readings method. These methods have a fixed form, thereby making them incapable of handling non-linearities in data. Thus results obtained from such models are inaccurate.
ii. Artificial neural networks have equally been used to model mud plastic viscosity. However, existing models are limited to predicting mud viscosity at surface conditions. None has been developed for modelling mud viscosity at downhole conditions where temperature and pressure play dominant roles. In addition, although ANN models possess

good predictive power, the models evolved by the technique often come at the price of some higher difficulties in optimization, interpretability and generalizability (local optima issues). Furthermore, ANNs require time to search for the optimal number of hidden neurons, require lots of data, and the evolved models are complex (due to the numerous weights and biases involved). Using more hidden neurons than required will add more complexity to the model.

iii. The MGGP technique was selected in this work from the array of artificial intelligence techniques because it can provide the explicit mathematical equations with high accuracy. In addition, the MGGP technique does not need a large data size for modelling

2. Review of Related Literature

A summary of existing models for predicting plastic viscosity is presented in Table 2.1 For ease of reference, the researches are arranged from the earliest to the latest as presented by different researchers. In a bid to make the summary detailed, the modelling technique used by each researcher is highlighted, the drilling fluid type used, the number of data points, the input variables as well as the correlation developed by each researcher and their performance where applicable. From Table 2.1, the following are observed. First, model inputs and mud type varied in the examined literature. For most of the rheological models highlighted in Table 2.1, the input variables: mud density, marsh funnel viscosity and solid content runs through most of them.

Table 2.1: Previous works on modelling of mud plastic viscosity

Author, year	**Method used**	**Mud type**	**Input parameters**	**Output parameter**
American Petroleum Institute (2010)	-	For HTHP wells	Effective viscosity at the temperature T1 ; effective viscosity at the pressure P1, temperature, pressure	Effective viscosity
Makinde et al. (2011)	Regression	WBM	Aging time and temperature	Plastic viscosity
Guria et al (2013)	-	-	Shear stress at 600 RPM and 300 RPM	Plastic viscosity
Elkatatny *et al* . (2016)	ANN 3 – 12 – 1	Invert emulsion mud	Marsh funnel viscosity, solid content, and mud density	Plastic viscosity
Al-Azani *et al.* (2018)	ANN 3 – 11 – 1	OBM	Marsh funnel viscosity, mud weight, solid percent	Plastic viscosity
Avci (2018)	ANN 2 – 12 – 1	Water-based drilling fluid	Shear rate, temperature	Shear stress
Tchameni et al. (2018)	ANN [2 – 6 – 1]	Waste vegetable oil biodiesel	Biodiesel content and aging temperature	Plastic viscosity

Author, year	Method used	Mud type	Input parameters	Output parameter
		modified WBM		
Elzenary (2019)	ANN ANFIS	Invert emulsion mud	Marsh funnel viscosity, mud weight, solid percent	Plastic viscosity
Elkatatny (2019)	ANN 3 – 30 – 1	NaCl water based drill-in fluid	Marsh funnel viscosity, mud weight, solid percent	Plastic viscosity
Gowida *et al.* (2019)	ANN 2 – 20 – 1	$CaCl_2$ brine	Marsh funnel viscosity, mud weight	Plastic viscosity
Elkatatny (2020)	ANN 2 – 38 – 1	NaCl mud	Mud weight and Marsh funnel viscosity	Plastic viscosity
Gomaa *et al.* (2020)	ANN 2 – 22 – 1	High-overbalanced bridging mud	Mud density and Marsh funnel viscosity	Plastic viscosity
Gowida *et al.* (2020)	ANN 2 – 20 – 1	WBM	Mud density and Marsh funnel viscosity	Plastic viscosity
Alsabaa *et al.* (2020)	ANFIS	Invert Emulsion Mud	Mud weight and Marsh funnel viscosity	Plastic viscosity

3. Materials and Methods

3.1 Data collection

Downhole mud viscosity values were obtained from daily drilling data reports from different drilling companies as well as from comprehensive review of literature on experiments conducted by various researchers. From this collection, 88 data points were collated for the oil based mud viscosity while 149 data points were collated for the downhole viscosity of water based mud. Table 3.1 summarises the input variables from the data collected and their respective units of measurement. Basically three inputs were isolated namely: Mud initial viscosity, downhole temperature and downhole pressure.

Table 3.1: Input variables in data collected for the study

Input variable	Initial mud viscosity	Downhole temperature	Downhole pressure
Unit	Centipoise (cP)	Degree Fahrenheit (°F)	Pounds per square inch (psi)

3.2 Statistical features of data collected

The descriptive statistics of the data obtained is shown in Table 3.2a and Table 3.2b for water based mud and oil based mud respectively.

Table 3.2a: Descriptive statistics of downhole viscosity data for water based mud

	Initial plastic viscosity	Downhole Temperature	Downhole pressure	Downhole Plastic viscosity
Mean	21.00375839	89.74765101	8799.187919	16.73147651
Median	19.98	93	4000	16
Mode	20	26	3000	20
Standard deviation	11.89730451	56.84331188	9257.161923	8.610828457
Maximum	43.8	200	24801	47
Minimum	4.94	4	14.5	2.91
Range	38.86	196	24786.5	44.09

Table 3.2b: Descriptive statistics of downhole viscosity data for oil based mud

	Initial plastic viscosity	Downhole Temperature	Downhole pressure	Downhole Plastic viscosity
Mean	62.93636364	108.6489899	5332.136364	34.20379503
Median	51.1	100	870	29
Mode	93.9	65.55555556	870	19
Standard deviation	25.5026083	60.81594779	8855.519641	23.81652133
Maximum	93.9	315.5555556	40000	105.6603774
Minimum	29	20	0	6.79245283
Range	64.9	295.5555556	40000	98.86792453

3.3 Method adopted for the study

In this study, the software tool EUREQA is used to execute the multigene genetic programming algorithm for the estimation of downhole viscosity of water and oil based muds. This software is a new “Genetic Programming and Symbolic Regression” code written based on multi-gene GP for use as a standalone software. The MGGP method is applied to the datasets collected in Section 3.1.

3.4 An Overview of Multigene Genetic Programming (MGGP)

Multi-gene genetic programming (MGGP) is a modified form of genetic programming in which the genes are weighted together to form the approximation function (Kusznir and Smoczek, 2022).

In MGGP, there is an additional high-level crossover operation. As long as the maximum number of genes is not exceeded, an individual's genes can be switched with the genes of another individual.

According to Niazkar (2023), MGGP is essentially one of the artificial intelligence models and is capable of looking for an appropriate relationship between any input and output collection of data. Given its adaptable design and robust search engine, it inevitably has the ability to be used for resolving a variety of issues.

The goal of the MGGP is to produce "multi-gene" mathematical models of predictor response data, that is, linear combinations of low-order nonlinear transformations of the input variables. The evaluation of a single tree (model) expression serves as the foundation for the conventional GP representation (Gandomi and Alavi, 2012). A single GP individual (program) in multi-gene representation is built from a number of genes, each of which is a tree expression (Searson et al., 2010).

3.4.1 Procedure for Model Development

The MGGP algorithm would follow the following steps:

i. Set the initial parameters (e.g. the function and terminal set, the number of generations, the population size and the maximum depth of gene)
ii. Randomly generate the initial population of genes.
iii. Using the method of least squares, construct the models by combining a set of genes.
iv. Based on the fitness function, evaluate the models performance.
v. Carry out the genetic operations; then construct a new population.
vi. Evaluate the performance of the models by benchmarking it with the termination criterion; if not satisfied then go to
vii. Else select the evolved model as the best.

3.5 Parameter settings for implementing MGGP

Trial-and-error approach used to select the parameter settings is shown in Table 3.3. The broader set of elements is chosen in the function set since this can provide a broader class of non-linear mathematical models. The elements in the terminal set are the three input process variables and random constants in the range [−10 10]. The population size is the number of models generated in one generation. The number of generations is the number of iterations that an algorithm makes before the termination criterion is satisfied. Their adjustment depends on the nature of the regression problem. In the present study, the population size is set to a value of 300 and the number of generations is set to a value of 40. The size of search space and number of models searched within the space are directly influenced by the maximum number of genes and maximum depth of the gene. Based on the problem, the maximum number of genes and maximum depth of gene are kept at 8 and 6, respectively.

Table 3.3: Parameter settings for the MGGP method

Parameters	Values assigned
Runs	20
Population size	300
Number of generations	40
Tournament size	2
Maximum depth of tree	6
Maximum genes	8
Functional set (F)	(Multiply,plus, minus, divide, tan, tanh, cos)
Terminal set (T)	IPV, T, P [-10 10]
Crossover probability rate	0.85
Reproduction probability rate	0.10
Mutation probability rate	0.05

4. Results and Discussion

4.1 Explicit Representation of the Developed Models

The capacity to replicate a model—that is, to get the same results using the same data and code—is improved by explicitly presenting the models. Most research that use machine learning overlook the two concepts of reproducibility and replicability (Mikowski et al., 2018). As stated by Stroebe and Strack (2014), very few published machine learning research contain source code, and those that do almost never provide details on how the model was built. The model developed for the downhole viscosity of water based muds is shown in Equation 4.1 while the model for downhole oil based mud viscosity prediction is shown in Equation 4.2.

$$Downhole\ viscosity\ for\ WBM = (Initial\ PV) + (0.000195Pressure) - \cos(-3.83 * 10^4 * initial\ PV) - 2.78\sin(103 * initial\ PV) - (9.22 * 10^{-5} * Temperature * initial\ PV^2) - 1.56 * 10^{-6} * Temperature * initial\ PV^3 * \sin(\sin(9.76 * Temperature)) \quad \text{Equation 4.1}$$

$$Downhole\ viscosity\ for\ OBM = 40.5 + 0.00525P + \frac{22.7*IPV}{T} + (1.47 * 10^{-5} * IPV * T^2) + \frac{(-0.0021*IPV^2)}{\cos(IPV)} - (0.224 * T) - (0.273 * IPV) - (2.71 * 10^{-5} * P * T)$$

Equation 4.2

Where IPV = Initial plastic viscosity; T = temperature; P = pressure

4.2 Model Performance Metrics

A statistical or machine learning model's performance and efficacy are measured quantitatively using evaluation metrics. These metrics aid in comparing various models or algorithms and offer information on how well the model is working. In this work, the metrics used include: goodness of fit (R^2), mean square error (MSE), mean absolute error (MAE) and root mean square error (RMSE).The performance metrics for the water based mud downhole viscosity is presented in Table 4.1 while the oil based mud downhole viscosity is presented in Table 4.2.

Table 4.1: Model performance evaluation for downhole viscosity of water based muds

Metric	**R^2**	**MSE**	**MAE**	**RMSE**
Value	0.8166	0.1418	2.256	0.3766

Table 4.2: Model performance evaluation for downhole viscosity of oil based muds

Metric	**R^2**	**MSE**	**MAE**	**RMSE**
Value	0.9499	0.25	3.12	0.5

4.3 Comparison of Developed Model Predictions Against Actual Data

Figures 4.1 and 4.2 are the plots of the actual data against the predictions from the developed MGGP models for WBM and OBM respectively. From both figures, it can be seen that the developed models have the capacity to capture to a reasonable extent the non-linearities associated with the prediction of drilling fluid plastic viscosity at downhole conditions.

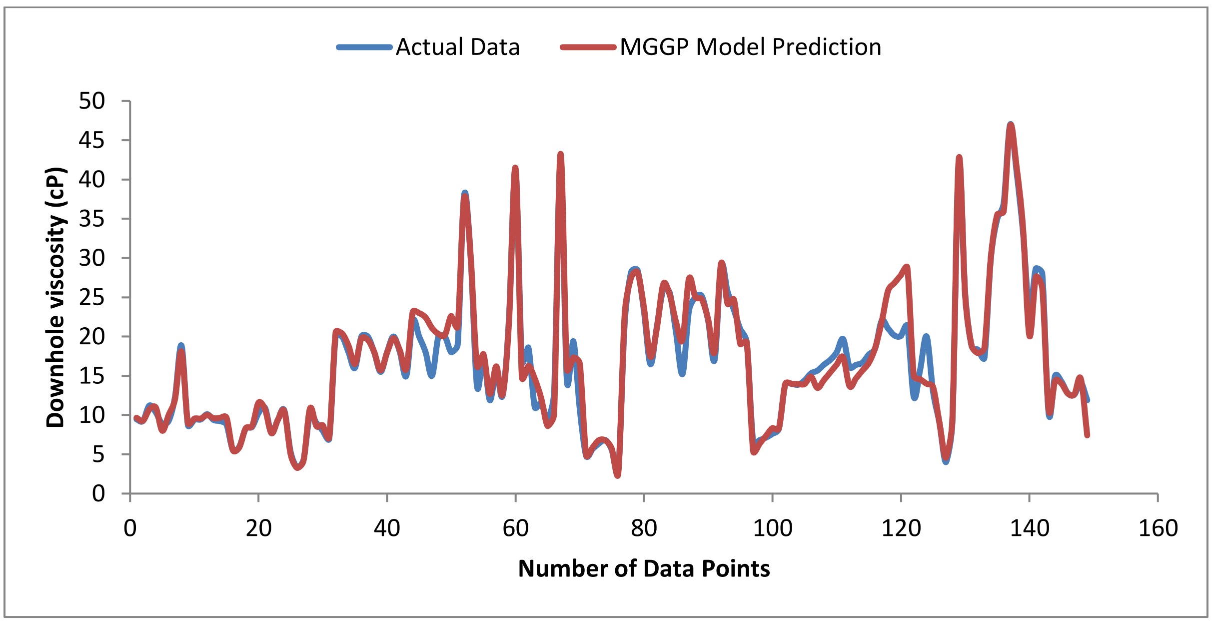

Figure 4.1: Comparison of actual values and MGGP model predictions for WBM viscosity at downhole conditions

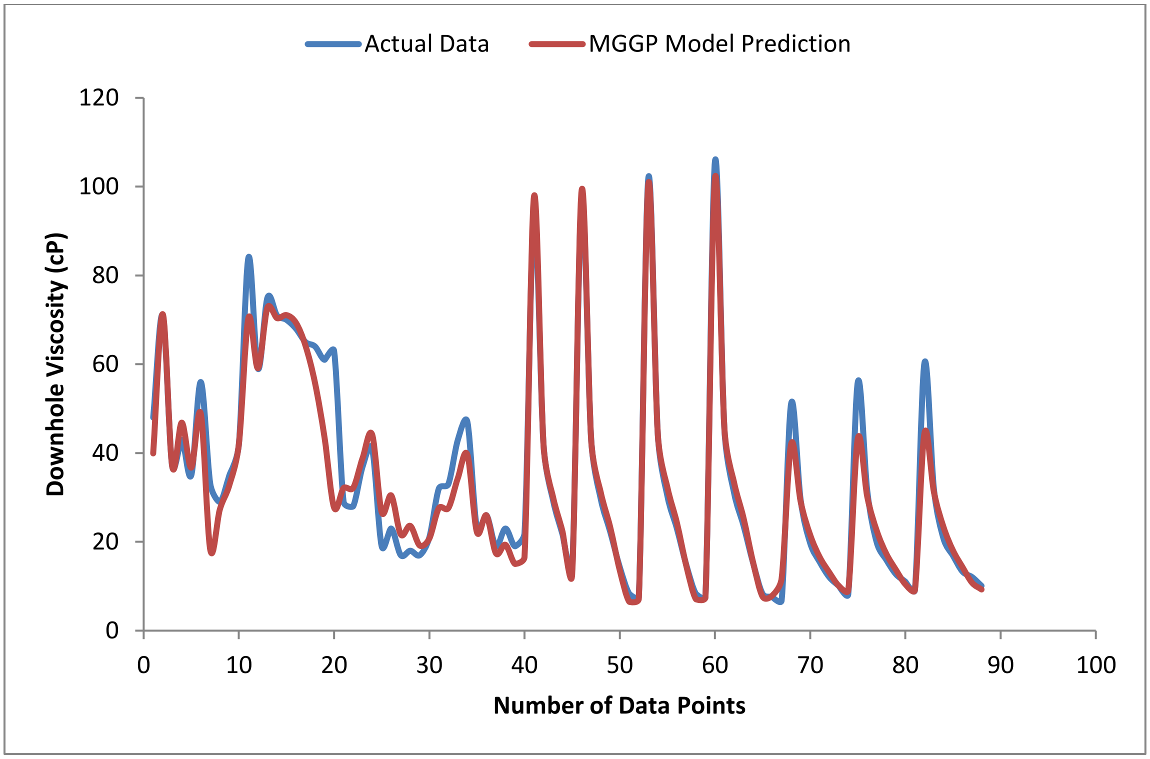

Figure 4.2: Comparison of actual values and MGGP model predictions for OBM viscosity at downhole conditions

4.4 Variable Sensitivity Analysis

According to Tunkiel *et al*. (2020), there is little research on traditional sensitivity analysis of machine learning regression models. The majority of data-driven models are complicated "black boxes" with little opportunity for mathematical knowledge of the underlying, self-assembled model. Sensitivity analysis might reveal unpredictable behaviour resulting from overfitting or a small training sample. Additionally, it can direct the use and evaluation of models. Table 4.3 shows the sensitivity analysis for downhole WBM viscosity while Table 4.4 shows the sensitivity analysis for downhole viscosity of OBMs.

Table 4.3: Model variable sensitivity for WBM downhole viscosity

Variable	Sensitivity	% Positive	Positive magnitude	% Negative	Negative Magnitude
Initial PV	18.874	58%	9.2513	42%	32.105
Temperature	7.921	50%	5.5545	50%	10.288
Pressure	0.20512	100%	0.20512	0%	0

Table 4.4: Model variable sensitivity for OBM downhole viscosity

Variable	Sensitivity	% Positive	Positive magnitude	% Negative	Negative Magnitude
Temperature	1451.2	4%	362.12	96%	1493
Initial PV	4.84	0%	0	100%	4.84
Pressure	0.48288	100%	0.48288	0%	0

Sensitivity: This is the relative impact within this model that a variable has on the target variable. Given a model equation of the form: $z = f(x, y \ldots.)$, the influence metrics of x on z are defined for sensitivity as follows:

$$Sensitivity: \left|\frac{\partial z}{\partial x}\right|.\frac{\sigma(x)}{\sigma(z)}$$

The sensitivity is evaluated at all input data points.

% Positive: The likelihood that increasing this variable will increase the target variable. Mathematically, % positive is the percentage of data points where $\frac{\partial z}{\partial x} > 0$. Since % positive is 58% for initial plastic viscosity, then 58% of the time, increases in initial plastic viscosity leads to increases in the downhole viscosity. This is the same with the downhole temperature. In this case, 50% of increases in the downhole temperature leads to increase in the downhole mud viscosity. However, for downhole pressure, 100% positive means that at all times an increase in downhole pressure always leads to an increase in downhole mud viscosity.

% Negative: This factor indicates that the likelihood of increasing this variable will decrease the target variable. Mathematically, % negative is the percentage of data points where $\frac{\partial z}{\partial x} < 0$. In this case, for mud initial plastic viscosity, 42% of the time, increases in the initial mud plastic viscosity leads to a decrease in downhole mud viscosity. The same applies to the downhole temperature. Half the time, an increase in downhole temperature leads to a decrease in downhole mud viscosity. However, for the downhole pressure that has a %negative of 0%, this means that no matter the increase in downhole pressure, there is no likelihood that it would decrease the downhole mud viscosity.

Positive magnitude: This is essentially how big the positive impact is. It is derived when increases in a variable leads to increases in the target variable. Mathematically, positive magnitude is represented as $\left|\frac{\partial z}{\partial x}\right|.\frac{\sigma(x)}{\sigma(z)}$ at all points where: $\frac{\partial z}{\partial x} > 0$. In the case of the three input variables considered, the positive impact that the initial mud viscosity has is the largest (9.25) followed by the downhole temperature (5.55) while the downhole pressure had the least value of 0.205.

Negative magnitude: This is essentially how big the negative impact is. It is derived when increases in a variable leads to decreases in the target variable. Mathematically, positive magnitude is represented as $\left|\frac{\partial z}{\partial x}\right|.\frac{\sigma(x)}{\sigma(z)}$ at all points where $\frac{\partial z}{\partial x} < 0$. In the case of the three input variables considered, the negative impact that the initial mud viscosity has is the largest (32) followed by the downhole temperature (10) while the downhole pressure had the least value of 0.

Where: $\frac{\partial z}{\partial x}$ is the partial derivative of z with respect to x; $\sigma(x)$ is the standard deviation of x in the input data; $\sigma(z)$ is the standard deviation of z; $|x|$ denotes the absolute value of x and $\bar{x}$ denotes the mean of x.

4.5 Computational Speed of the Developed Models

In order for a mathematical model to be useful, it needs to be deployed in software. The efficiency of a model in software is assessed on one part by the computational burden of the model. This involves the speed of computation by the model and the memory the model consumes. According to Khan Academy (2022), an efficient algorithm is essentially that which takes the least execution time and lowest memory footprint while still providing a correct output. Estimating the algorithm complexity is an important part of the design of an algorithm since it gives important information about its envisaged performance.

Simply counting the number of computations a model performs gives a sense of its speed. This is commonly measured in FLOPs, or floating point operations per second. FLOPs will be applied to the amount of computation for a given task (e.g., a prediction or inference pass), by referring to the number of operations, counting a multiply-add operation pair as two operations (Desislavov *et al.,* 2023). We often count operations like addition, subtraction, multiplication, division, exponentiation, square roots, etc. as a single FLOP when computing FLOPS. For example, y = x * 2 * (y + z*w) is 4 floating-point operations. From Table 4.7,

The models in Equation 4.1 and Equation 4.2 for calculating downhole viscosity involve several mathematical operations, including addition, subtraction, multiplication, exponentiation, cosine, sine, and nested trigonometric functions.

To estimate the floating-point operations (FLOPs) for this formula, we need to consider the number and complexity of these operations.

Assuming each operation counts as a single FLOP, we can break down the FLOPs count for the WBM downhole viscosity in Equation 4.1 as follows:

- Addition and subtraction: 2 FLOPs (one each)
- Multiplication: 7 FLOPs (one for each multiplication operation)
- Exponentiation: 1 FLOP (one exponentiation operation)
- Cosine and sine: 7 FLOPs (one for each cosine and sine evaluation)
- Nested sine: 1 FLOP (one sine evaluation within the other sine evaluation)

Therefore, the total FLOPs count for the given formula is approximately 18 FLOPs.

To calculate the FLOPs (floating-point operations) for the given formula for downhole viscosity in OBM, we can break down the operations involved and count the number of FLOPs:

- Addition and subtraction: 4 FLOPs (two additions and two subtractions)
- Multiplication: 9 FLOPs (five multiplications)
- Division: 1 FLOP (one division)
- Exponentiation: 1 FLOP (one exponentiation)
- Cosine: 1 FLOP (one cosine evaluation)

Therefore, the total FLOPs count for the given formula is approximately 16 FLOPs.

Table 4.5: Speed comparison of developed models using FLOPs computations

Model		**FLOPs**
WBM downhole plastic viscosity model	$Downhole\ viscosity\ for\ WBM = (Initial\ PV) + (0.000195 Pressure) - \cos(-3.83 * 10^4 * initial\ PV) - 2.78 \sin(103 * initial\ PV) - (9.22 * 10^{-5} * Temperature * initial\ PV^2) - 1.56 * 10^{-6} * Temperature * initial\ PV^3 * \sin(\sin(9.76 * Temperature))$	18
OBM downhole plastic viscosity model	$Downhole\ viscosity\ for\ OBM = 40.5 + 0.00525P + \frac{22.7*IPV}{T} + (1.47 * 10^{-5} * IPV * T^2) + \frac{(-0.0021*IPV^2)}{\cos(IPV)} - (0.224 * T) - (0.273 * IPV) - (2.71 * 10^{-5} * P * T)$	16

From Table 4.5, a comparison of the FLOPs of the developed models for mud viscosity estimation was carried out; it is found that the OBM model developed in this study has a small number of FLOPs, implying that its speed of computation would be faster than the WBM model. This makes this model useful for real time deployment in the field where mud PV data are required in real time

4.5 Application of Developed Models in a Typical Drilling Fluid Circulating System

The real essence of developing a machine learning model (ML) is to work out the solution to a problem; and a ML based model can only achieve this when it is deployed and used actively by the end users. Thus proposing a means by which the developed models can be deployed is one way of ensuring the aim of developing the models is achieved. This is so because it takes time, energy and cost to create a model, hence if there is no clear cut plan, then there is no need embarking on the venture. First, machine learning models require data and lots of it. Hence the data source for the model developed if to be deployed in a drilling fluid system has to be ascertained. In this case, the data for the model inputs would be obtained from sensors that transmit it to a database that can be stored on-premise, in cloud storage, or in a hybrid of the two. Two sensors are proposed in this study. Each sensor collects data temperature and pressure data as the well depth increases. Now, the data would be pre-processed and retrieved in real time. An interface box or analogue to digital converter (ADC) is required to transform the analogue data emanating from the sensors into a digital data format that can be processed by a computer. Since real time predictions are to be made, an inference engine would retrieve the input data automatically and prediction is carried out immediately the inference request is made. The third input parameter which is the initial plastic viscosity is obtained from a one-time viscometer measurement made at the surface before the start of drilling operations. This value would be pre-inputted into the model. The other parameters pressure and temperature would now be fed into the model as a continuous stream. Figure 4.3 illustrates this. Since the proposed MGGP models would not train, run, and deploy itself, therefore software and hardware that help in the effective deployment of the MGGP model is required. The procedure of building any computer software starts with identifying the main purposes of that program and the tasks it is going to perform, then the most compatible environment and programming language are chosen. Some examples of frameworks that can be utilized include: Tensorflow, Pytorch, and Scikit-Learn coupled with a programming language like Python. The framework option to be chosen is fundamentally important since it has a huge influence on the continuity, maintenance and use of a model. The framework and the platforms it can support is another area to be noted. For instance, it is important to find out whether the framework would support mobile or web environments. A platform (Windows, Linux or Mac OS) should be chosen. It is proposed that the windows platform is adopted. Since downhole mud viscosity is required in real time, it is important to know how to get feedback from a model while drilling is in progress and how to ensure that a continuous record of outputs. The outputs could be in graphical form.

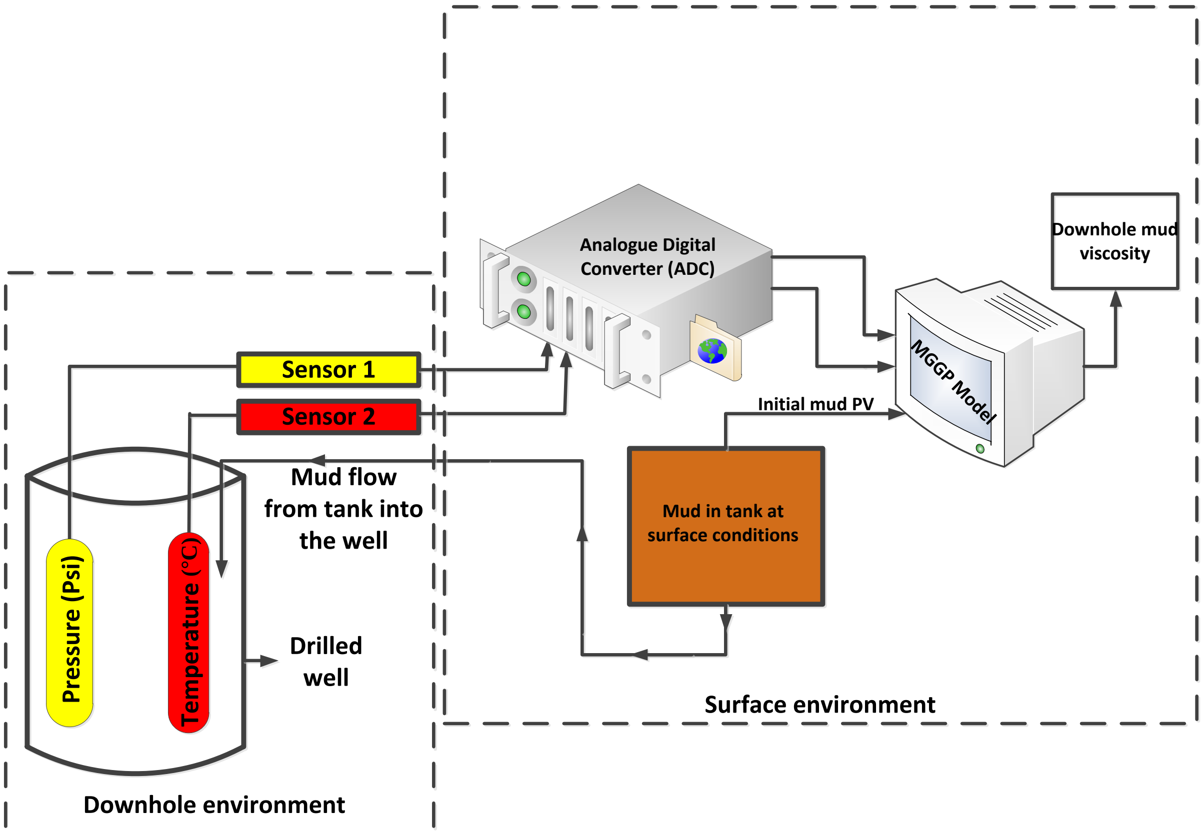

Figure 4.3: Schematic representation of the proposed implementation of the developed models for field utilization

5. Conclusion and Recommendation

5.1 Conclusion

On the basis of the results obtained in this study, the following are the main conclusions:

i. Most of the existing correlations for predicting mud plastic viscosity are useful for estimating mud plastic viscosity at the surface and not at downhole conditions where temperature and pressure have pronounced effects on mud rheology. Therefore using these models to estimate mud viscosity at downhole conditions result in erroneous values.

ii. There existing correlations for mud plastic viscosity at downhole conditions were essentially developed with a small range of data. This makes the models limited in terms of their prediction range.

iii. The MGGP model presented in this study has an explicit nature thus making it deployable in software applications as opposed to the black box nature of other AI based models.

iv. The results from this study give a positive indication of the potential offered by artificial intelligence techniques for analysing the available field data and creating models to predict the downhole mud plastic viscosity. This can be of great assistance for avoiding costly and time consuming HTHP viscometer experiments.

5.2 Recommendations for Further Studies

There are still some things to think about despite the study's innovative conclusions. These include:

i. In this study, MGGP was solely employed to forecast downhole mud plastic viscosity. The predictive power of the model can be increased by combining MGGP with evolutionary algorithms. There are various alternatives to try out in the world of evolutionary algorithms. Particle swarm optimization, artificial bee colonies and ant colony optimization are three of the most intriguing. Another area that needs investigation is which of them would be better suited for optimizing the wellbore cleaning procedure during drilling by using the mud plastic viscosity. This can be done by thoroughly comparing all of them.

ii. Another issue that merits investigation is how to enable the developed algorithms to handle a stream of evolving data rather than fixed data such as the one used in this study.

iii. It is necessary to run models against various datasets to evaluate their effectiveness. To assure data availability for the testing, extensive experiments and/or numerical simulations should be run under diverse scenarios.

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