С Е К Ц И Я 6

ТЕХНОЛОГИИ ОЦЕНКИ, УПРАВЛЕНИЯ И РАЗРАБОТКИ МЕСТОРОЖДЕНИЙ НЕФТИ И ГАЗА, МОДЕЛИРОВАНИЕ И ЦИФРОВЫЕ ТЕХНОЛОГИИ

A ROBUST HYBRID REAL-TIME MODEL FOR HOLE CLEANING CONDITIONS BASED ON CONCENTRATION OF CUTTINGS IN THE ANNULUS

Mohammed Al-Shargabi[1], Shadfar Davoodi[1], Mohammed Al-Rubaii[2], V.S Rukavishnikov[1]
[1]National Research Tomsk Polytechnic University, Tomsk, Russia
[2]Saudi Aramco, Saudi Arabia

The main problem with hole cleaning is ineffective removal of cuttings from the wellbore. This can lead to accumulation of cuttings in the wellbore which causes problems like stuck pipe, increased drag and torque, loss of drilling fluid etc. Cleaning is more challenging in deviated and horizontal wells where cuttings can settle out on low side of the wellbore. Therefore, it is important to develop a robust hybrid real-time model based on concentration of cuttings in annulus (CCA_{RM}) and apply the artificial intelligence (AI) as it allows continuous monitoring and evaluation of hole cleaning conditions during active drilling operations. The model incorporates main drilling parameters like rate of penetration (ROP), flow rate, density etc as input to calculate CCA and help identify any issues with hole cleaning in real-time. This enables timely corrective actions to be taken to prevent problems and improve drilling performance. This helps identify issues promptly and take corrective actions to avoid problems like stuck pipe. It also helps optimize drilling parameters for better performance. The novel robust hybrid real-time model (CCA_{RM}) is delineated by the subsequent Equation 1 [1,2]:

$$CCA_{API} = \frac{ROP \cdot OH^2}{1471 \cdot GPM \cdot TR} \quad (1)$$

where ROP is the rate of penetration (ft/h), OH is the diameter of the hole size (inch), GPM is the mud pump's flow rate (gal/min). Moreover, New it suggested an improved CCA model for the vertical conveyance of materials in a stable condition inside a tube (see Equation 2). In addition, Mitchell provided empirical data that supports the development of a concentric concentration model. This model includes the pre-connection circulation that happens when drilling stops and the post-connection circulation that happens before drilling resumes. The temporal phase, known as the connection circulation period, is often acknowledged as the following one. The annulus represents the specific area defined by the given equation, enabling us to compute the average cutting volume percentage as determined by Equation 3 [2, 3].

$$CCA_1 = -\frac{1}{2}\left(\frac{Vann_m}{V_{sa}} - 1\right) + \left(\frac{1}{4}\left(\frac{Vann_m}{V_{sa}} - 1\right)^2 + \frac{Vann_m}{V_{sa}}\frac{Vc}{\frac{GPM}{7.48}}\right)^{0.5} \quad (2)$$

$$CCA_2 = \frac{1}{1 + \left(1 - \frac{OD}{OH}\right)\left(\frac{Vann_m - V_{sa}}{30}\right)\left(\frac{1800}{1 + ROP} + \frac{V_{sa}}{V_{ann.dc} - V_{sa}} \cdot T_{PC}\right)} \quad (3)$$

where $Vann_m$ denotes the altered velocity of the drilling fluid within the annular space (ft/min) in according with [4], $V_{ann.dc}$ denotes the annular velocity across the drill collar (ft/min), T_{PC} denotes the preconnection circulation time refers to the duration necessary for the cuttings to circulate to a sufficient height, thereby preventing their settlement at the bottom of the borehole while establishing the connection (min), V_{sa} is the average velocity of cutting slip (ft/min), and V_c is the volumetric rate of cuttings entering the annulus (ft/min). Moreover, an automated developed model was developed based on GPM and ROP (Equation 4) [5].

$$CCA_{\text{at}} = \frac{1 - \frac{(GPM - ROP)}{(GPM + ROP)}}{10} \quad (4)$$

Accordingly, utilizing Equations 1–4, the robust hybrid real-time model can be obtained from Equation 5.

$$CCA_{RM} = \frac{CCA_{API} + CCA_1 + CCA_2 + CCA_{\text{at}}}{4} \quad (5)$$

Based on the calculated results of the developed model, the modified CCA_{RM} is considered to have a high degree of cuttings accumulations when CCA_{RM} value is more than 0.05. CCA_{RM} values ranging from 0 to 0.03 are considered acceptable and fall within the required range as no accumulations of cuttings. CCA_{RM} values between 0.03 and 0.05 signify an appropriate and optimised condition.

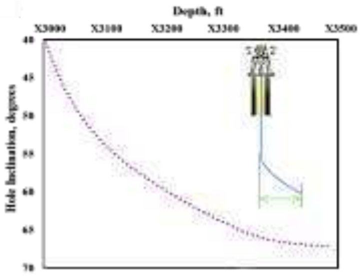

Fig. 1. A schematic well configuration used in the study

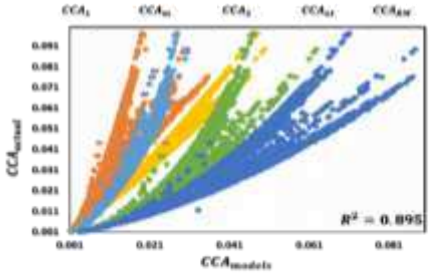

Fig. 2. The novel CCA_{RM} vs CCA1, CCA2, CCAat, and CCAm

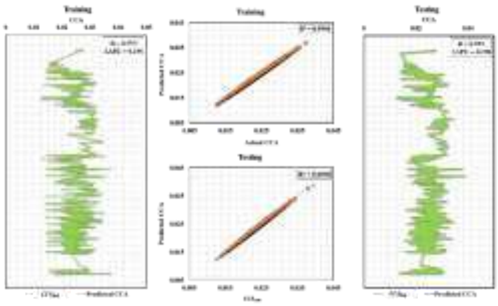

Fig. 3. Comparison of field applications with AI applications using the novel model CCA: Training and Testing prediction with coefficient of determination (R^2)

Methodology and methods

The new CCA_{RM} model was successfully demonstrated during directional drilling operations of the offshore $12^{1/2}$ well, Well-A in case of stuck pipe (Fig. 1). The well showed significant deviations and was used to evaluate hole cleaning conditions in the intermediate section, specifically at depths ranging from X3000 to X3500 ft. The drilling encountered sandstone, limestone, and shale formations, with temperatures ranging from 140 to 155 °F, porosity varying between 0.15 and 0.25, and washout phenomenon ranging from 10 % to 30 %.

Applications in the Field Utilizing the Novel Models

The novel CCA_{RM} model was successfully applied in real-time as an indicator for cuttings accumulations during drilling operations, as demonstrated by its high accuracy and strong correlation with the actual CCA values (R^2 value of 0.895). This indicates that the model can effectively predict cuttings accumulations and provide early warnings of potential stuck pipe situations, allowing for prompt interventions and mitigation strategies to be implemented [3–6]. The CCA_{RM} model's accuracy and reliability make it a valuable tool for drilling operators, as it can help to improve drilling efficiency, reduce costs, and enhance safety by minimizing the risk of stuck pipe occurrences. Additionally, the model's ability to provide real-time data analysis and visualization enables operators to make informed decisions quickly and effectively, allowing for more efficient drilling operations. More importantly, the application of artificial neural network (ANN) to the CCA_{RM} model was important because it allowed for the development of a highly accurate and flexible model that can predict hole cleaning performance with a high degree of accuracy. The graphical representation of the data provided by the ANN also helped to provide insights into the underlying mechanisms that affect hole cleaning performance. Figure 3 showcases the ANN application of the novel model CCA_{RM}, which boasts a high accuracy of prediction with an R^2 value of 0.9996. This is evident in the graphical representation, where the novel model for CCA_{RM} produces similar results.

Conclusions

In conclusion, the modified CCARM model is a reliable and accurate tool for predicting cuttings accumulations during drilling operations. The model's high accuracy and strong correlation with actual CCA values demonstrate its effectiveness in providing early warnings of potential stuck pipe situations. The CCARM model's ability to provide real-time data analysis and visualization enables operators to make informed decisions quickly and effectively, allowing for more efficient drilling operations. The application of ANN to the CCARM model was important because it allowed for the development of a highly accurate and flexible model that can predict hole cleaning performance with a high degree of accuracy. The graphical representation of the data provided by the ANN also helped to provide insights into the underlying mechanisms that affect hole cleaning performance. Overall, the novel CCARM model is a valuable tool for drilling operators, as it can help to improve drilling efficiency, reduce costs, and enhance safety by minimizing the risk of stuck pipe occurrences.

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HORIZONTAL WELL PRESSURE PREDICTION APPLYING MACHINE-LEARNING MODEL

Piskunov S., Davoodi S.
Scientific advisor professor L.M. Bolsunovskaya
National Research Tomsk Polytechnic University, Tomsk, Russia

Predicting pressure parameters is an important prerequisite for successful field development. Accurate prediction of pressure behavior is essential for drilling plans, enhanced oil and gas recovery programmes and reservoir development strategies. Knowledge of these parameters greatly increases the chances of successful and efficient production. It also helps to make the economic model more accurate and predictable [1].

The most common approach to determining well pressure worldwide is the diffusivity equation [2]. The diffusivity equation relates the pressure and time, radius. This equation is based on material balance and Darcy's law [5]. According to this equation, the main factors affecting the fluid pressure are viscosity of liquid, permeability, porosity, total compressibility, wellbore radius, radial distance from well, time [6]. It is considered to use time and radius in a dimensionless form. The well design must also be taken into account [1]. It becomes a difficult task to evaluate all the above factors in the process of field development, as there is a constant change in formation energy (pressure, aquifer), deterioration of bottomhole zone (skin factor), decrease in phase permeability due to flooding of the near-wellbore zone, the influence of relative phase permeability (RPP), formation fluid properties (PVT), and reservoir heterogeneity in general.

Nowadays, there are various methods of well pressure prediction. Nevertheless, they have different accuracy and take different amounts of time. The mathematical approach is the fastest, but on the other hand, it has the lowest level of accuracy and a number of assumptions. At the same time, the method of using simulators is more accurate than the mathematical method, but it requires large time expenditures. In order to determine the well pressure a large amount of information about the field is needed, which introduces its uncertainty in the final prediction. The essence of the method lies in the use of software packages that allow, using the law diffusivity equation and geological information, to iteratively calculate well pressure. This approach allows to replace complex analytical formulas with numerical calculations: the solution based on simplification (approximation) by simpler expressions [1]. Simulators are the most accurate possible way to predict well pressure, which helps to estimate the production profile. They allow evaluating the uncertainty and risks of further development. However, at the same time, it requires many calculations and a large amount of time to create these profiles. To ensure the accuracy of the simulator and the speed of mathematical calculations, it is proposed to use machine learning. This approach will identify the patterns and analytical formulae embedded in the simulator, which will allow further use of this model for rapid production and risk assessment in general [1].

In recent years, attempts have been made to apply machine learning and AI in oil and gas area. For example, in drilling [9], geophysics [8], reservoir engineering [7]. This method is not only easy to implement, but also can capture the complex relationship between input and output datasets. This approach is based more on data analysis, interaction and correlation of system parameters rather than physical processes.

The main purpose of this paper is the development of a machine-learning model to quantify well pressure based on geological properties at different time steps. The object of the research is stock of horizontal wells in a gas condensate field in Western Siberia.

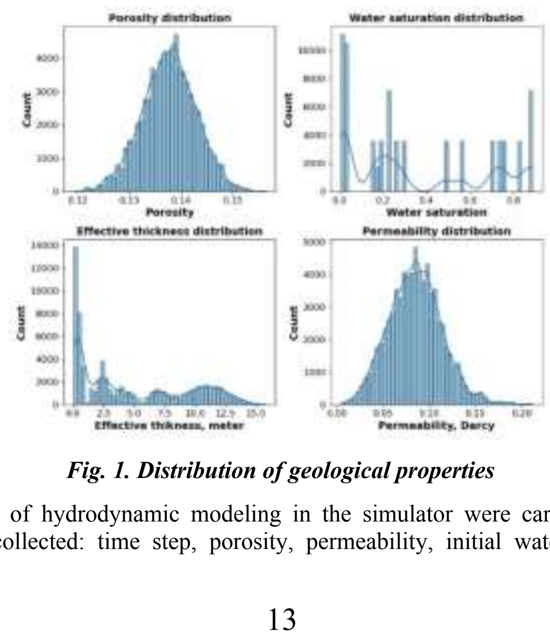

Fig. 1. Distribution of geological properties

At first, 300 iterations of hydrodynamic modeling in the simulator were carried out. An initial data set with the following parameters was collected: time step, porosity, permeability, initial water saturation, reservoir thickness,