Australian Journal of Science and Technology

ISSN Number (2208-6404)
Volume 8; Issue 2; June 2024

Original Article

Performance evaluation and application of apparent viscosity models based on marsh funnel viscosity and mud density using high-temperature high-pressure field data

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ABSTRACT

The exponential increase in global demand for energy has necessitated increased oil and gas operations in harsh terrains. This in turn requires high-level precision in operations as errors may lead to great implications on cost and resources. Drilling fluid plays a key role in the success of every oil and gas drilling operation. Therefore, monitoring and engineering of drilling fluid in real time to ensure its sustained suitability as it goes through different formations and conditions remain a priority. Different mathematical models have been researched to complement this effort. However, practical application of these models has not been addressed, creating a gap between theoretical solutions and practical applications. Field data from five different wells were used to evaluate the performance of five models in predicting the apparent viscosity of drilling fluids based on marsh funnel and mud density test results. The best prediction had root mean square errors of 2.57; R-squared of 0.71; mean absolute percentage error of 5%; and mean absolute error of 2.16. It was found that mathematical models could be used to predict apparent viscosity with high accuracy and that the models could be used to identify regions of concern during the drilling process by a simple history matching and comparing of the performance of the models on previous data using a particular model and comparing the result with results from other models to observe patterns. This work, for the first time, gives a practical application of mathematical models based on marsh funnel and mud density tests.

Keywords: Apparent viscosity, drilling fluid, Marsh funnel, model, mud weight, performance

Submitted: 05-05-2024, **Accepted:** 04-06-2024, **Published:** 30-06-2024

INTRODUCTION

The role of drilling fluid in the success of a drilling operation cannot be overemphasized. The drilling fluid is a complex mixture required to meet multiple needs during its useful life cycle.[1] This expectation necessitates a thorough understanding of the behavior of the fluid during the entire process. The properties that describe such behavior are called rheological properties.[2] This understanding of the behavior of fluids is very crucial in the drilling industry where errors can lead to catastrophic consequences like in the case of blowouts. Considering the high cost of drilling, getting it right becomes an imperative. Rheological properties of drilling fluid are critical in the efficiency and overall success of a drilling program. This importance ranges from transporting cuttings to the surface during the drilling process, suspending the cuttings during change of bit, cooling the bit and drill string, to overcoming subsurface pressure.[3] However, the operational conditions under which drilling fluids are used necessitate constant monitoring of the rheological properties as these properties undergo changes during drilling operations. The need for constant monitoring becomes even more demanding when operational activities move into harsh environments like deep sea and environments characterized by high temperature and pressure.[1] This has necessitated the use of different technologies in the pursuit of improved monitoring of the down-hole properties of the drilling mud in real time.[4]

Different studies have been performed to propose mathematical models that could serve as an inexpensive yet accurate alternative in predicting the down-hole properties of drilling fluids in real time.[1,5] Despite a considerable amount of studies

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on the prediction of rheological properties, there is little systematic understanding of how these models can be applied in different real-life scenarios to achieve real-time predictions. As such, there is no standardization of the use of these models, which in turn makes them of little or no use in the industry.

LITERATURE REVIEW

Since the advent of the marsh funnel as a device to help in ensuring the continuous engineering of drilling fluid properties to ensure optimum operations, deliberate attempts have been on to constantly improve on the level of control over the drilling process, especially as it concerns the quality and efficiency of the drilling mud. Numerous studies have been conducted on different rheological properties[1] of drilling fluid, ranging from density,[6-8] apparent and plastic viscosities[9] under different conditions[1,4,5,10] as well as different mud types such as spud mud.[11] In a study, different methods were used to obtain and evaluate an analytical model that took into consideration discharge flow time.[12] A research was conducted Agwu *et al*.[13] on the use of a flexible regression technique known as Multivariate-Adaptive-Regression-Splines to accurately forecast the down-hole viscosity of the mud that was examined in the study. The study by Agwu *et al*.[13] employed an algorithm known as self-adaptive differential evolution to artificial neural network (ANN) to obtain accurate predictions of specific properties of the drilling fluid studied.

Some studies focused on the environment and conditions that the drilling mud are subjected to during drilling operations. For example, Quitian-Ardila *et al*.[14] studied a water-based mud (WBM) under high-temperature high-pressure conditions by varying both the pressure and temperature concurrently to ascertain the effect of the variation on the rheological properties of the mud. An equation was proposed to capture the simultaneous effect of pressure and temperature on the rheology of the drilling mud. Furthermore, Alderman *et al*. [15] studied the rheology of WBM from 300C to 1300C and from 1 to 1000 bar and obtained a method that enabled measurements of rheology made at the surface to be extrapolated to describe mud rheology under down-hole conditions. The need to measure mud rheology over a wide range of shear-rate and temperature was highlighted. Some researchers Agwu *et al*.[1] in a study that reviewed different methodologies employed in the study of the rheology of muds used in high-temperature high-pressure (HTHP) conditions, stated that HTHP wells are the most complex wells to deal with when considering drilling fluid rheology. Different countries where HTHP fields are found were mentioned and the pressure/temperature profile was given. Some examples of additives used under these conditions and the temperature at which they degrade were also given. Studies that focused on mathematical modeling of the rheology of muds under this condition were categorized as using one of four common methods, namely, multiplicative factor method, regression method, non-linear regression method, and relative dial reading method, while others used least square method, Gaussian elimination method, and Herschel–Bulkley method. To achieve the goal of optimizing drilling hydraulics, the rheology of the drilling mud must be adequately described by appropriate models to achieve accurate results.[16] The dearth of sufficient databases to enable in-depth study and analysis of mud rheological properties. This, together with the unavailability of the data used for previous studies, makes it difficult to carry out thorough investigation and comparison of previous studies on different aspects of mud rheology. A gap exists between theoretical solutions and practical solutions used in the industry.[17] This work seeks to investigate the applicability of solutions proffered by different researchers to real-life scenarios.

Studies on the rheology of drilling fluids using marsh funnel and mud density tests as one of or the only inputs required abound. Such studies including: [9] worked on Calcium Carbonate WBM;[18-20] worked on inverted emulsion mud but used different methods such as ANN, multiple non-linear regression and adaptive neuro-fuzzy inference system (ANFIS);[21] worked on high overbalanced WBM used in ultra-deep gas well;[22] worked on KCI polymer mud;[23] worked on an all-oil mud;[24] worked on calcium chloride drill-in fluid;[25] worked on flat rheology synthetic-based mud (SBM);[26] worked on Ferro Chrome Lignosulfonate WBM together with Salt saturated WBM;[27] worked on a WBM that wasn't particularly specified; and[2] worked on Max-bridge oil-based mud. Two studies, Al-Khdheeawi and Mahdi,[26] Bispo *et al*.[27] worked on apparent viscosity only, while all other works covered other rheological properties including apparent viscosity. The methodologies used in the different studies included SaDe-ANN, response surface methodology, ANN, feed-forward multilayer perceptron, multiple non-linear regression, and ANFIS.

A comparative analysis of the performance of two most common models based on marsh funnel and mud density was done during the review of literature. This comparison is based on the findings of different authors in their studies of the use of marsh funnel viscosity and mud density to predict the apparent viscosity and other rheological properties of drilling fluids. In most of the studies, Almahdawi *et al*. model outperformed Pitt model; however, in others, Pitt model outperformed Almahdawi *et al*.[28,29] This tends to indicate the performance of a model could be mud-specific, that is, certain models may more fitted to a particular mud type than others.

METHODOLOGY

Data Gathering and Cleaning

Final well reports of five high-temperature gas wells were obtained from openly available data. All the wells were deep water gas producer wells, with four of them characterized as high-temperature wells. The wells are labeled well 01, well 02, well 03, well 04, and well 05. Details of mud data were obtained for each well on drilled-section basis. The well sections indicate the diameters of the drilled portions of the wells and are labeled A, B, C, D, and E. The details included marsh funnel viscosity, mud density, plastic viscosity, and yield point. A total of 215 mud data with a total of 14 sections and six distinct mud types were obtained. The mud types include WBM (Floropro, KCI Polymer, Klashield, and Spud mud), and SBM (Kronos and Novatech). Details of the sections include: well 01 section A, well 01 section B, well 01 section C; well 02 section A, well 02 section B, well 02 section C; well 03 section A, well 03 section B; well 04 section A, well 04 section B; well 05 section A, well 05 section B, well 05 section D, and well 05 section E. Section A involved the use of Klashield WBM, Section B used Kronos SBM, Section C involved the use of Floropro WBM, Section D involved the use of spud (water based) mud and Section E involved the use of Novatech SBM.

The data were cleaned by identifying and correcting erroneous inputs, completely eliminating data points with missing data (as such were not suitable for the studies).

Data Analysis

Apparent viscosity values for each data point were obtained using equation 1. Equation 1 was used to obtain the apparent viscosity for each data point for all the mud samples. Five easily reproduced models from literature that required only marsh funnel viscosity and mud density as inputs were used to predict the apparent viscosity from the two inputs. This was done for each of the 14 sections gotten from the five wells considered. Furthermore, all the sections that involved the same mud type were aggregated into groups to further study the performance of the models on each mud type. A total of six groups, each representing a specific mud type used in different wells, were obtained. The performance of the models was evaluated using r-squared (R^2), mean absolute error, mean absolute percentage error, and root mean square errors (MAE, MAPE, and RMSE, respectively). The performance of each model on the mud data used in each of the 14 sections was evaluated, followed by an evaluation of the mud data grouped on mud type basis. The models used in this study include the models by Pitt,[29] Almahdawi *et al*.,[28] Elkatatny,[22] Al-Khdheeawi and Mahdi,[26] and Ofoche and Noynaert.[30] They are given by equations (2 – 6). The constants A_1 to A_6 in equation (5) are as given in.[26]

$$\mu_a = \frac{1}{2}\left[2PV + YP\right] \tag{1}$$

$$\mu_a = \rho\ (t\text{-}25) \tag{2}$$

$$\mu_a = \rho\ (t\text{-}28) \tag{3}$$

$$\mu_a = 18.833 \times \rho \times \log\ (t\text{-}30.9) + 0.9186 \tag{4}$$

$$\mu_a = A_{1\rho} + A_1\rho^{A3} + A_4\, t + A_5\, t^{A6} + A_7\rho t + A_8 \tag{5}$$

$$\mu_a = \frac{1}{2}(-11.5 + (3.708*\rho) - (0.01089*\rho^2) + (0.6174*t) - (0.00151*t^2) - \left(\frac{109.2*\rho}{4*(t-24.5)}\right) + 79.56\left(\frac{\rho}{4*(t-24.5)}\right)^2 \tag{6}$$

RESULTS

The results of the performance of all the five models on: Section A of each well is given in Figure 1; Section B of each well is given in Figure 2. The results of the performance of all the models on Sections C, D, and E of each well are given in Figure 3. The performance of the models on the mud-based analysis is given in Figure 4. Pitt model[29] had its best prediction on Well 04 Section B (Kronos section), followed by Well 01 Section C (Floropro section) and Well 02 Section B (Kronos section) but performed worst on Well 05 Section D (spud mud section), Well 05 Section C (Novatech section) and Well 05 Section E (Novatech section). Almahdawi *et al*. model[28] made its best prediction on Well 04 Section B (Kronos section), Well 01 Section C (Floropro section), and Well 02 Section B (Kronos section) but performed worst on Well 05 Section D (spud mud section), Well 05 Section B (Novatech section) and Well 04 Section A (Klashield section). It performed worst on spud mud. Elkatatny *et al*. model[19] made its best prediction on Well 04 Section B (Kronos section), followed by Well 01 Section C (Floropro section) and Well 04 Section A (Klashield section) but performed worst on Well 05 Section D (spud mud section), Well 03 Section B (Kronos section) and Well 02 Section C (Floropro section). Al-Khdheeawi and Mahdi[26] model made its best prediction on Well 03 Section A (Klashield section), Well 01 Section C (Floropro section), and Well 01 Section A (Klashield section) but performed worst on Well 05 Section B (Novatech section), Well 05 Section E (Novatech section), and Well 02 Section A (Klashield section). Ofoche and Noynaert model[30] made its best prediction on Well 01 Section A (Klashield section), Well 02 Section A (Klashield section), and Well 05 Section D (spud mud section) but performed worst on Well 03 Section B (Kronos section), Well 01 Section B (Kronos section) and Well 02 Section C (Floropro section). Also, it performed best on Klashield and KCI polymer.

DISCUSSION

The mud-based analyses showed that Almahdawi *et al*., Pitt, models[28,29] performed best on Kronos SBM and Floropro WBM; and Elkatatny model[22] performed best on Klashield WBM, KCI polymer (water-based) mud. The mud-based

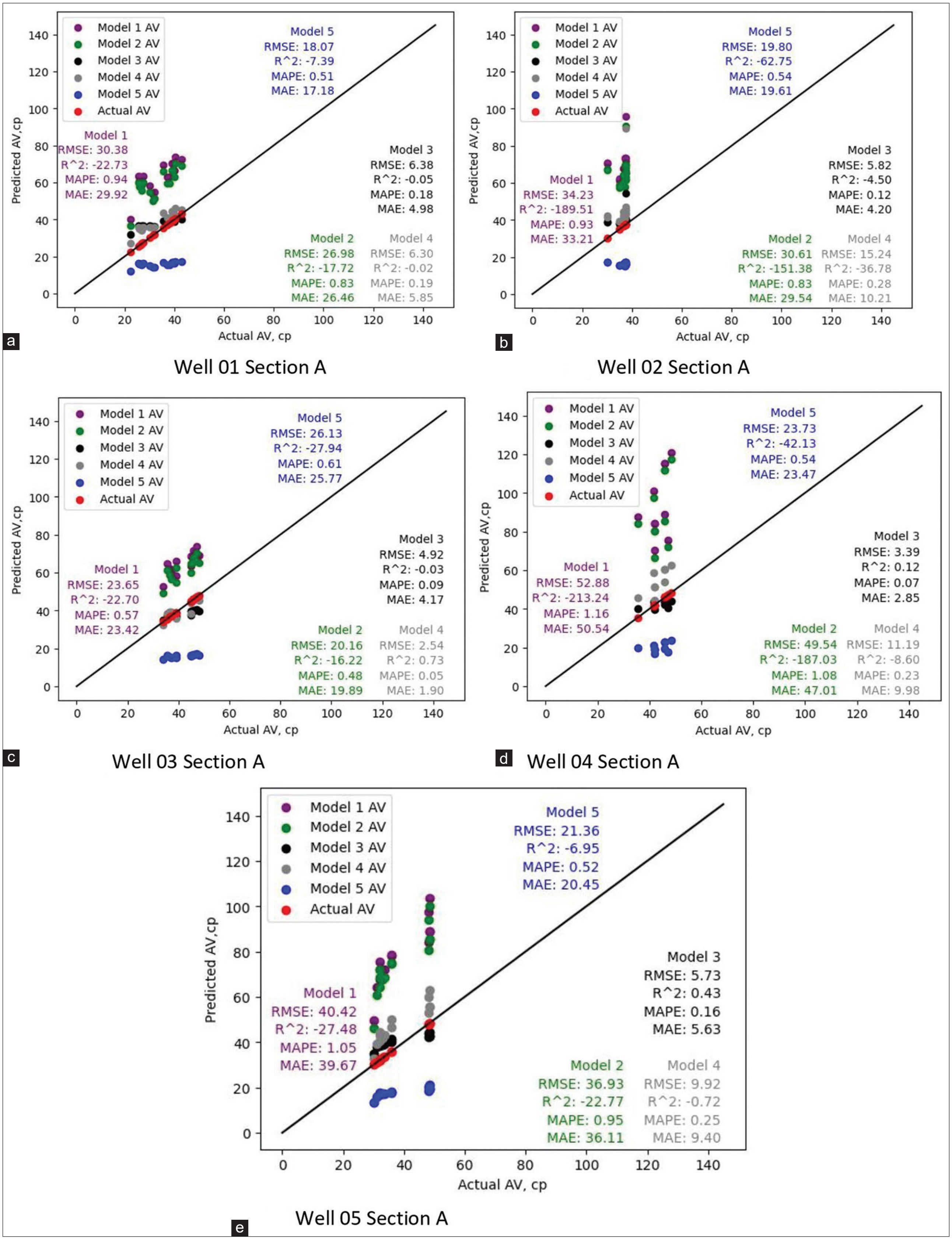

Figure 1: Performance of the models for Section A of different wells

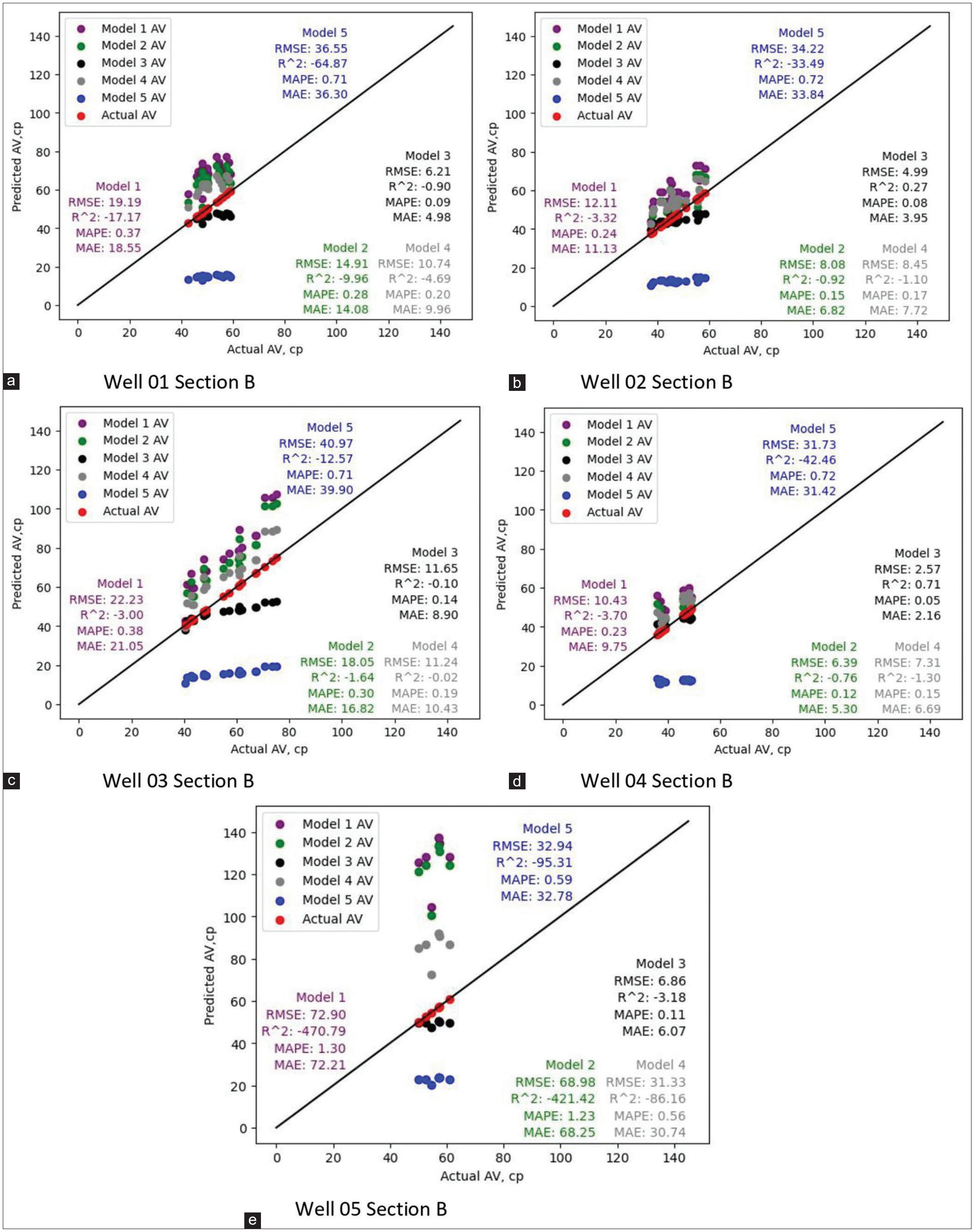

Figure 2: Performance of the models for Section B of different wells

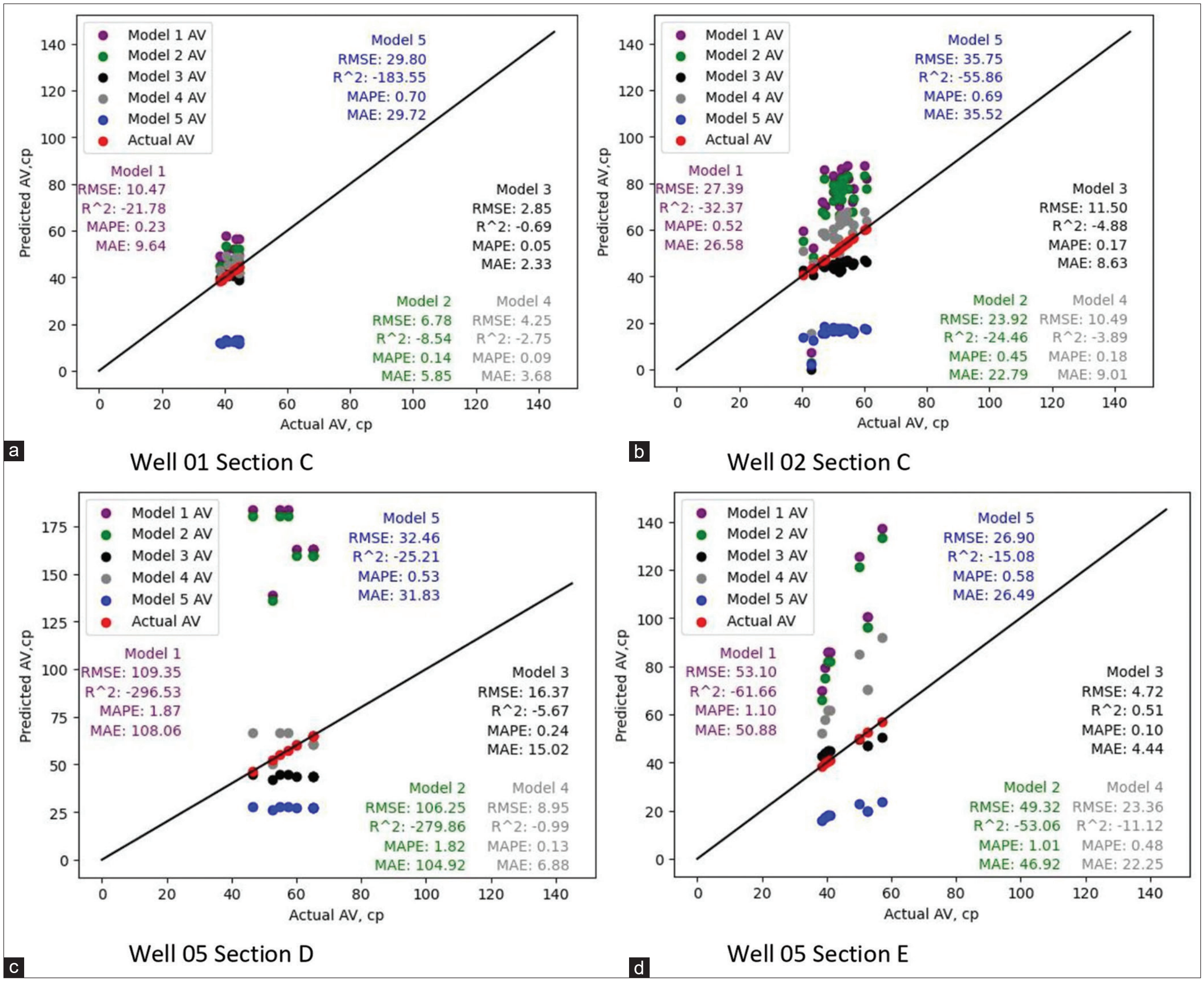

Figure 3: Performance of the models for Section C, D and E of wells 01, 02, and 05

analysis also showed that Al-Khdheeawi and Mahdi[26] model performed worst on Novatech. Al-Khdheeawi and Mahdi[26] were the only model that performed best on spud mud (followed by Kronos SBM) while Ofoche and Noynaert model[30] performed best on KCl Polymer and Klashield. Even though the models performed best on different models, it was found that a combination and comparison of the results of the different models were helpful in identifying mud sections where there was a likelihood of remarkable changes and also gave an idea of the magnitude of such change.

The Pitt model[29] performed differently for the same drilling fluid used in similar sections of two different wells having similar characteristics (Well 01 Section C and Well 02 Section C). It was seen from the well report that this shows that mathematical models can be used to identify anomalies in drilling fluids in real-time. From the drilling report, Well 01 Section B experienced an increase in pore pressure up to a certain point followed by a decrease in pore pressure. Well 02 Section C also experienced similar change in pore pressure. However, this seemed to be lesser to a certain degree than that of Well 01. Again, this may account for the slight variation in the accuracy level of the model on the mud used in these two sections having similar characteristics.

Four of the models predicted the RMSE of Well 02 Section C to be twice the RMSE of Well 01 Section C. This prediction could be traced to the wide gap between the average total gas and the peak gas, as well as the greater number of peaks experienced by Well 02 Section C compared to Well 01 Section C. This effect is more pronounced in Pitt and Almahdawi *et al*. model compared to Elkatatny model.

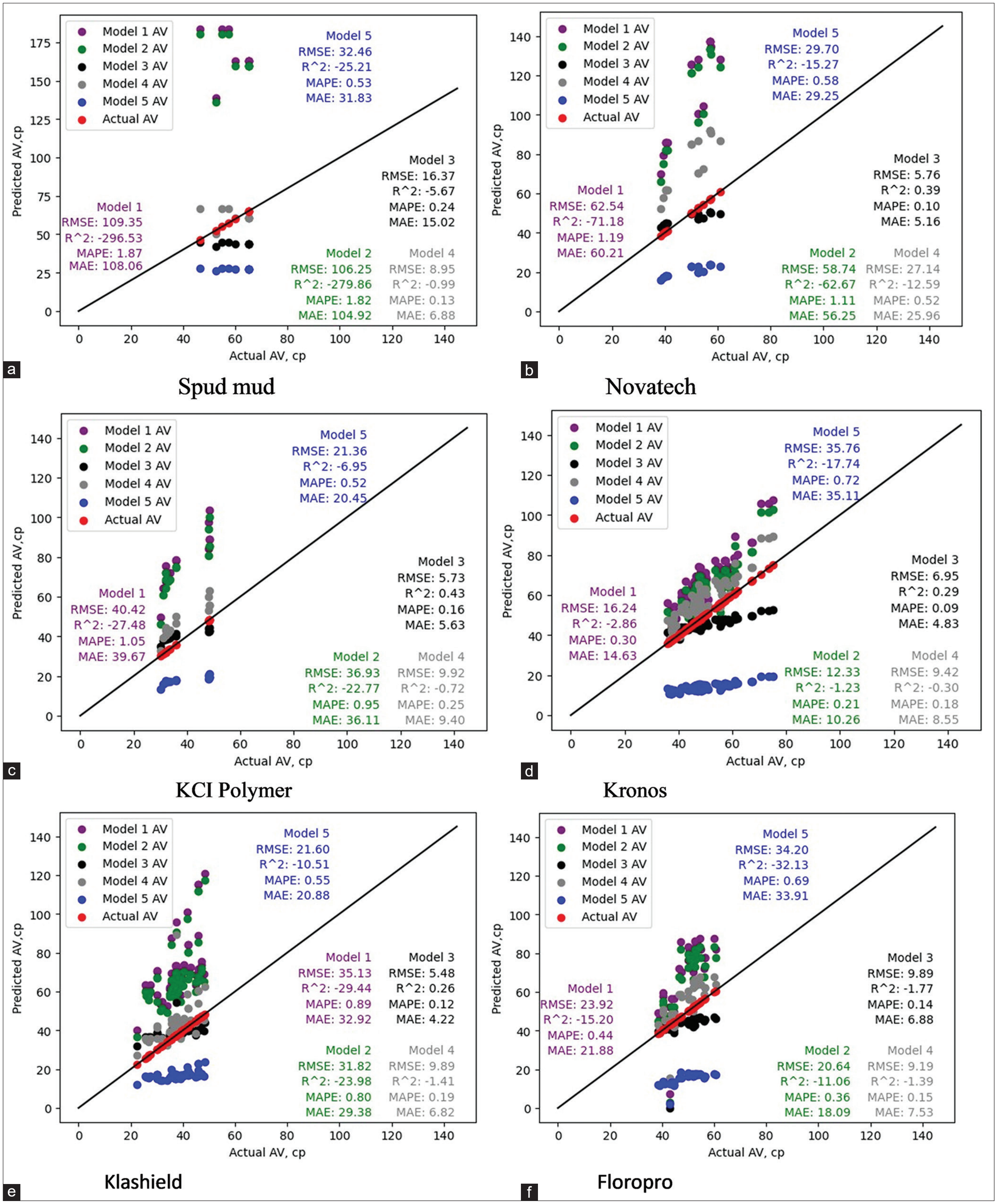

Figure 4: Performance of models on six different mud samples

Comparing the results from the models on Well 01 Section B and Well 02 Section B, it can be said that the differences in the accuracy measure could be due to occurrences in the well. This can be associated with the slightly greater fluctuation in pore pressure experienced in Well 01 Section B than that experienced in Well 02 Section B. Comparing this result with the Well 03 Section B, it can be said that a combination of the pore pressure fluctuation, moderate temperature range and moderate fluctuation in background gas may be the reason for the greater accuracy of the models on the mud in this section. The clear difference between the accuracy of the models on Well 03 Section B and the three other similar sections indicates a distinction in the conditions of that section. One of the possible reasons could be that this section had more gas peaks compared to the three other sections being compared.

The five models had greater accuracy on Well 05 Section E than on Well 05 Section B. This could be as a result of the marginal increase in the pore pressure experienced in the later section. Furthermore, the temperature gradient was higher in the later section than in the former section.

Unlike other sections where the different models showed a similar pattern in the results, the Klashield section did not show uniformity with regards to model performance. It is also worthy of note to reiterate that only one model made a prediction with an error values <10 on the spud mud used in this study. This goes to indicate that all available models must be history matched on available data before choice of the best predictor or model to be used as a benchmark.

Application to Real-Time Prediction

This work has shown that different models perform best on different drilling fluids. This implies that for a model to be chosen for a specific drilling fluid; there should be a history match of the models with previous drilling fluid data for that particular fluid, for each section of the well under consideration. The best performing model can then be chosen as the standard for the prediction process.

The use of the models can be in two forms. The first is a comparison of results generated by an individual model to ascertain an increase or decrease in value as a basis for identifying anomalies. That means the predicted values for the new data are compared with the predicted values for the data used for history matching. Given that the well conditions are the same, the results should be similar. Therefore, deviations from the history match would indicate a sign for further investigation. The second is a comparison of results from three models, the most accurate model and two other models to identify patterns of prediction to ascertain the possibility of an anomaly by comparing the trends in the prediction of the three models. This repeats the first step but does it for three other models with the goal of further identifying patterns. Furthermore, the models can be tuned, by adjusting some of the constant values, using real-time data to increase accuracy of predictions.

CONCLUSION

This work has shown that models based on marsh funnel viscosity and mud density tests can be used for real-time monitoring of mud properties to ascertain changes that would require attention. Just like marsh funnel tests do not point to the particular reasons for the changes in properties of the drilling fluid, these models do not proffer prediction as to the reasons for changes in mud properties but give a quick indication that there is a change in property so as to enable the drilling team to respond to such changes without having to wait for the more thorough routine tests required to ascertain such changes.

Furthermore, this work shows that these simple mathematical models can be used together with other available tests to further enhance the monitoring of the rheological properties of drilling fluid in real time. By investigating models based on marsh funnel tests, this work has shown the practical extension of the use of the marsh funnel in predicting and/or diagnosing drilling problems.

It is recommended that the models should not be used in isolation but as a family. That means using the different models to observe the behavior of the drilling fluid as described by the different models. This helps to give a broader spectrum of interpretation of the behavior of the models and thus helps to give a more robust interpretation to the behavior of the drilling fluid itself.

There is need for a similar study to be conducted with a larger database so as to ascertain the full scope of the usefulness of the proposed method.

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