ACCELERATING ROD LIFT OPTIMIZATION THROUGH AI-POWERED DYNACARD ANALYSIS: FIELD VALIDATED RESULTS

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ABSTRACT

The upstream oil and gas industry faces significant challenges in optimizing production from aging assets, particularly in managing the vast amounts of unstructured data generated by rod lift equipment and associated automation. This paper presents field results from the deployment of Cognitive Card Recognition ("CCR"), a machine learning-based solution for automated dynacard analysis and anomaly detection for rod lift operations.

The CCR system, developed through collaboration between rod lift subject matter experts, data scientists, and oil producers, employs multiple machine learning models trained on nearly 100,000 expert-labeled dynacards. Current models achieve 85-95% accuracy in identifying twelve distinct non-normal operating conditions, including fluid pound, gas interference, worn pumps, and rod parts. The system continuously improves through regular incorporation of additional labeled data and model retraining.

Field deployments demonstrate that CCR implementation enables operations teams to transition from reactive to proactive maintenance strategies, leading to reduced deferred production, decreased well downtime, and optimized maintenance scheduling. This technological advancement represents a significant step forward in leveraging artificial intelligence ("AI") to improve oil production efficiency, worker productivity, and equipment reliability in aging fields.

INTRODUCTION

Optimizing oil production from aging rod lift assets requires timely identification and correction of equipment issues. Rod lift systems, widely used in the industry due to their simplicity and reliability, often experience various operational challenges that negatively affect production. These issues range from equipment wear and tear to subsurface complications, all of which can significantly disrupt operations if not quickly addressed. Traditional diagnostic approaches involve manual interpretation of dynacards - graphical representations of subsurface pump performance - which are not only labor-intensive but also susceptible to human error and inconsistency. Furthermore, manual methods typically lead to delayed responses, resulting in prolonged downtime and increased operational costs.

Recent advancements in AI enable a robust solution by automating and streamlining the dynacard analysis process. AI-driven tools such as CCR facilitate rapid, accurate identification of anomalies, enabling operations teams to shift from reactive troubleshooting to proactive maintenance practices. This transition represents a critical improvement in operational efficiency and asset management, particularly relevant to aging oil fields where equipment reliability and production optimization are paramount.

TECHNICAL BACKGROUND

Rod lift systems, also known as beam pumping systems or sucker rod pump systems, are among the oldest and most widely utilized artificial lift methods in the oil and gas industry. These systems mechanically lift oil from a reservoir to the surface using a pump driven by a surface pumping unit. Central to the performance analysis of rod lift systems is the pump. The pump acts as the heart of a rod lift system. Wells equipped with a load cell and a pumpoff controller ("POC") visualize data points in the form of dynacards, graphs representing the load on the rod string plotted against rod position throughout each stroke cycle. Dynacards provide critical diagnostic insights into subsurface pump operations, equipment condition, and reservoir performance. The optimization objective for rod lift systems is simple - align pump displacement with reservoir inflow.

Historically, dynacard interpretation has been a manual process conducted by experienced production engineers, artificial lift technicians, or lease operators. This manual interpretation involves visual analysis of dynacard shapes to identify common anomalies, including fluid pound, gas interference, mechanical wear (e.g., worn pumps or barrel wear), and mechanical failures, such as parted rods or holes developing in tubing. While experienced personnel can effectively diagnose many issues, the manual process is subjective, labor-intensive, and susceptible to human error, fatigue, and inconsistency. Furthermore, as the number of rod-pumped wells grows - often numbering into the thousands per operator - the efficiency and scalability of manual dynacard analysis decreases. This is precisely the gap that CCR fills - optimization at scale.

The introduction of advanced digital sensors and telemetry has exponentially increased the volume of data produced by rod lift systems. Operators now have access to large-scale data streams of near real-time dynacard information, collected continuously, often on a per-stroke basis. This amount of data surpasses the human capacity for manual analysis, leading to delayed anomaly detection, increases in non-producing time (NPT), reactive maintenance strategies, and, consequently, reduced operational efficiency.

METHODOLOGY

To address these challenges, advanced artificial intelligence ("AI") and machine learning ("ML") methodologies have been implemented through Ambyint's Cognitive Card Recognition ("CCR") solution. CCR leverages state-of-the-art deep learning techniques—including deep convolutional neural networks ("CNNs") and transformer-based architectures—to perform accurate card classification. Initially trained on approximately 8,000 to 9,000 expert-labeled dynacards derived from field data, the training data sets have since been scaled significantly to nearly 100,000 expert-labeled dynacards, enhancing both accuracy and reliability.

Features used for classification are extracted from stroke data and standardized, accounting for different sampling frequencies, varying pump sizes, and other relevant operational variables. Initial model training emphasized achieving high precision and recall rates above 90%, ensuring robust diagnostic reliability.

The CCR system includes a structured retraining pipeline for continuous model improvement. Every seven days, unlabeled dynacards are automatically selected from operational data and queued for labeling. Labeling jobs are initiated, with labeling requests distributed to rod lift subject matter experts (“SMEs”) for validation. Upon completion, labels are systematically consolidated using a custom decision tree methodology, addressing any discrepancies or disagreements among SMEs, with the final results securely stored for future reference and model retraining.

Model performance is continuously monitored through defined evaluation metrics, including precision and recall. Should these metrics fall below the established threshold of 90%, the retraining process is automatically triggered. Retrained models, along with updated features and calculated metrics, are stored in AWS S3s for seamless version control and deployment management. A new model version is deployed into production environments only when it demonstrates measurable improvement over the preceding iteration, ensuring the operational reliability and continual enhancement of the CCR system.

The development of CCR involved collecting, digitizing, and creating an extensive dataset containing millions of dynacards, many of which have been labeled by rod lift SMEs. The labeling process categorizes dynacards into multiple predefined classes corresponding to known operational states and anomalies, such as fluid pound, gas interference, rod parts, hole in tubing, worn pumps, and other mechanical irregularities. Supervised learning techniques are applied, where machine learning models are trained iteratively using this labeled dataset to learn characteristic dynacard signatures associated with each anomaly type to better improve model performance and implementation.

One critical aspect of CCR's architecture is its multi-model approach. Rather than relying on a single generalized model, CCR employs an ensemble of specialized machine learning models optimized for distinct anomaly categories. This ensemble methodology enhances diagnostic precision, reducing false positives and false negatives, and ensuring consistent performance across diverse operational conditions and equipment configurations.

CCR also includes automated retraining workflows to ensure sustained accuracy improvements. As operational data accumulates and new dynacards are validated by SMEs, these data points are continuously incorporated back into the training set. Regular retraining cycles allow the CCR models to adapt dynamically to changes in field conditions, equipment behavior, and dynamic downhole circumstances, ensuring long-term reliability and accuracy.

Integrating CCR into operational workflows transforms rod lift diagnostics from a reactive, manual effort into a proactive, automated process. By automating dynacard analysis, operators achieve early and reliable detection of anomalies, enabling timely interventions. Consequently, this technological progression results in significant operational benefits, including reduced downtime, optimized maintenance schedules, decreased deferred production, and enhanced overall asset reliability.

RESULTS AND DISCUSSION

CCR currently includes twelve models fully deployed into production and a number of additional models that are under development and field testing. This paper will provide detailed results from three unique CCR use cases.

Rod Part

In the first field example, CCR was able to successfully identify a rod part failure. Rod part failures represent a severe operational risk due to their potential for immediate cessation of pump function and the significant secondary damage they can inflict on downhole equipment if left unaddressed. Under certain conditions, particularly with deeper rod parts, conventional pump-off controllers (POC) may fail to promptly shut off the pumping unit due to setpoint malfunctions or incorrect detection thresholds. In these scenarios, the continued operation of the pump despite a parted rod can induce additional damage, resulting in extended downtime, higher repair costs, and increased deferred production.

CCR identified a rod part event, immediately alerting operators even before the POC system recognized the downhole issue. This proactive detection allowed operators to promptly initiate a shutdown and schedule an efficient workover. As a result, the well resumed normal production—approximately 200 barrels of fluid per day—within 15 days following CCR’s anomaly identification. Figure 1 and 2 below illustrate the rod part event and subsequent workover in additional detail.

Figure 1 - Anomaly Detected 5 Days Prior to Failure

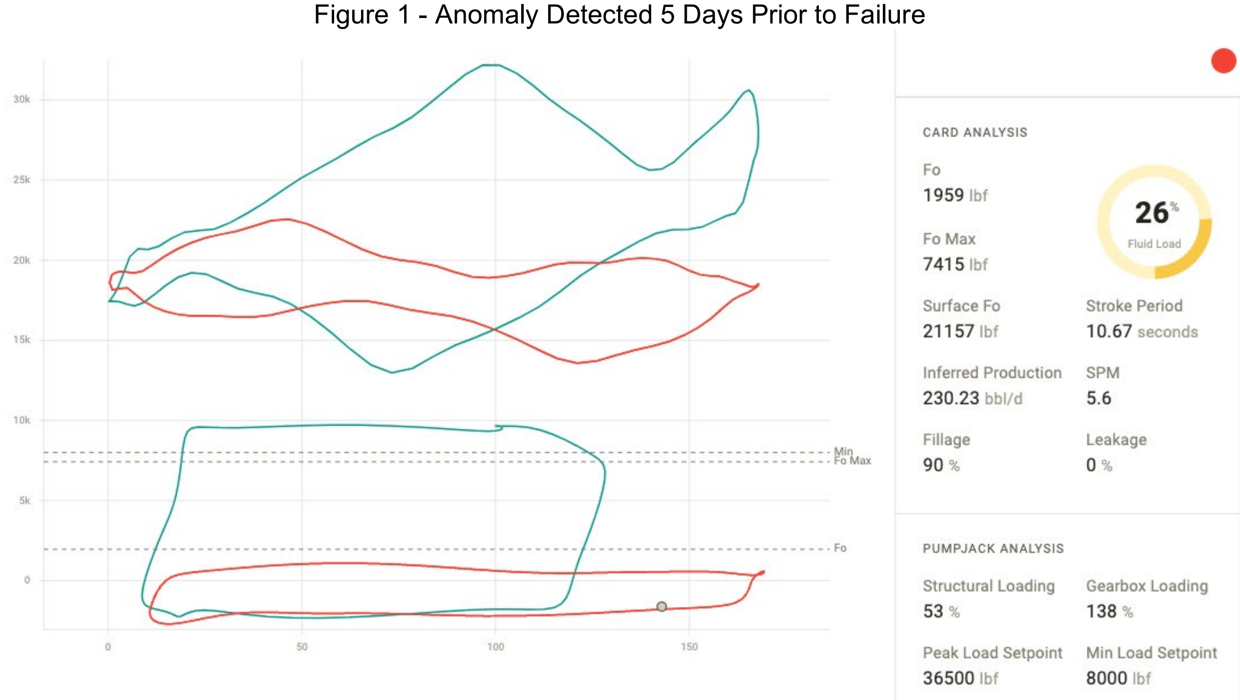

Figure 2 - Dynacards Depicting Rod Part

Worn Pump Detection Working in Collaboration with Automated Setpoint Management

Another use case for CCR is the benefit of anomaly detection when working in parallel with Autonomous Set Point Management ("ASPM"). In this example, CCR identified the well as experiencing a worn pump. In a typical worn pump scenario, production slowly falls as the pump becomes less effective at lifting fluid. However, with CCR and ASPM, when CCR identified a worn pump (see orange in vertical bar chart), over a period of two months, nine speed-up recommendations were automatically implemented, increasing max working speed from 4.5 SPM to 6.0 SPM.

Instead of reduced production week over week, oil production was maintained as the well was slowly sped up by ASPM. Finally after two months of an increasingly severe worn pump, the pump finally failed, experiencing a complete loss of pump action (see dark blue in vertical bar chart), with oil production falling to zero. Figure 3 demonstrates this as it occurs. In this example, the operator was able to sustain current oil production for over 2 months, and extend useful life of equipment by the same amount.

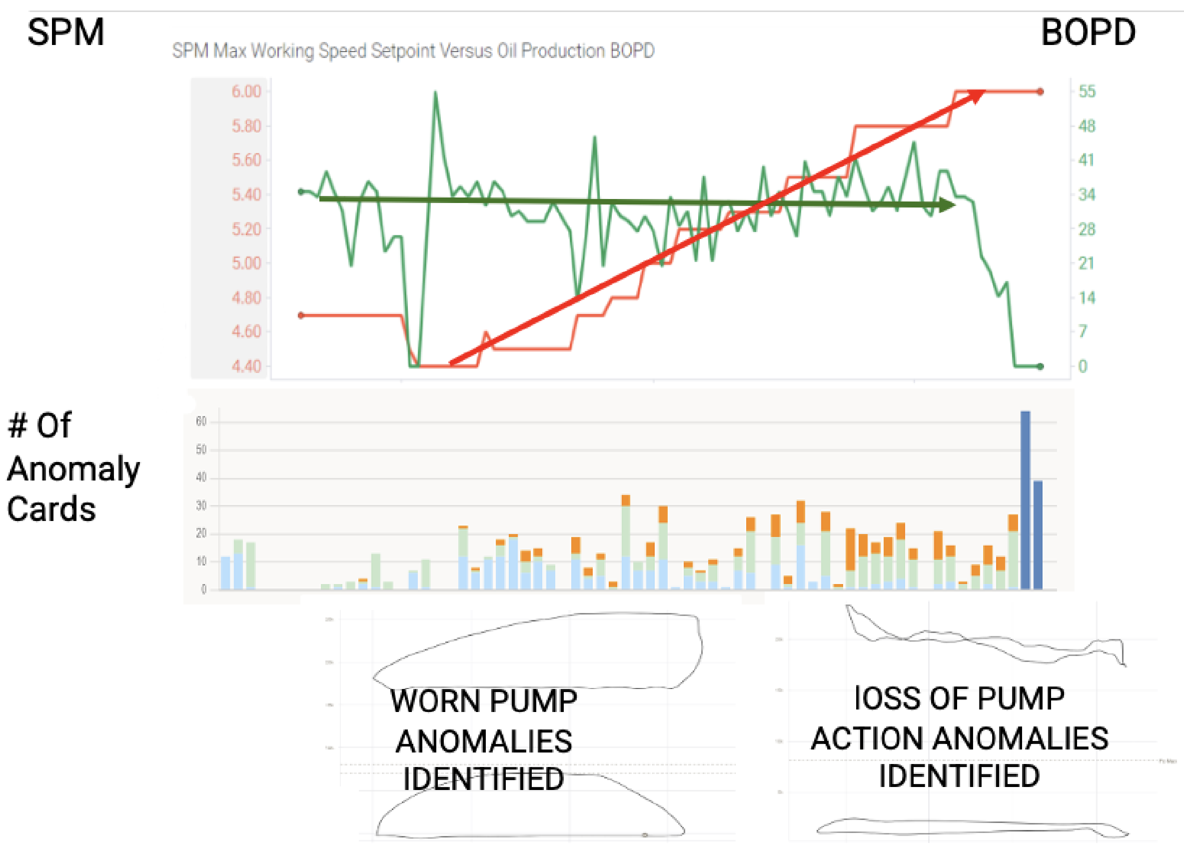

Figure 3 - CCR Working in Parallel with ASPM to Detect and Respond to a Worn Pump

Sticking Pump

A common and very pertinent operational challenge for many operators in the Bakken region is the early identification of pumps beginning to stick. Sticking pumps are characterized by blocked inflow and inefficient pump fillage. Through advanced CCR analytics, sticking pumps have been successfully detected by observing clear trends in stroke length ratios and fluid load ratios over time.

A representative example is illustrated in Figure 4, depicting a rod lift well exhibiting classic signs of a sticking pump. The analysis occurring in this well specifically shows stroke length ratio and fluid load as a function of time. Figure 5 displays the model in terms of stroke length ratio and fluid load as a function of strokes per minute (SPM). The reason for this is to combat friction due to variable frequency drive (VFD) slowdowns. In highly deviated wells, a sticking pump signature is often found in wells that operate at varying speeds as a result of friction. As a result, data scientists built out a model to track performance in terms of stroke length and fluid load ratio as a function of strokes per minute (SPM).

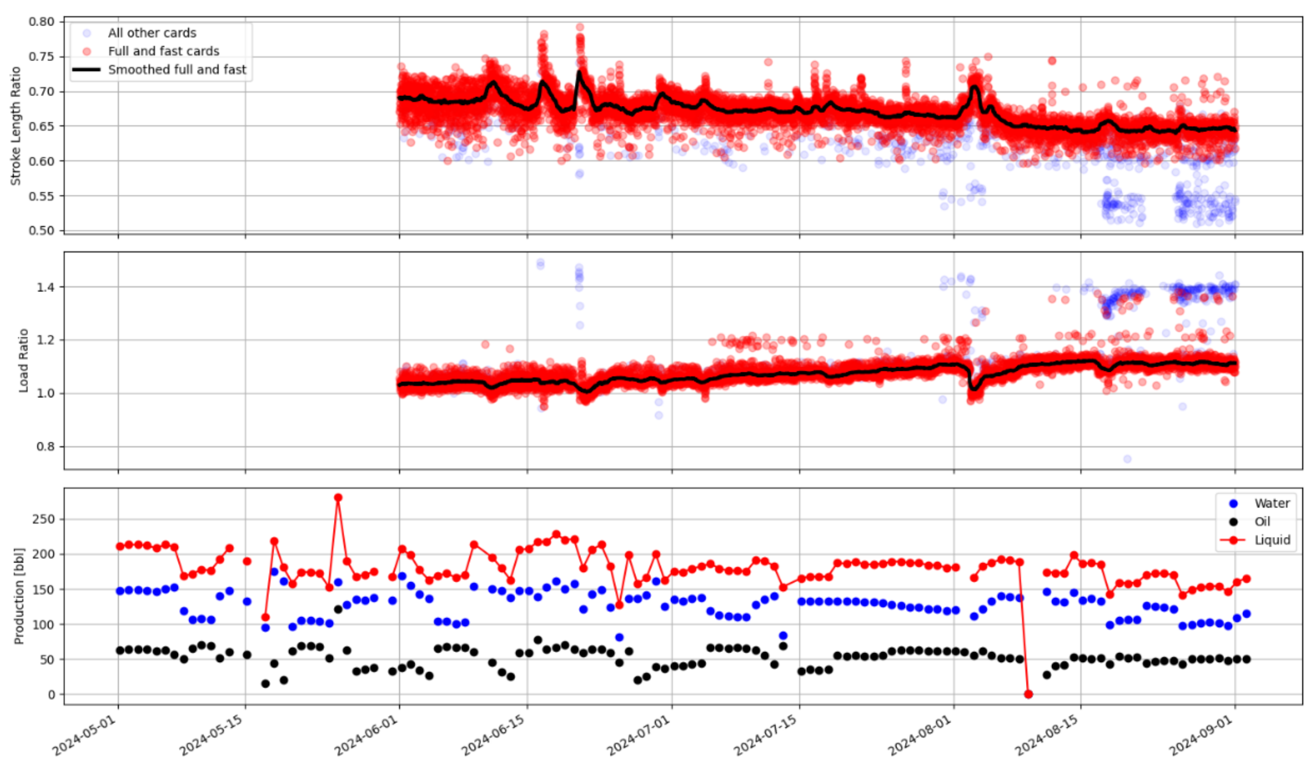

Figure 4 - Sticking Pump Model as a Function of Time

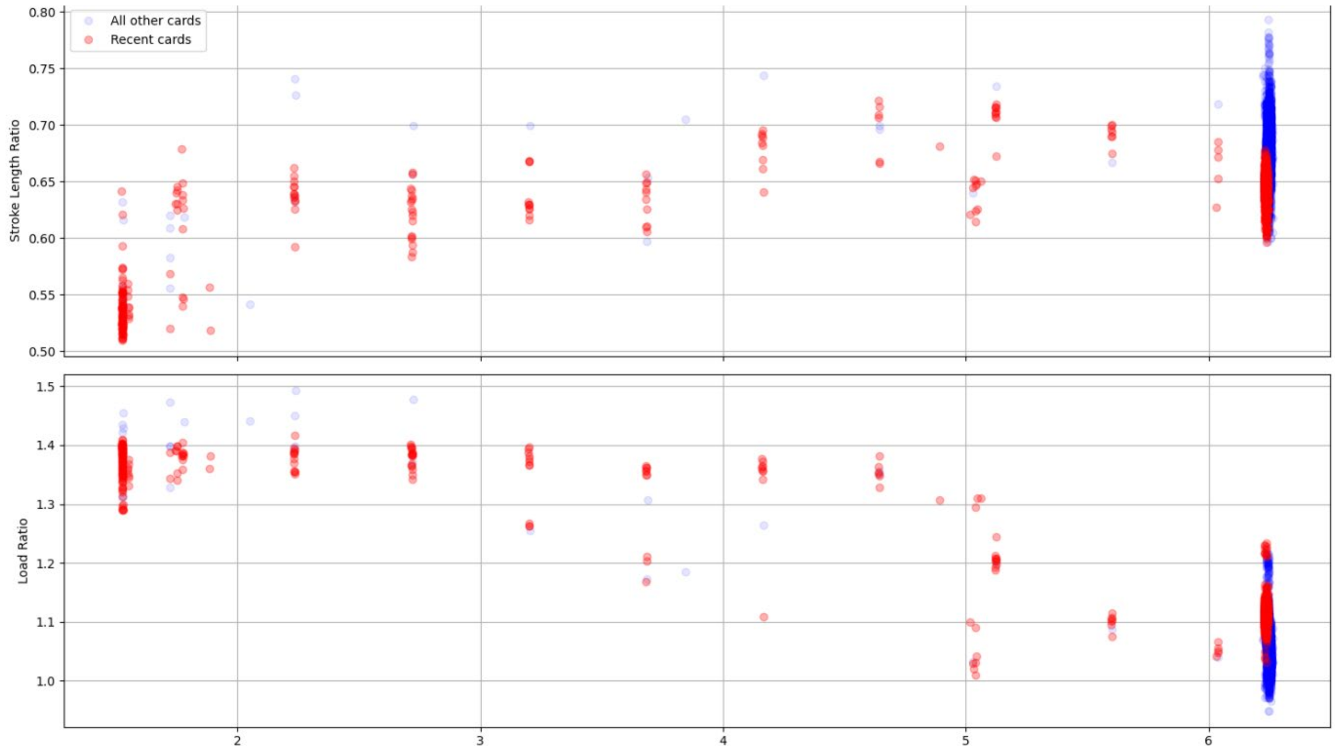

Figure 5 - Sticking Pump Model as a Function of Strokes Per Minute

The graphical trends clearly demonstrate a progressive decline in stroke length ratio, coupled with a corresponding rise in fluid load ratio, indicative of restricted fluid entry into the pump barrel. The distinctive dynacard pattern—shorter and wider—is consistent with the presence of inflow blockages, confirming the operational anomaly.

The secondary trigger for this procedure involves the incorporation of CCR to analyze waviness in surface cards. Any potential for surface vibrations, irregular shapes, and features, are modeled in every stroke. Higher frequencies of this anomaly are flagged with the corresponding drops in stroke length and increase in stroke length, effectively providing more accurate results pertaining to the precision and the recall. LightGBM (Ke, 2017), which stands for Light Gradient Boosting Machine, was chosen as the machine learning model for detecting stuck pumps in this research. Recognized for its efficiency and speed, LightGBM is a state-of-the-art algorithm. Nevertheless, other decision tree-based models such as Random Forests (Breiman, 2001) are also feasible choices for addressing this specific problem.

In the model inference stage, the features computed in the data transformation step are inputted into the model, which then outputs an estimated probability of a pump getting stuck. A pump is classified as sticking if the probability exceeds 50%. If a well exhibits a probability of greater than 50%, it is flagged and sent to the designated SME for a manual screening process. Once complete and if a sticking well is flagged, the model ingests the data and continues to retrain and fine-tune parameters to improve its prediction matrix. Early identification of such sticking conditions allows operators to proactively schedule remedial interventions, minimizing prolonged downtime and preventing costly secondary damage to downhole equipment.

CCR also creates an environment promoting proactive management practices by monitoring dynacard patterns in wells undergoing active treatment strategies, such as periodic flushes to mitigate sticking pumps and maintain production efficiency. In one recent field example, an operator performed a flush intervention on a well identified by CCR as likely experiencing sticking conditions. This proactive action not only significantly increased the total stroke length but also restored the well's production to levels previously recorded seven months earlier. Immediately preceding the flush intervention, oil production was 23 BOPD (7-day average), compared to 36 BOPD (7-day average) after the intervention, an increase of 56%.

Figure 6 and Figure 7 below highlight the effectiveness of such proactive interventions for a well actively managed by regular flushing.

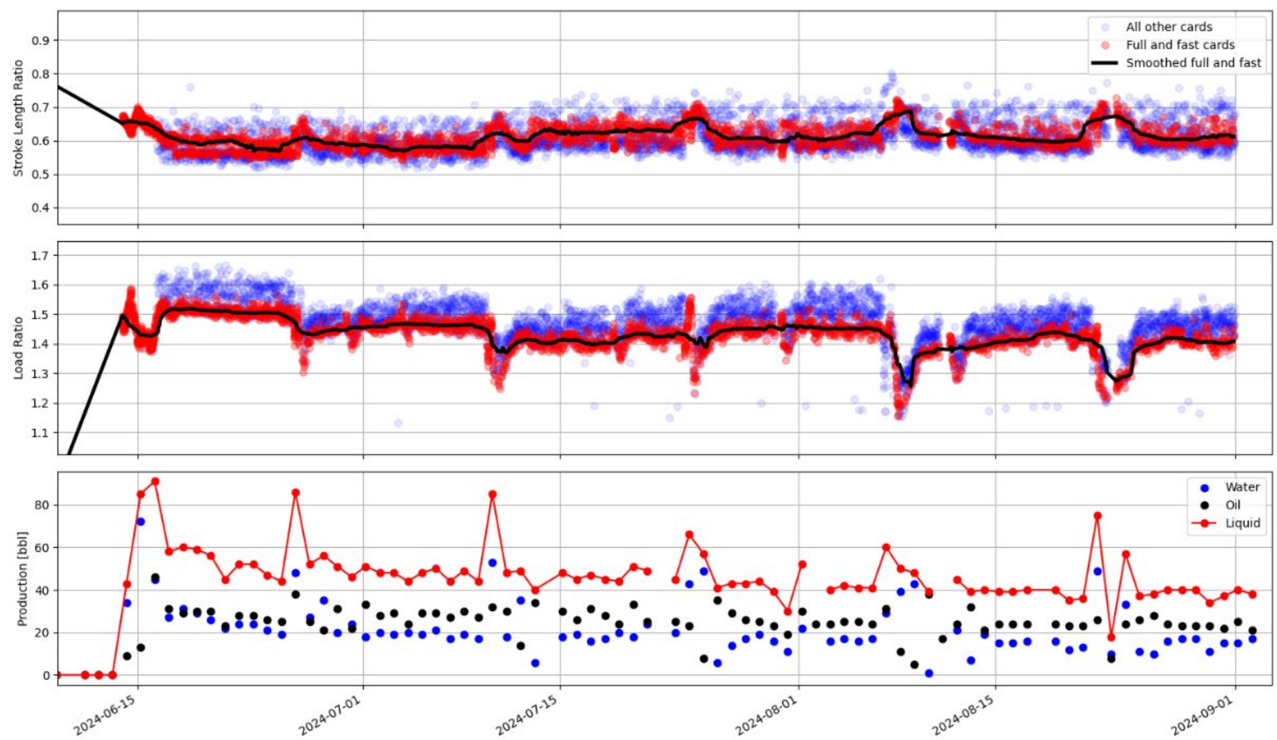

Figure 6 - Sticking Pump Model as a Function of Time in a Well Actively Being Treated

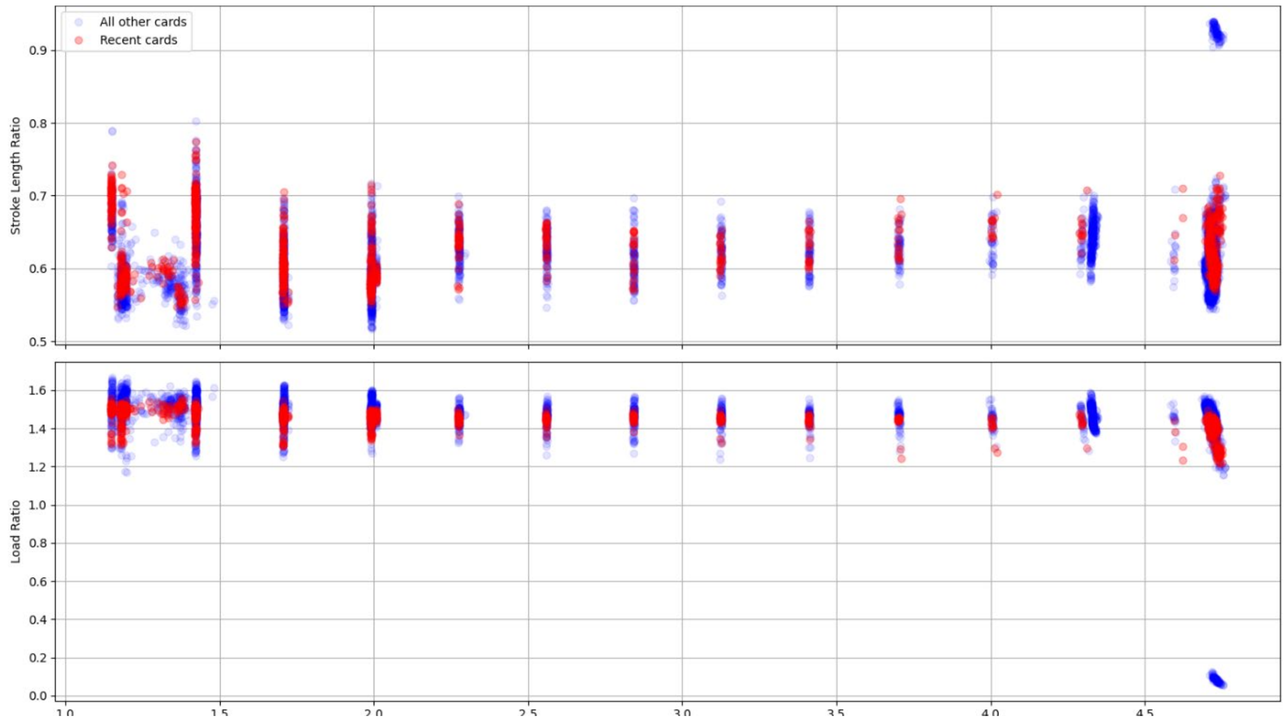

Figure 7 - Sticking Pump Model as a Function of Strokes Per Minute in a Well Actively Being Treated

Trends in stroke length and fluid load ratios illustrate a stable, optimized operational environment, reflecting the immediate impact and effectiveness of these maintenance activities. CCR’s continuous monitoring ensures timely adjustments and confirms successful interventions, significantly reducing the likelihood of unexpected pump failures and production losses. The integration of CCR analytics into operational workflows thus empowers teams to validate and optimize proactive maintenance programs, resulting in measurable enhancements in production uptime, reduced maintenance costs, and improved operational reliability across rod lift assets.

In addition to tracking stroke length and fluid load ratios, the CCR sticking pump model employs frequency-based analysis to identify subtle operational anomalies related to pump sticking. Sticking events often occur through rapid, irregular micro-movements—commonly referred to as waviness—occurring as the pump encounters resistance and intermittently slips through impediments. This waviness, while challenging to detect visually on standard dynacards, is clearly revealed by analyzing the load versus position plots through spectral density transformations. By evaluating spectral density over the pump stroke cycle, CCR effectively distinguishes sticking from normal operation, as sticking pumps consistently exhibit localized, high-frequency signals, indicative of irregular micro-movements caused by restricted pump barrel inflow. Figure 8 showcases this scenario, plotting spectral density over position.

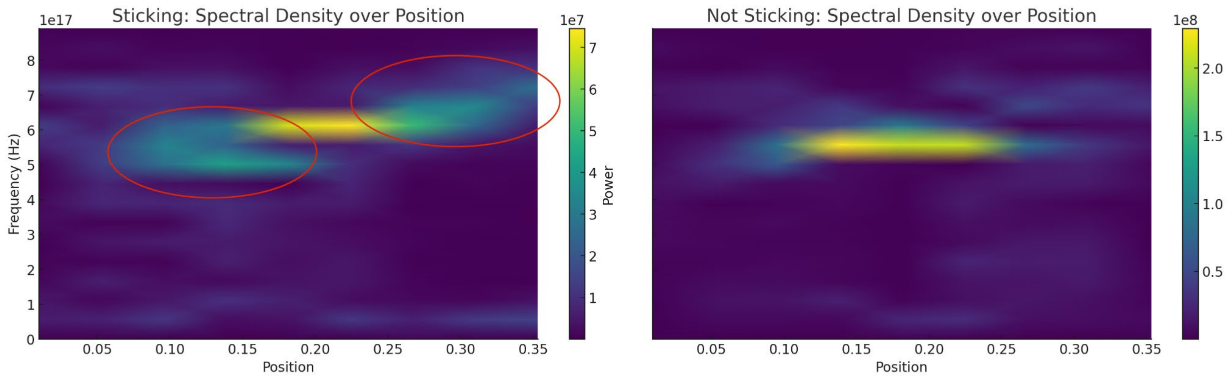

Figure 8 - Spectral Density Over Position Plot

Further refinement in the CCR methodology involves applying a band-pass filter to remove smooth, low-frequency stroke trends, emphasizing the high-frequency waviness unique to sticking conditions. This filtered signal significantly clarifies the presence of sticking-induced irregularities, allowing for a more precise and timely identification. The detection capability derived from this spectral density analysis, coupled with the band-pass filtering technique, improves the model's predictive precision, enabling operators to intervene at the earliest indication of sticking. Figure 9, demonstrates this process.

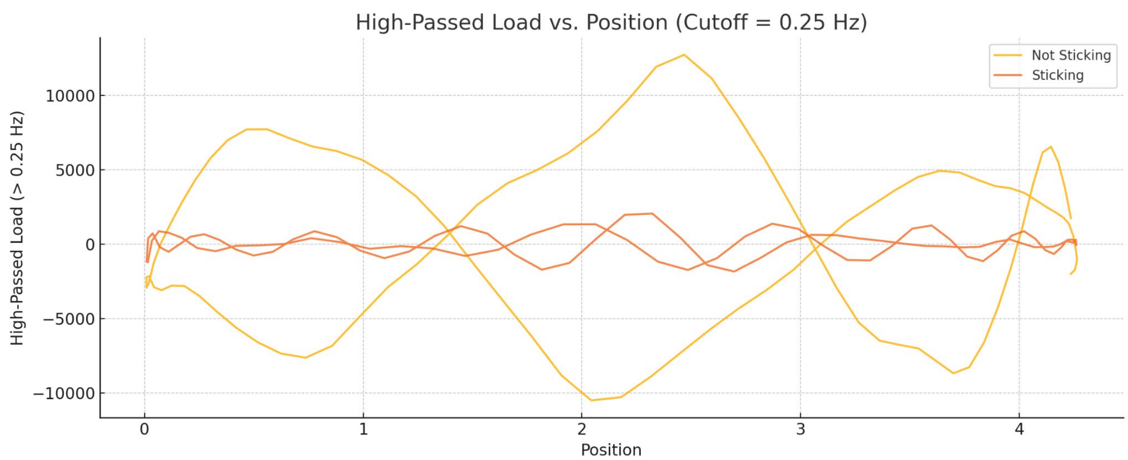

Figure 9 - Band-Pass Filter Removing Smooth Stroke Trend

To enhance the detection of sticking pumps, CCR incorporates targeted statistical features derived from spectral density analysis, peak statistics to characterize the dynamic behavior of sticking-induced waviness, and total high-frequency power, calculated as the sum of the power spectral density using Welch’s method, providing a thorough measure of the intensity of micro-movements. Variance derivative calculations further quantify fluctuations in pump operation. These selected features are utilized to train a Random Forest classifier on SME-labeled dynacards, demonstrating strong predictive performance as evidenced by the confusion matrix results, confirming higher accuracy in distinguishing wavy (sticking) from normal dynacard signals. Figure 10 shows the confusion matrix after training the model on the individual components.

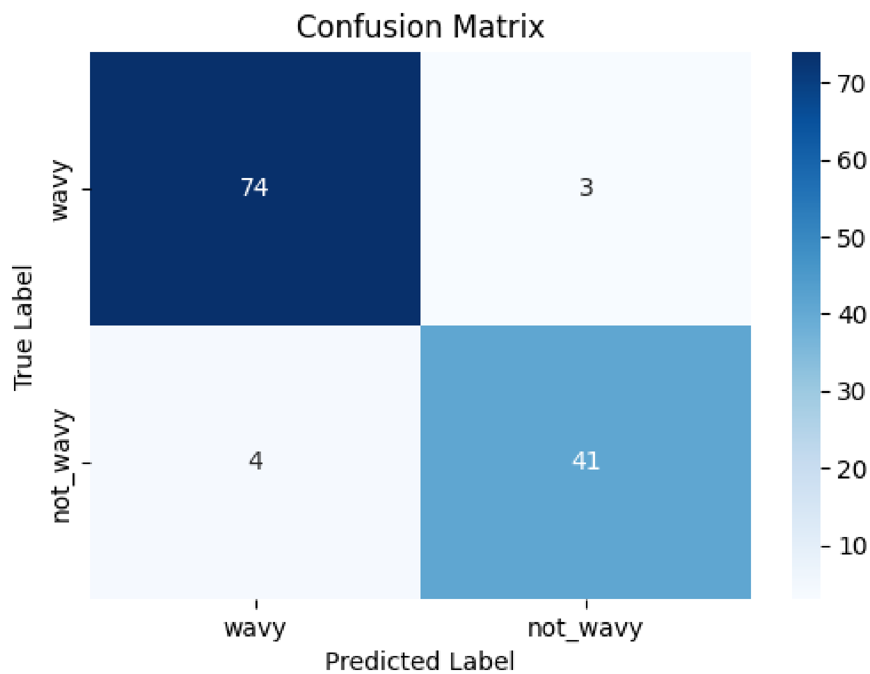

Figure 10 - Confusion Matrix After Training The Model

<u>CONCLUSION</u>

Optimizing production from aging rod lift assets remains a critical operational priority within the upstream oil and gas industry. Traditional diagnostic practices, relying primarily on manual dynacard interpretation, have proven insufficient in scaling effectively to the vast amount of data generated by modern rod lift systems. CCR addresses these limitations through advanced artificial intelligence and machine learning technologies, enabling rapid, accurate, and proactive anomaly detection at a scale previously unattainable.

Field deployments of the CCR system underscore significant operational advantages. By leveraging advanced deep learning architectures, CCR achieves consistently high accuracy in identifying and classifying common rod lift anomalies, including fluid pound, gas interference, worn pumps, rod parts, and many others. These machine learning models are continuously refined through structured retraining processes, incorporating new SME-labeled dynacards on a weekly basis and ensuring consistent diagnostic accuracy over time.

CCR's identification of rod part anomalies before conventional pump-off controllers further highlights the system's value. As illustrated in a case study above, CCR's proactive identification and alerting capabilities reduced failure response time by 1-2 days, minimizing deferred production, preventing additional equipment damage, and effectively extending asset longevity while reducing the NPT of the well.

A critical operational benefit demonstrated by CCR has been its early detection capability for sticking pumps, a prevalent issue in rod lift operations. By analyzing stroke length ratios and fluid load trends over time, CCR successfully flags wells exhibiting early symptoms of inflow blockage, enabling operators to intervene proactively with low cost treatments. Field case studies demonstrate how early anomaly detection provides actionable insights, prompting timely maintenance actions and mitigating downtime and equipment damage. Additionally, proactive maintenance strategies, including periodic flushing, are considerably enhanced by continuous CCR monitoring. Trends clearly show stable, optimized production when wells are actively managed using CCR insights, emphasizing the system's critical role in producing better operational efficiency.

Ultimately, integrating CCR into operational workflows represents a fundamental shift from reactive troubleshooting to proactive maintenance management. By continuously enhancing detection accuracy through structured machine learning practices and SME collaboration, CCR ensures that operators can reliably predict and mitigate equipment failures, streamline maintenance schedules, and optimize overall asset performance, thus boosting total production output and reducing operational costs.

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