AUTONOMOUS EDGE APPLICATIONS FOR SUCKER ROD PUMP OPTIMIZATION: A CASE STUDY IN THE BAKKEN BASIN

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Introduction

Artificial lift systems (ALS) play a critical role in global oil and gas production, with approximately 84% of oil wells and 42% of gas wells utilizing some form of ALS. Among these, sucker rod pumps (SRPs) remain the most widely used method, accounting for approximately 40% of the global installed base, followed by electrical submersible pumps (ESP) at 24%, gas lift at 20%, and plunger lift at 9% (Research, 2022)

In the United States, over 88% of oil wells require an ALS, with SRPs being the most preferred method, making up 54% of all ALS wells. In key basins, rod lift remains dominant— in the Permian Basin alone, approximately 100,000 wells operate on SRPs, while the Bakken and other major basins also rely heavily on this technology. The widespread use of SRPs highlights the significant potential for improving production optimization through advanced methodologies.

Automation is increasingly shaping artificial lift operations, with approximately 72% of artificially lifted wells in North America utilizing some form of automation (Research, 2022). However, operators have identified key areas for improvement, including enhanced data accuracy, predictive analysis with AI, improved communication and data transfer, frequent software updates, and more cost-effective solutions to support production optimization. As the industry shifts toward data-driven decision-making, the adoption of predictive production optimization solutions is expected to grow, allowing operators to improve efficiency and production outcomes through remote operational capabilities.

Rod pump production optimization has been an ongoing focus in the industry, with the primary objective of maximizing well production potential while minimizing failures due to mechanical wear, excessive cycling, corrosion, or fatigue. Failures in SRPs remain a persistent challenge, and early detection is crucial for maintaining efficiency. A study on a subset of eight wells demonstrated that the mean time between failures improved from 7 months to 21.4 months after implementing Edge Technology (Jared Bruns, 2022) reinforcing the value of advanced optimization solutions.

However, rod lift optimization presents challenges, particularly in achieving precise pump speed control and dynamically adjusting to reservoir conditions. Traditional optimization approaches rely heavily on operator experience and rule-of-thumb practices, often using pump-off controllers (POCs) and variable speed drives (VSDs). With increasing levels of well instrumentation, edge computing technology is emerging as a powerful solution to enhance real-time production optimization. By leveraging edge devices and automation, operators can improve efficiency, reduce failure rates, and optimize pump performance with greater precision.

Rod Pump Speed Control: Present-Day Practices and Challenges

Pump-Off Controllers (POCs) play a crucial role in sucker rod pump (SRP) operations, using predefined settings to manage pump speed and cycling. However, these settings require manual adjustments, introducing subjectivity and potential inefficiencies. Misconfigured speed setpoints—whether too high, too low, or improperly calibrated—can lead to pump failures, excessive cycling, or production losses. The most common optimization method, Pump Fillage (PF) control, relies on PID algorithms to maintain target PF values. However, these setpoints are static, failing to adapt to reservoir changes over time. As a well's deliverability declines, the optimal PF and strokes per minute (SPM) must also adjust dynamically. The Production Optimizer algorithm presented in this paper overcomes these limitations by enabling real-time, automated optimization, allowing SRPs to operate beyond rigid POC-defined ranges. By integrating IIoT and edge computing, this approach enhances efficiency, reduces failures, and ensures wells produce at their optimal performance throughout their lifecycle (Gambaretto, Yermekova, Srivastava, & Hyder, 2024).

Present Day Solution

This paper presents an advanced workflow designed to improve the efficiency and performance of SRP systems. It builds on existing POC capabilities, which traditionally prevent over-pumping and optimize SRP operations. This innovative approach integrates edge-based technologies, significantly enhancing automation and intelligence. By incorporating machine learning (ML) algorithms, the system can classify dynamometer card patterns in real time, enabling precise identification of operational events and anomalies.

Utilizing high-frequency dynamometer card and pump data, the system autonomously adjusts SRP operational setpoints to maintain optimal performance, minimize energy consumption, and reduce equipment wear. Additionally, a holistic approach is employed, where well parameters and operational data are automatically fed into a solver to determine optimal frequency setpoints for continuous production optimization. This interconnected framework not only enhances data reliability and accuracy but also ensures seamless integration with broader digital oilfield initiatives. The key challenge was to harmonize these workflows to enable autonomous SRP optimization without any conflicting processes.

Proposed Edge - Based Workflows

1. **Real-Time Dynamometer Card Analysis and Classification**

POCs generate dynamometer cards for each stroke of a surface pumping unit (SPU) or pumpjack using load cells and inclinometers. However, POCs are limited in their ability to analyze and classify every card in real time. Edge computing overcomes this limitation by processing every single dynamometer card directly at the wellsite, instantly identifying and classifying SRP operating conditions without delays.

Leveraging advanced ML and deep learning (DL) techniques, the Edge system continuously analyzes high-frequency dynamometer data, detecting operational patterns and anomalies as they occur. This enables real-time classification of six key SRP behaviors: normal operation, fluid pound, gas interference, tagging, flatlining, and distortion (Fig. 1). Unlike POCs, which cannot classify every individual card, Edge computing ensures that no critical data is missed, providing a comprehensive and immediate understanding of pump performance.

Additionally, the ML algorithm provides both primary and secondary classifications for each card, along with probability scores indicating classification confidence. Classified cards undergo reclassification as needed and are added back into the ML training pool to improve model accuracy over time. In cases where a card is reclassified, a Subject Matter Expert (SME) reviews and validates the updated classification before incorporating it into the training dataset.

Following edge-based analysis, a subset of dynamometer cards—typically at one-minute intervals—is transmitted to the cloud. This allows engineers to remotely visualize and monitor well performance through an application, enabling proactive decision-making and optimization without requiring physical presence at the wellsite (Z. Hyder, 2024)

2. **Fast Loop Mitigation Based on Dynamometer Card Classification**

This workflow enables autonomous mitigation of well conditions classified as abnormal. When consecutive dynamometer cards indicate issues like gas interference, fluid pound, tagging, or flatlining, the Edge system adjusts the rod pump's speed in real time to stabilize operations. Once normal conditions resume, the pump returns to its original speed.

Mitigations help prevent unnecessary shutdowns by intervening before secondary pump fillage (PF) limits trigger a shutdown. Safety checks ensure that speed adjustments remain within allowable limits, protecting SRP equipment. Flatlining, a critical issue where energy is used but no liquid is produced, prompts immediate mitigation. If initial speed adjustments fail, the system escalates by sending alarms and, if necessary, shutting down the pump to prevent further inefficiency (Z. Hyder, 2024).

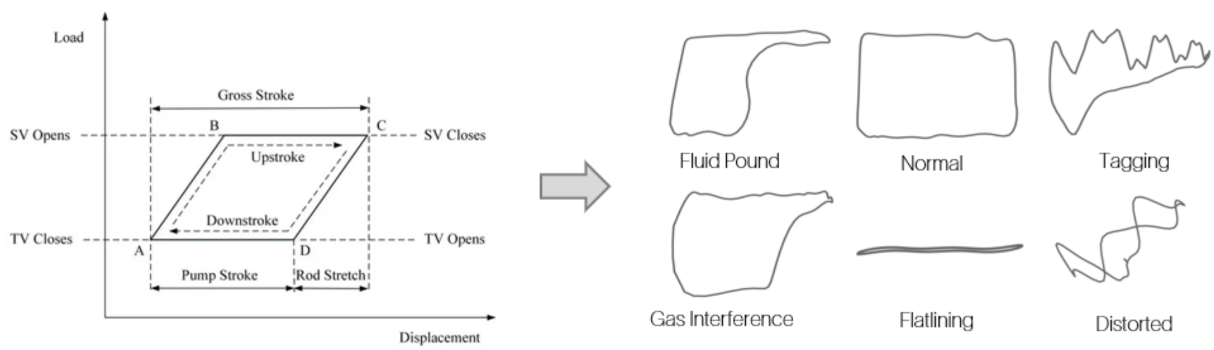

Figure 1: Theoretical dynamometer card shape (Cheng et al. 2020) vs. actual card shapes for different operating conditions

3. **Production Optimizer**

The Production Optimizer (POPT) algorithm is designed to enhance SRP performance by dynamically adjusting pump speed based on real-time well conditions. Unlike traditional methods that rely on static PF setpoints, the POPT (Gambaretto, Yermekova, Srivastava, & Hyder, 2024) algorithm uses a rolling window approach to continuously evaluate operational parameters and determine the optimal speed for maximum production efficiency.

The workflow begins with data ingestion and preprocessing, where key well parameters—mainly PF, strokes per minute (SPM), shutdown events, runtime, shutdown duration, and cycle counts—are collected and enriched with additional features. The algorithm activates automatically when enabled on a well, continuously learning from incoming data.

Following preprocessing, the algorithm categorizes the well's historical performance by pump operating speeds and calculates key performance indicators (KPIs) to assess production efficiency. The three primary indicators are:

- Production Indicator (PI): Identifies the speed setpoint that maximizes fluid production.
- Combined Indicator (CI): Balances uptime and production by penalizing excessive shutdowns.
- Combined Indicator – Quadratic Penalty (CI-QP): Applies stricter penalties on excessive cycling to stabilize wells with high secondary PF setpoints or VFD speeds.

Once these indicators are computed, the algorithm assesses whether adjusting the current VFD speed will increase production while maintaining pump health. The optimization logic follows these key rules:

1. If increasing speed improves production, the algorithm raises the VFD frequency incrementally.
2. If production declines at higher speeds, the algorithm reduces the VFD frequency to avoid inefficient operation.
3. If production remains stable at the current setpoint, no changes are made until further optimization is required.

A crucial aspect of the algorithm is its ability to detect extreme PF conditions. When the system encounters very high or very low PF scenarios, it assesses whether the well can produce more efficiently at an alternate speed range. If the well experiences high PF but low production, the algorithm gradually increases speed to test for improved output. Conversely, if the well exhibits low PF with high speed, the algorithm slows down the pump to reduce stress on equipment and improve efficiency (Fig 2).

By leveraging continuous real-time monitoring and adaptive control logic, the POPT algorithm ensures that each well operates at its most efficient and economical speed. This autonomous optimization approach eliminates the need for manual adjustments, reduces operator intervention, and enhances overall production stability.

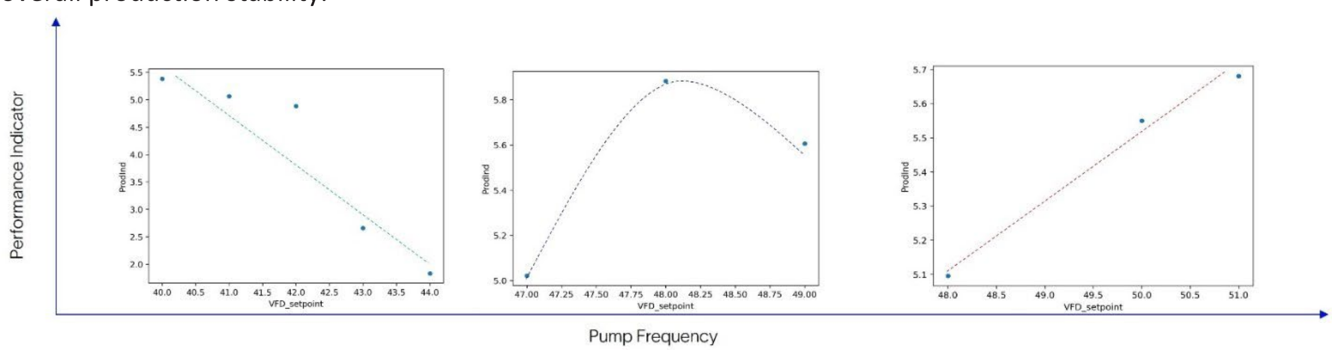

Figure 2: Rolling window examples of KPIs vs frequency set points

Case Study – Bakken (Williston) Basin

A pilot was conducted on 8 wells from the Bakken Shale located in the Williston Basin. These were deep horizontal wells completed using multi-stage hydraulic fracturing techniques. In this pilot, the POPT algorithm was tested while working in parallel with fast loop mitigations. During the simultaneous algorithms working together, we prioritize mitigations first, as it helps to solve the local & immediate pump issues. Multiple workflows, complimenting each other were tested on the wells. As can be seen in figure 4, an instance in time between 22:00 and midnight is analyzed, where several systems work in unison to maintain continued operations on well A. The graph showcases the following parameters, Pump Fillage (percentage – %), VFD Maximum Working Speed (Hertz – Hz), Measured Speed (strokes per minute – SPM) and the states of the Gas Interference Mitigation & Tagging Mitigation algorithms.

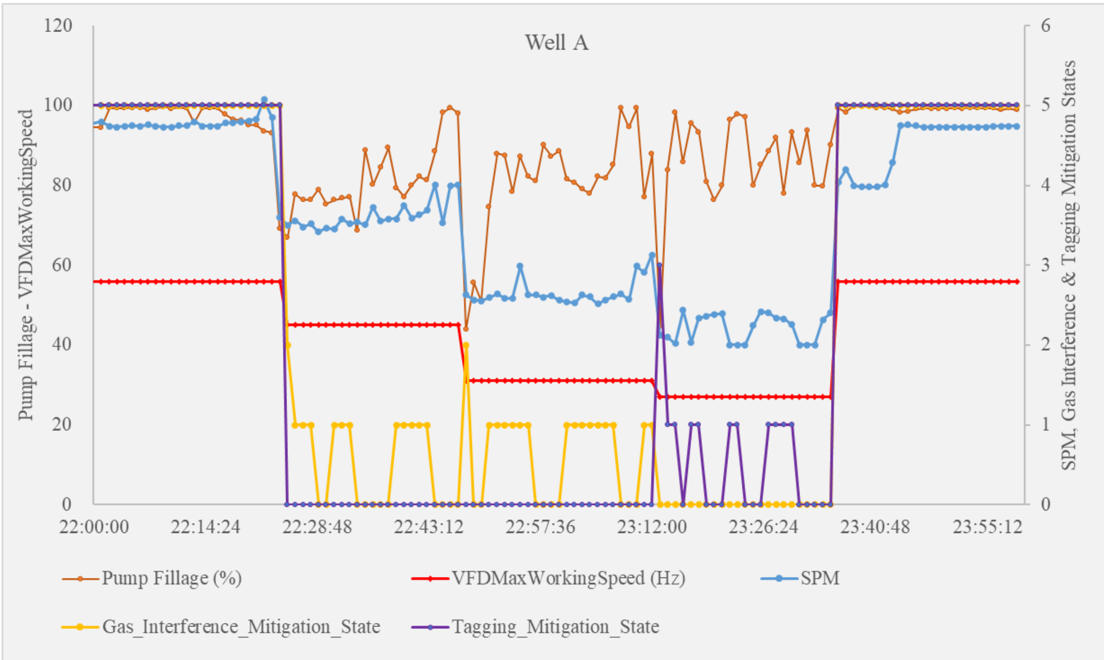

Figure 3: Multiple mitigations & POC control engaging on Well A

As can be seen in figure 3, an instance in time between 22:00 and midnight is analyzed, where several systems work in unison to maintain continued operations on well A. The graph showcases the following parameters, Pump Fillage (percentage – %), VFD Maximum Working Speed (Hertz – Hz), Measured Speed (strokes per minute – SPM) and the states of the Gas Interference Mitigation & Tagging Mitigation algorithms. The algorithm logics monitor the classification of dynamometer cards as they are generated by the POC and analyzed by the edge gateway. Each step in the algorithm is assigned a state value so that the user can quickly identify where in the logic process the algorithm is.

Some state values are generic. A value of 0 signifies a dynamometer card classification other than the active mitigation algorithm e.g., a state value of 0 for the gas interference mitigation signifies that a dynamometer card classification other than gas interference has been assigned. A value of 1 signifies that a dynamometer card classification of the active mitigation algorithm has been assigned e.g. a state value of 1 for the gas interference mitigation algorithm signifies that a dynamometer card classification of gas Interference has been assigned, whereas a state value of 1 for the tagging mitigation algorithm signifies that a dynamometer card classification of tagging has been assigned. A value of 5 indicates that the last 5 dynamometer cards have been analyzed as normal.

Certain values are unique to specific mitigations. A value of 2 indicates that a gas interference dynamometer card has been identified with other parameters being outside user-defined ranges. These parameters vary between the different mitigations and include all or some of the following SPM, PF, load, etc., which would warrant a control action in the form of either increasing or decreasing the VFD Maximum Working Speed setpoint. Similarly, a value of 3 indicates that a tagging dynamometer has been identified with other parameters being outside user-defined ranges, warranting a VFD Maximum Working Speed setpoint change.

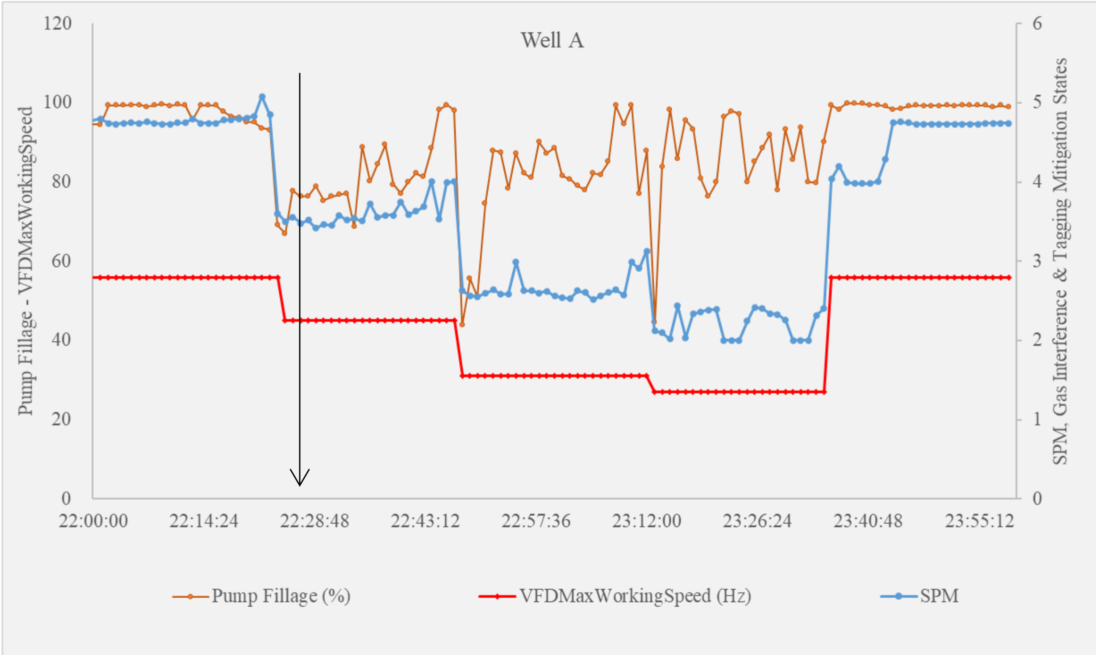

Figure 4: Speed control by POC utilizing primary pump fillage setpoint.

Figure 4 plots the PF against SPM& VFD Maximum Working Speed. As can be observed, the well is producing at a high PF of approximately 100% and at a relatively stable SPM from 22:00 to 22:20. The VFD Maximum Working Speed setpoint during this time is set to 56Hz.

At 22:24 a significant drop in the PF is read at a value of 69.2%, which is below the primary PF setpoint of 70% for the well. The POC engages its logic and reduces the speed of the pumpjack from an average of 4.8 to approximately 3.6. It should be noted that the VFD Maximum Working Speed was not altered since this functionality is only available through the edge gateway and not the POC.

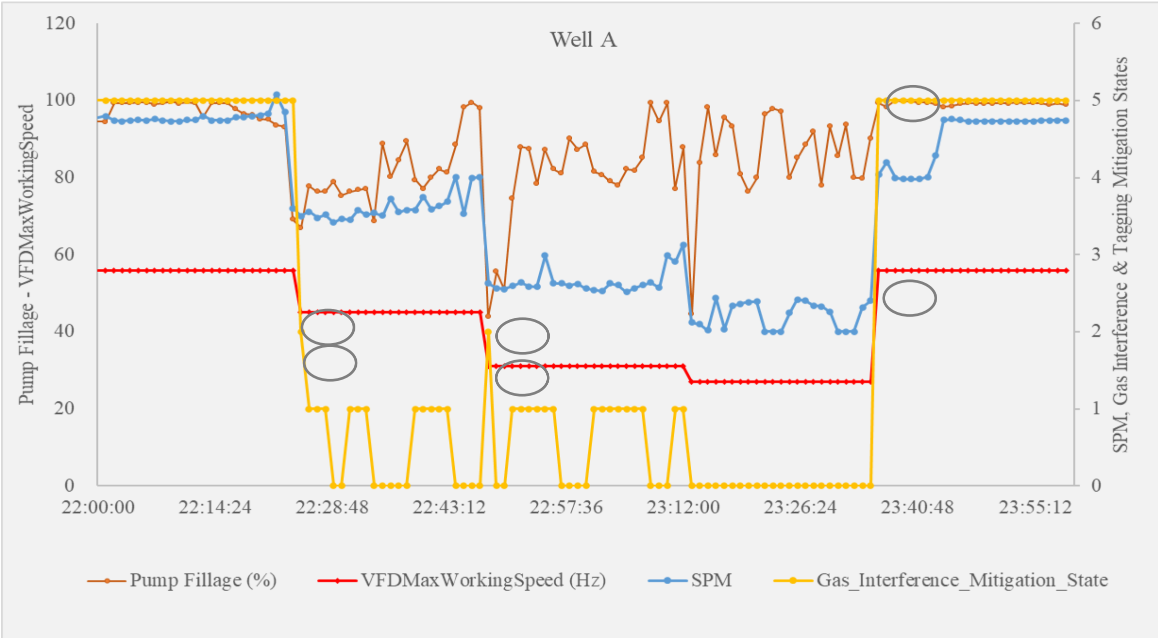

Figure 5: Speed control by edge gateway utilizing the gas interference mitigation algorithm.

In addition to the parameters in Figure 4, Figure 5 also plots the gas interference mitigation states. This will allow us to observe the conditions under which the algorithm makes changes to the VFD Maximum Working Speed setpoints and where it does not.

At both 22:25 & 22:48, the gas interference mitigation state displays a value of 2 which indicates that gas interference dynamometer cards along with other parameters being outside user-defined ranges were identified. This prompts the algorithm to make changes to the VFD Maximum Working Speed setpoints, changing it from 56 to 45 at 22:25 and from 45 to 31 at 22:48. The step change values are different since they are calculated utilizing a function as well.

Gas interference dynamometer cards are observed multiple times within the 2-hour span however since other observable parameters are within acceptable ranges, the algorithm does not take action to change the VFD Maximum Working Speed setpoint. At 23:36, the value of gas interference mitigation state changes to 5, indicating that the last 5 dynamometer cards analyzed were classified as normal, thereby prompting the algorithm to change the VFD Maximum Working Speed setpoint to a value of 56 Hz, which was the setpoint the pumpjack was running at prior to the gas interference mitigation engaging.

This "original" VFD Maximum Working Speed setpoint is influenced by the POPT algorithm, which is discussed earlier in this paper under "Workflow #3". This feature in the algorithm allows for optimized speed to be resumed once short-term issues, identified by the ML model are addressed through the fast loop mitigations.

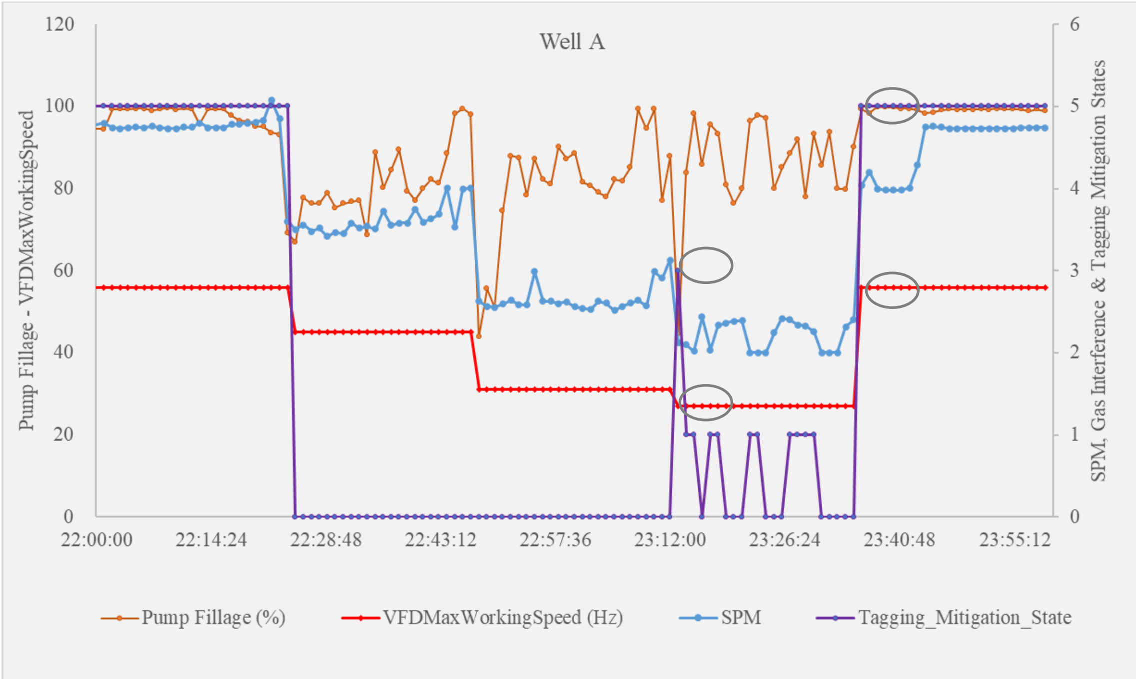

Figure 6: Speed control by edge gateway utilizing the tagging mitigation algorithm.

Figure 6 replaces the previous graph's gas interference mitigation states with the tagging mitigation states. This will allow us to observe the conditions under which the tagging mitigation algorithm makes changes to the VFD Maximum Working Speed setpoints and where it does not.

At 23:13, the tagging mitigation state displays a value of 3 which indicates a tagging dynamometer card along with other parameters outside of user-defined ranges was identified. This prompts the algorithm to make changes to the VFD Maximum Working Speed setpoint, changing it from 31 to 27. Similar to the gas interference mitigation algorithm, the tagging mitigation algorithm utilizes a function to calculate the step change value.

Tagging dynamometer cards are observed multiple times within the 2-hour span of the graph however since other observable parameters are within acceptable ranges, the algorithm does not take action to change the VFD Maximum Working Speed setpoint. Again, like the gas interference mitigation, at 23:36, the value of the tagging mitigation state changes to 5, indicating that the last 5 dynamometer card analyzed were classified as normal, thereby prompting the algorithm to change the VFD Maximum Working Speed to the value of 56 Hz, which was the "original" VFD Maximum Working Speed setpoint prior to the tagging mitigation engaging.

Overall, it can be observed that even though different controllers (POC and edge gateway) are monitoring the well for different parameters, all algorithms function in unison, complementing each other's functionality to address operational issues being experienced by the well.

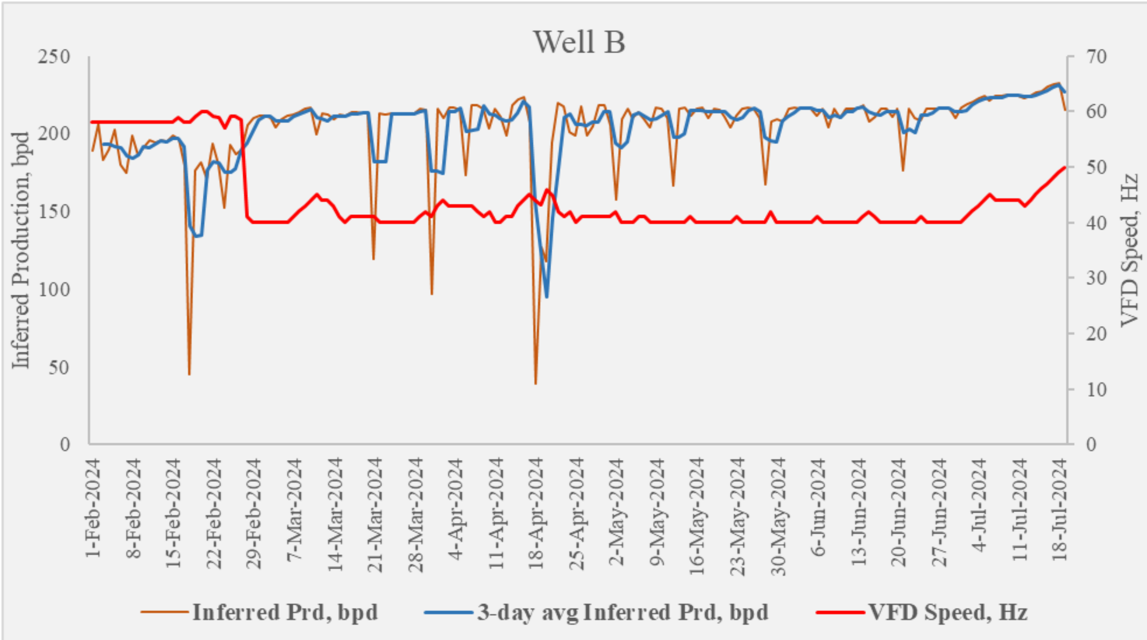

Figure 7: Well B; Inferred Production (bpd) & VFD Speed (Hz)

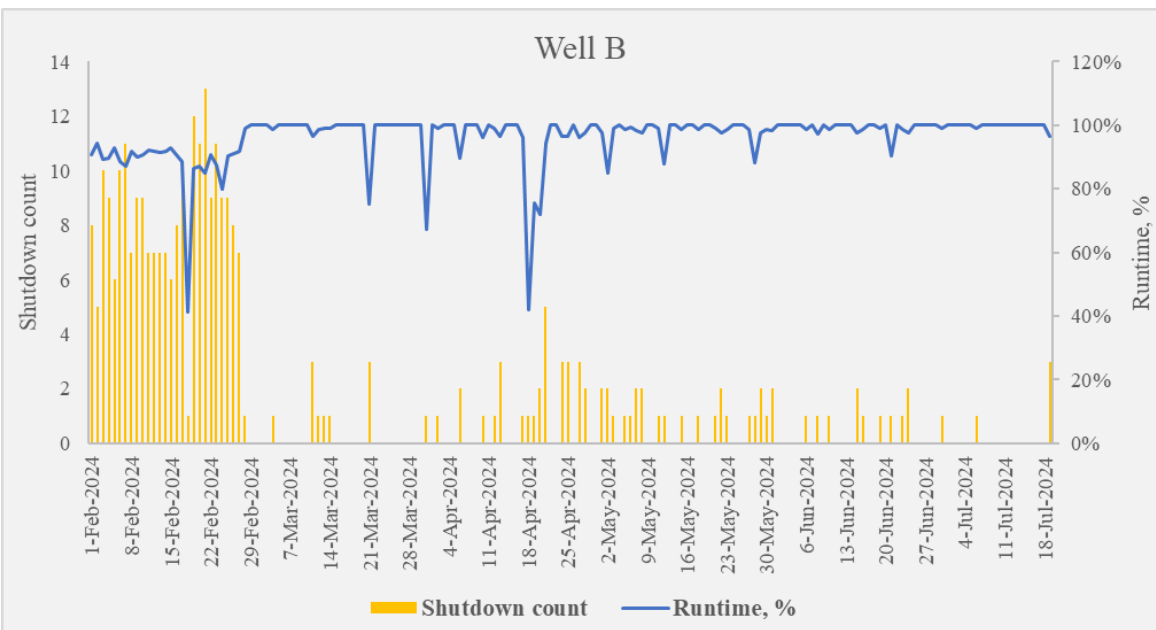

Figure 8: Well B; Shutdown Count & Runtime (%)

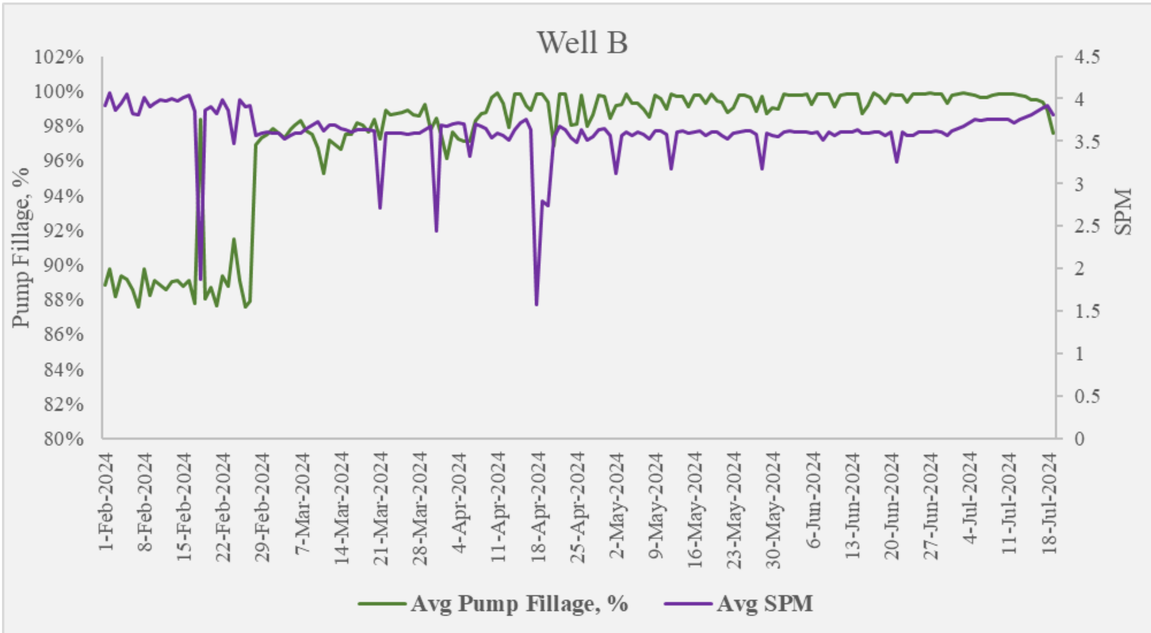

Figure 9: Well B; Average SPM & Pump Fillage (%)

Workflow #3 is achieved through the utilization of the POPT algorithm. Well B (results showcased in Figures 8, 9 & 10) was run with the CI mode of the POPT algorithm due to the considerable number of cycles/shutdowns that were being experienced by the well. After comparing yesterday's values for SPM, PF, shutdowns etc. to the values recorded over the last 7 days (figure 8), the POPT algorithm can calculate KPIs and then make recommendations and implement to the new VFD Maximum Working Speed setpoint for the next day. Reviewing the results shows that after the initial data gathering phase, the POPT algorithm systematically reduces the VFD Maximum Working Speed of the well allowing for an increase in PF and an increase in the well's inferred production volumes. This overall speed reduction also led to a drastic reduction in the daily number of cycles/shutdowns from an average of 6 to 1 (figure 9).

Conclusion

The pilot successfully demonstrated that the edge-based algorithms, including the ML model for dynamometer card classification, mitigation algorithms for short-term issue resolution, and the Production Optimizer (POPT) algorithm for overall well optimization, can operate autonomously with minimal human intervention. The positive results, including increased inferred production, reduced shutdowns, and improved pump performance, validate the effectiveness of this autonomous workflow. These findings highlight the potential of intelligent control logic in optimizing artificial lift systems dynamically, without relying on one-size-fits-all solutions, thereby enhancing operational efficiency and reducing manual surveillance efforts.

Building on these promising results, ongoing efforts are focused on refining the mitigation and POPT algorithms to enhance their adaptability. The mitigation algorithms are being updated to allow more user-defined parameters, enabling tailored responses to similar conditions across different wells. Additionally, research is underway to improve the POPT algorithm's handling of extreme pump fillage conditions, ensuring it explores optimal speed ranges for maximizing economic production. These enhancements aim to further advance autonomous well production management, contributing to the industry's digital transformation journey.

Bibliography

A. Gambaretto, S. S. (2023). *Approches to Sucker Rod Pump Optimization.* Docker No. IS23.0296-US-PSP.

Cheng, H., Yu, H., Zeng, P., & Osipov, E. (2020). Automatic Recognition of Sucker-Rod Pumping. *Sensors*, 15.

Gambaretto, A., Yermekova, M., Srivastava, S., & Hyder, Z. (2024). Autonomous SRP Optimization Using an Edge-Based Data-Driven Solution. *SPE Conference at Oman Petroleum & Energy Show*, 12.

Jared Bruns, A. S. (2022). Optimizing Rod Lift Operations with Edge Computing. *Southwestern petroleum short course*, 10.

Opiah, A. (2024, May 8). *Edge computing: The latest innovation in the oil and gas industry*. Retrieved from Edgeir.com: https://www.edgeir.com/edge-computing-the-latest-innovation-in-the-oil-and-gas-industry-20240508

Research, K. I. (2022). *Rod Lift Supplier Report.* Kimberlite International Oilfield Research.

Z. Hyder, M. Yermekova (2024). Enhancing Edge-Based SRP Production Optimization Algorithm with Fast Loop Mitigation. *OnePetro*, 13.