Data-Driven Modeling in Drilling in Well Operations

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Swab and surge pressure fluctuations are decisive during drilling for oil. The axial movement of the pipe in the wellbore causes pressure fluctuations in wellbore fluid; these pressure fluctuations can be either positive or negative, corresponding to the direction of the movement of the pipe. For example, if the drill string is lowering down in the borehole, the drop is positive (surge pressure), and if the drill string is pulling out of the hole, the drop is negative (swab pressure). The intensity of these pressure fluctuations depends on the speed of the lowering down (tripping in) or withdrawing the pipe out (tripping out). High tripping speed corresponds to higher pressure fluctuations and can lead to fracturing the well formation. Low tripping speed leads to a slow operation, causing non-productive time, thus increasing the overall well budget.

swab and surge pressure | drilling for oil | tripping-in | tripping-out | models for swab and surge

1. Introduction

Swab and surge is a well-known problem for drilling and well construction operations. Researchers have been investigating this problem since the 19th century. Swab and surge refer to pressure fluctuations due to lowering or withdrawing the pipe from the hole. See **Figure 1**.

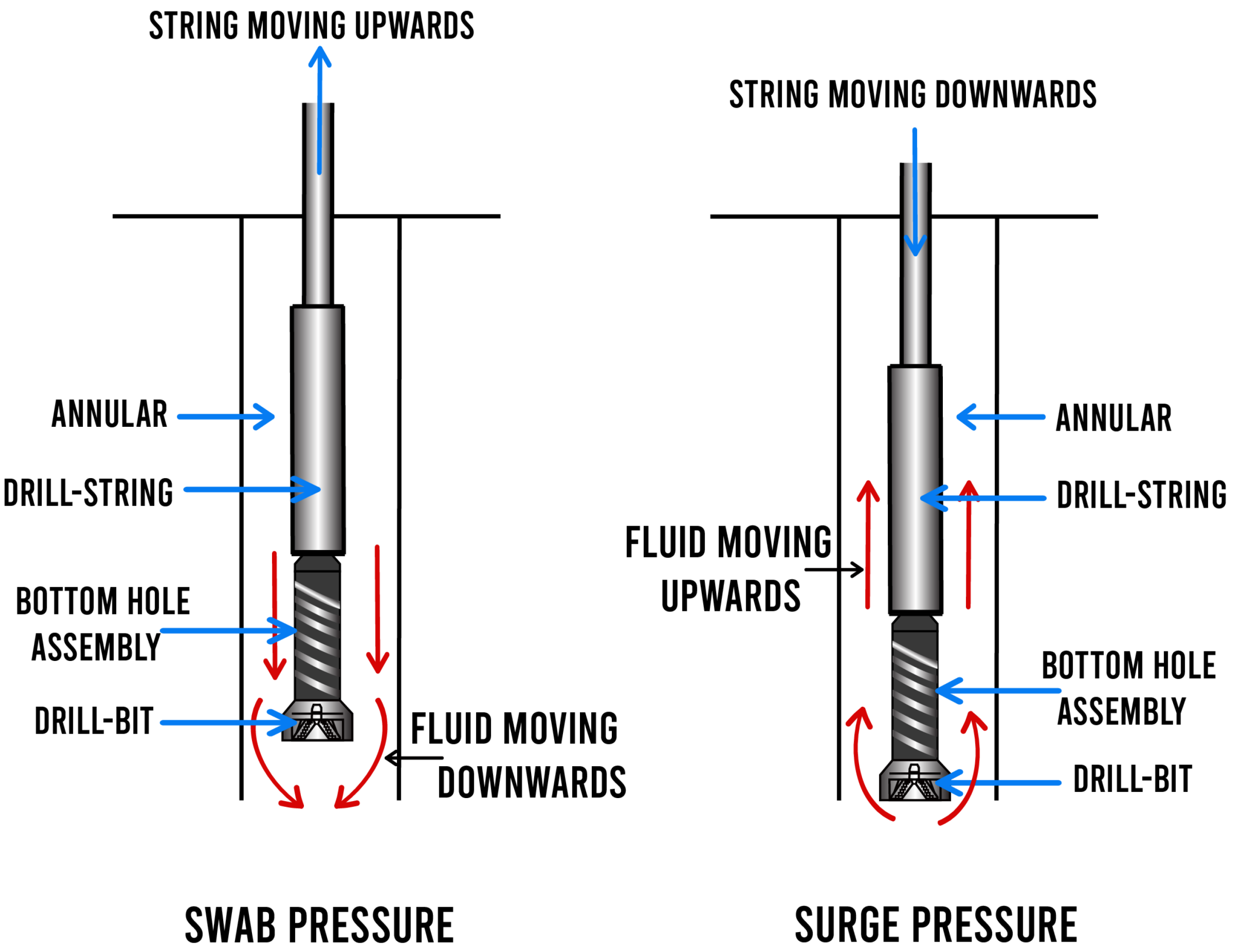

Figure 1. Swab and surge pressure fluctuations.

Swab and surge pressure fluctuations are either positive or negative. They are positive when lowering down the pipe and negative when withdrawing the pipe. The intensity of these pressure fluctuations depends on the speed of the lowering down (tripping in) or withdrawing the pipe out (tripping out). If the tripping speed is very high, the corresponding pressure fluctuation is high, and in some cases, this can be higher than the fracture pressure of the formation. This will cause fracturing the formation, partial or in some cases full losses, and in a worst-case scenario well collapse can occur. If the tripping speed is too low, this leads to a slow tripping operation, which is considered non-productive time (NPT), increasing the overall well budget.

2. Data-Driven Modeling in Drilling in Well Operations

Many researchers have recently made a paradigm in drilling and well operations and implemented data-driven techniques to improve operational performance and reduce risks. Traditionally, the oil and gas industry, especially drilling, heavily relied on the analytical modeling approach. However, recent advancements such as big data, data analytics, machine learning modeling, and AI modeling have tremendous value creation in other industries. Hence, the oil and gas industry and drilling are also implementing these techniques to create value through performance improvements and reduce risks.

The oil and gas industry's decision-making process revolves around quantifying uncertainty, limiting risk, and maximizing profit, as well as speed. The ever-increasing amount of data collected due to technological advancements can drastically improve the intuitive judgments made in numerous day-to-day operations. However, the data's potential advantages can only be realized if the correct tools are used to combine various forms of data and translate it into valuable information that can be used to draw wise conclusions.

2.1. Applications of Data-Driven Techniques in Oil and Gas

Data-driven approaches are effective instruments for transforming information into knowledge. Due to a lack of well-organized data, historical data has not been used effectively in assessing operations. However, there is an enormous potential for turning terabytes of data into knowledge. Data-driven models have become increasingly commonly employed in the analysis, predictive modeling, control, and optimization of numerous processes due to improvements and implementation of data-driven approaches. Even though physics and geology are frequently included in this technique, the industry as a whole is still cautious of the adoption of data-driven methods since they are data-based solutions rather than traditional physics-based approaches [1].

2.2. Subsurface Characterization and Petrophysics

In the oil and gas industry, mathematical models are commonly employed. For example, Taner et al. [2] created a mathematical model that describes how complicated trace analysis is applied to seismic data and how it might be used in geologic interpretation. On the other hand, mathematical models have severe constraints and are more difficult to mimic. Therefore, several researchers in the oil and gas industry have also employed data-driven methodologies. Specifically, reservoir management and simulation, production and drilling optimization, real-time drilling automation, and facility maintenance are the key application areas [3]. This section will look at some of the applications of the stated data-driven methodologies in various industries.

Ouenes [4] investigated the usefulness of fuzzy logic and neural networks in fractured reservoir characterization, using three phases to compare the performance of two alternative models. Ouenes [4] showed that by employing fuzzy curves, the influence of each model input on fractures can be characterized, and the factors that may have a high link with fractures can be determined [5]. Al-Anazi et al. [6] presented research that used support vector regression (an SVM extension) to accurately estimate the porosity and permeability values for a field. Hosseini et al. [7] demonstrated how a random forest tree algorithm supported by a naive Bayesian operation might be utilized to analyze field permeability.

For intersecting and near-well fracture corridors, Ozkaya [8] demonstrated the use of decision trees. Chamkalani et al. [9], El-Sebakhy [10], Tohidi-Hosseini [11], and Ahmadi et al. [12] have used SVM and decision trees to predict gas PVT characteristics as well as oil–gas interaction. Analyzing logs and generating missing log tracts are two of the most common artificial intelligence applications. For example, to produce a sonic log to assess over-pressured zones at the Anardarko Basin, Cranganu et al. [13] used a Support Vector Regression technique.

Akande et al. [14] created a support Vector Regression approach supported by an evolutionary algorithm to generate the best hydrocarbon estimations from logs acquired from logs from a reservoir. Another use of machine learning was estimating a reservoir's Total Organic Content using log data [15]. Masoudi et al. [16] created a supervised Dymanic Bayseian Network (DBN) algorithm that learned from logs to produce a model for identifying reservoirs without the need for user-defined cut-offs. Anifowose et al. [17] suggested an ensemble SVM approach for predicting porosity and permeability values comparable to the random forest tree algorithm.

2.3. Drilling

Drilling has made significant progress, particularly in risk control, regulated rate of penetrations, and so on. Ahmadi et al. [12] utilized SVM to model the rheology of many drilling fluids under various environmental circumstances. Cross-verification also revealed a strong agreement between the forecast and the test data. Fatehi et al. [18] used deposition information to construct a transductive support vector machine system for mapping possible drilling targets during exploration. Zhang et al. [5] developed a Dynamic Bayesian Network (DBN) to efficiently analyze risk and uncertainty in controlled pressure drilling. This approach takes into account several elements to calculate uncertainty utilizing additional probability parameters. DBN was also utilized by Al-Yami et al. [19] to create a drilling expert system based on reservoir and fluid data. Bhandari et al. [20] developed a technique to anticipate the conditions that lead to an offshore blow-out, particularly during conducted measured pressure drilling and unbalanced drilling, as well as risk analysis. Sule et al. [21] conducted a similar study that looked at the robustness of system controls after recreating kick circumstances used in measured pressure drilling. Chang et al. [22] also used DBN algorithms to examine emergency riser disconnection modules. Six disconnected module criteria linked the DBN system and the failure tree investigation. Cai et al. [23] used a DBN to investigate the dependability of Blowout Preventer redundancy in deep-sea wells. Principal component analysis was utilized by Kormaksson et al. [24] to find economically viable sites for new wells. Bakshi [25] developed a unique nonlinear regression model to predict shale oil well performance, including optimal well sites and completion parameters. Temizel et al. [26] investigated the factors that impact vertical and horizontal well performance in confined reservoirs.

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