A ROBUST METHOD FOR DATA-DRIVEN GAS-LIFT OPTIMIZATION

Agustin Gambaretto
Kashif Rashid
SLB

ABSTRACT

Conventional for Gas-Lift Optimization methods heavily rely on reservoir and fluid data quality, which comes at the cost of additional OPEX and human resources efforts for data gathering and calibration. Even after thorough calibration, pseudo-steady-state models overlook complexities like multi-pointing conditions and slugging behavior. On top of that dynamic multiphase flow simulation could be a viable option, however it adds further complexity and manpower requirements, making full-field deployment unsustainable.

In a nutshell Gas-Lift Optimization revolves around the relationship between Well Production Rate and Gas-Lift Injection Rate. This paper proposes a data-driven, model-free approach aimed at eliminating the dependency on well models, correlations, and field personnel. By focusing solely on this relationship over time, this data-driven approach identifies optimal Gas-Lift Injection Rate setpoints and execute direct implementation of these setpoints via gas lift controllers.

Developed as an Edge Application and ran directly on site in an IIOT gateway device, this data-driven method leverages on the high-frequency data to provide predictive responses for single and multi-well optimizations. The application will execute iterative optimization cycles progressing towards system optimality, adapting to changing well conditions in a closed-loop manner.

A case study involving eight unconventional horizontal wells from the Permian basin in Texas demonstrates the effectiveness of the proposed approach. Despite the complexities associated with these being unconventional wells, including severe slugging and rapidly changing conditions, significant production improvements were registered ranging from 5% to 25%. The entire optimization process was conducted in a fully autonomous manner, eliminating the need for office and field personnel, as well as avoiding the requirement for well modeling.

This paper demonstrates the benefits of a fully autonomous and Data-Driven Gas-Lift Optimization workflow, covering the entire process, including data gathering, processing, edge computation, multi-well optimization, and direct well implementation via closed-loop control.

INTRODUCTION

When considering traditional gas lift optimization methods, a common reference is the typical gas lift performance curve (GLPC) as illustrated in Figure 1.

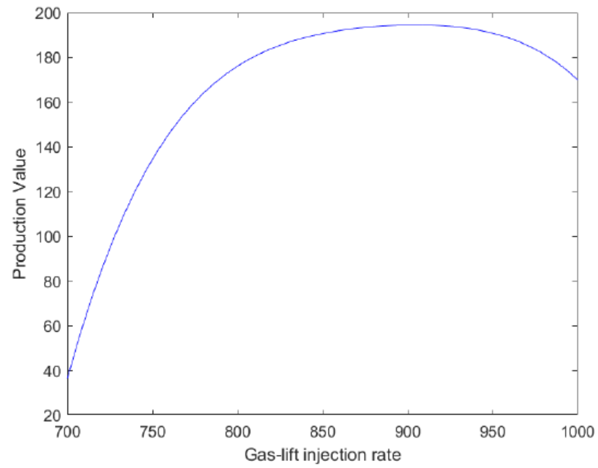


Figure 1: Gas Lift Performance Curve without noise

This curve provides a clear depiction of the relationship between well production and the Gas Lift Injection Rate (GLIR). However, obtaining this GLPC typically requires modeling the well using a multiphase flow simulator. Achieving a well calibrated model relies on the quality of reservoir and fluid data, alongside specialized knowledge. Yet, even with such efforts, pseudo-steady-state models often overlook complexities such as multi-pointing conditions and slugging behavior.

To circumvent the need for well models, an alternative approach involves utilizing real-time field data (well production and GLIR) to construct the GLPC. However, actual field data can significantly deviate from this idealized conception of well behavior, as demonstrated by the dataset depicted in Figure 2. This dataset was collected over a brief period from an unconventional well in the Permian basin, Texas, US.

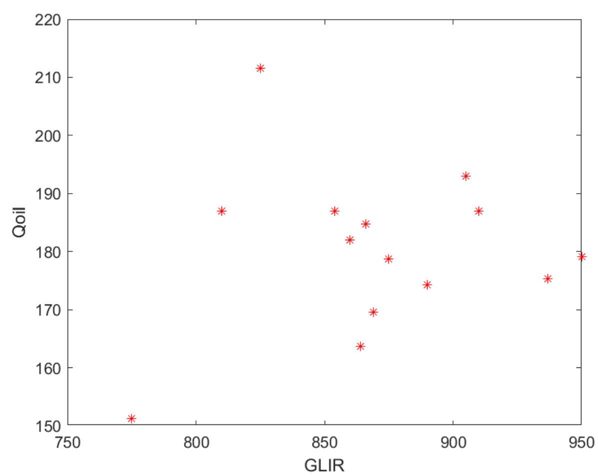


Figure 2: Example of real distribution for GLIR and well production data points

This dataset reveals an absence of a clear relationship between well rate and GLIR, making optimization less straightforward than implied by Figure 1. While the traditional GLPC approach isn't inherently flawed, the relationship between well rate and GLIR is more nuanced than often depicted. Hence, effective optimization requires consideration of noise in the dataset, as depicted in Figure 3, where synthetic noise based on real case data is added to illustrate a more realistic GLPC affected by inherent well dynamics and measurement noise.

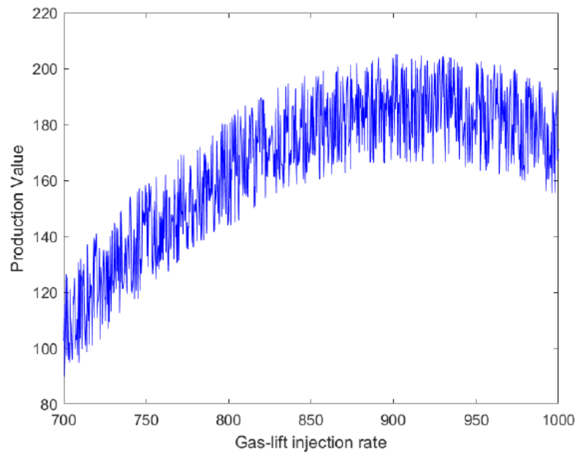


Figure 3: Gas Lift Performance Curve with noise

Consequently, the optimization process shifts from merely identifying a single GLIR setpoint for maximum production to identifying an operating envelope where the well has the potential to achieve peak production rates, as demonstrated in Figure 4.

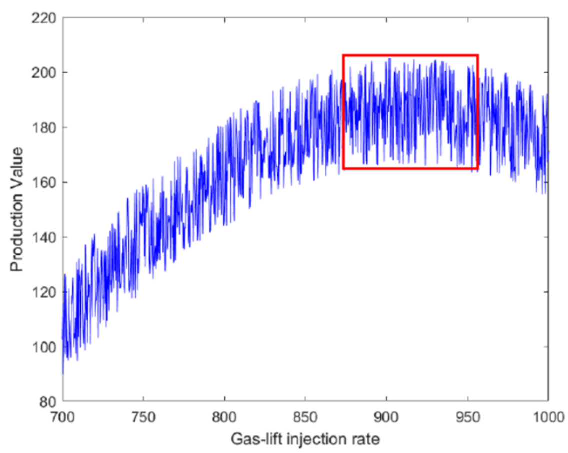


Figure 4: GLPC best operating envelope

This dynamic operating envelope, influenced by changing well conditions and reservoir pressure over time, presents a moving target for optimization. The following section elaborates on how the gas lift optimization algorithm can identify and track this desired operating range over time.

METHODOLOGY

Considering that the condition of the well evolves over time due to factors like water-cut increment and reservoir pressure decline, the optimal operating envelope will continually shift. The optimization process outlined in this paper has been deliberately structured to continuously iterate with different injection setpoints, ensuring that the Gas Lift Injection Rate (GLIR) remains within the optimal operating range over time. This iterative testing approach forms the core of the methodology presented here and underscores why executing this workflow effectively for multiple wells necessitates full autonomy.

The Data-Driven Gas Lift Optimization (DD GLO) process consists of two main sections:

1. Initial dataset generation

2. Optimization loop

Initial Dataset Generation

To kickstart the process, the algorithm requires a minimum dataset size (typically set to eight data points) for successful optimization. If this initial dataset isn't available, the algorithm triggers an autonomous process to generate sample data points. This involves introducing slight variations around the prevailing GLIR and recording associated production rates. Generating this initial dataset typically takes up to two weeks, with each setpoint evaluation undergoing a stabilization period of 48 hours. Once the minimum data points are collected, the optimization step begins. This initial dataset generation step is a one-time requirement after algorithm initialization. Subsequently, the optimization loop maintains the dataset updated by discarding old values and replacing them with new data as acquired.

Optimization Loop

The optimization loop process is the core of the DD GLO application, and it is divided in five main steps as show in Figure 5:

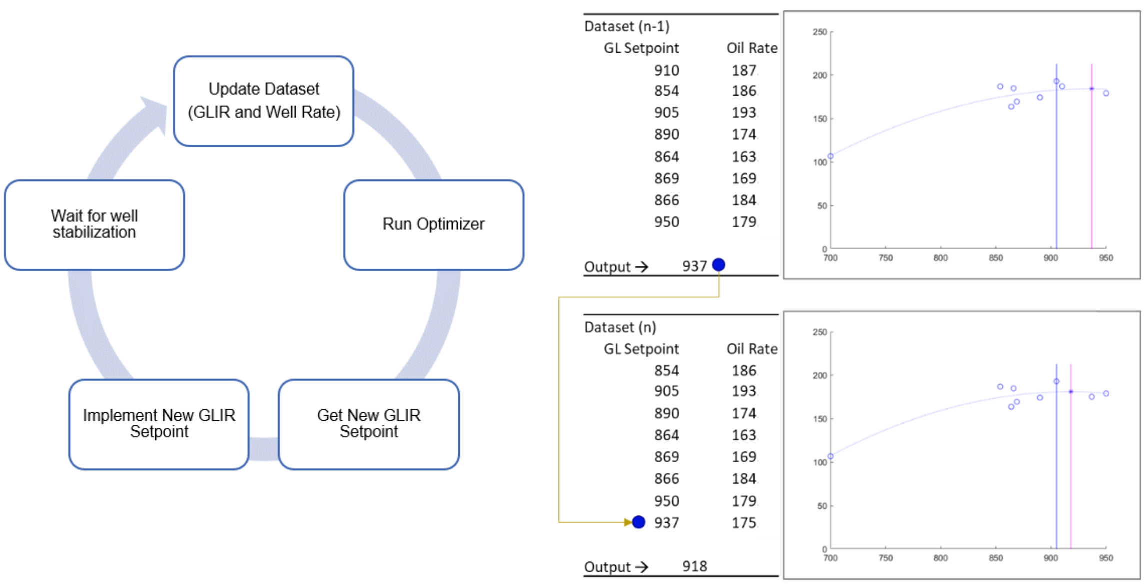


Figure 5: Data-Driven Gas Lift Optimization process

- Step 1: Compute well rate and update dataset

This step involves using the initial dataset generated or updating the dataset with the newly computed well rate after implementing the latest GLIR from the previous cycle: [937Mscfd, 175bopd].

- Step 2: Run optimizer

Once the dataset is updated, the application runs the optimizer, which involves fitting a concave curve through the provided data points. The objective of the solver is not to replicate the GLPC but to identify the operating region that moves the well towards system optimality over iterative cycles.

- Step 3: Get new GLIR setpoint

The output of the optimizer provides the new GLIR setpoint, typically the maximum value from the fitted curve. In the example presented in Figure 5, this new GLIR setpoint is 918Mscfd.

- Step 4: Implement new GLIR setpoint

The new setpoint is set for implementation in the field via closed-loop actuation at the well.

- Step 5: Stabilization period

After implementing the new setpoint, the well undergoes a transient period where the well rate starts to change. It's crucial for the algorithm to allow all wells to reach pseudo steady-state conditions before acquiring new well rates and starting the next cycle.

This iterative optimization process progresses towards system optimality, recognizing that system optimality is a moving target over time. Continuous and autonomous testing and production validation against new GLIR ensure dataset quality and adaptability to changing conditions.

Algorithm Capabilities

In addition to the core optimizer functionality, the algorithm offers diverse capabilities to enhance optimization:

- Multi-well Optimization: This feature efficiently manages multiple wells while adhering to constraints. By considering a global constraint for 'Total Available Gas Lift [Mscfd]', the solver allocates gas lift to maximize oil production across a well group
- Economic Optimization: The algorithm incorporates a cost function to optimize well production economically. This function factors in oil and gas selling prices, as well as the costs associated with processing gas and water, enabling the identification of the most economical GLIR setpoint
- Operational Constraints: The solver can impose constraints on individual wells or groups of wells, ensuring adherence to operational requirements. These constraints encompass total oil, water, and gas production, accommodating field-specific limitations. Additionally, a step-size limit prevents solutions from deviating too far from existing set points, maintaining stability and efficiency

FIELD EQUIPMENT REQUIREMENTS

Considering the iterative nature of the process and the frequent changes in setpoints required by the wells, manual operation is impractical. Thus, the following minimum field instrumentation is necessary for the successful execution of the DD GLO process:

- Gateway: A gateway linked to field instruments, capable of collecting all necessary field data, processing it, running the application, and implementing adjustments at the well via closed-loop actuation.
- GLIR Measurement: Equipment for measuring Gas Lift Injection Rate.
- Flow Control Valve (FCV): Essential for regulating flow rates.
- Flow Computer (FC): A remote-operable FC capable of PID control to set GLIR setpoints.
- Well Production Measurement: A Multi-Phase Flow Meter (MPFM) or equivalent device capable of real-time measurement of liquid, oil, and gas rates from the well. Additionally, Virtual Flow Metering solutions can be considered for more cost-effective setups.

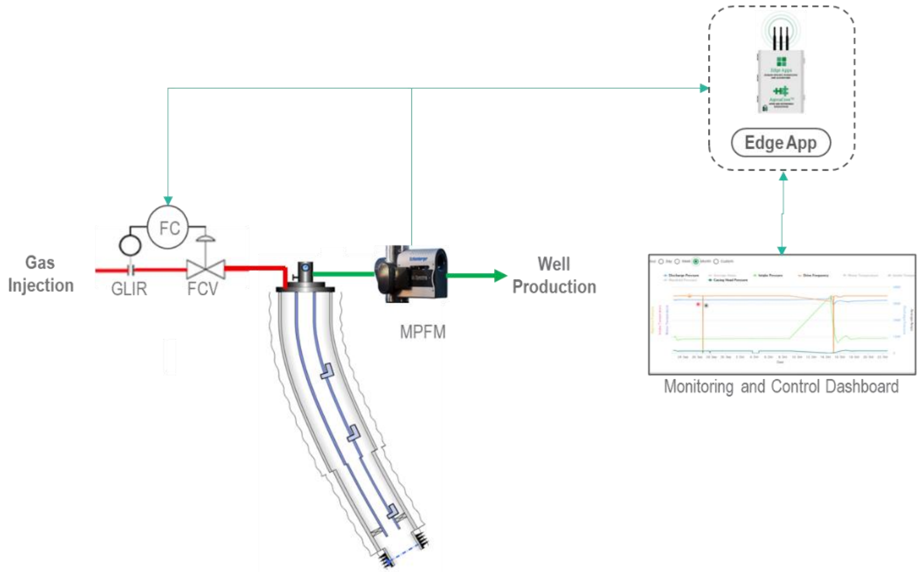


Figure 6: Example of field installation

FIELD IMPLEMENTATION AND RESULTS

Case Study 1

- Single Well Optimization
- Main Highlights:
    - Fully autonomous workflow execution
    - Production maintenance in-line with natural well declination
    - Satisfactory performance under changing conditions

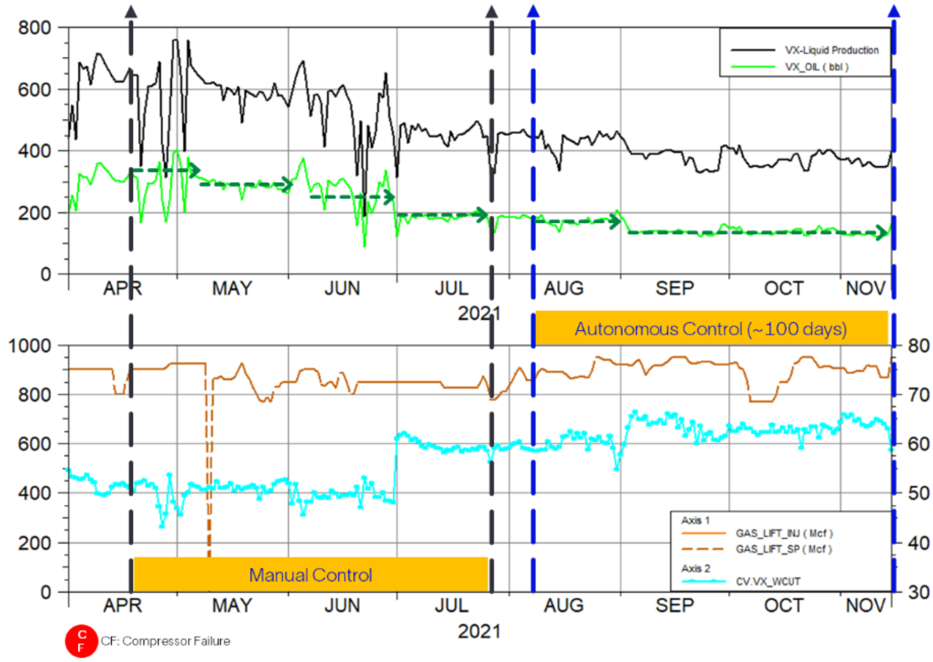


Figure 7: Production Profile for Case Study 1

Figure 7 illustrates the production profile of the study well both before and after the optimization algorithm was implemented. Although there wasn't a significant increase in production, it's reasonable that the well was already operating near its optimal condition. However, following the algorithm implementation, the algorithm effectively maintained the natural decline of the well production in a fully autonomous manner, without any intervention from field personnel. Particularly, from September to November, the algorithm successfully stabilized production for three months, demonstrating the value of the autonomous operation.

Another notable aspect of this application is its adaptability to changing conditions. Figure 8 compares the production profile of the study well with another well in the same pad that was managed according to the pre-established field operating philosophy via manual optimization processes.

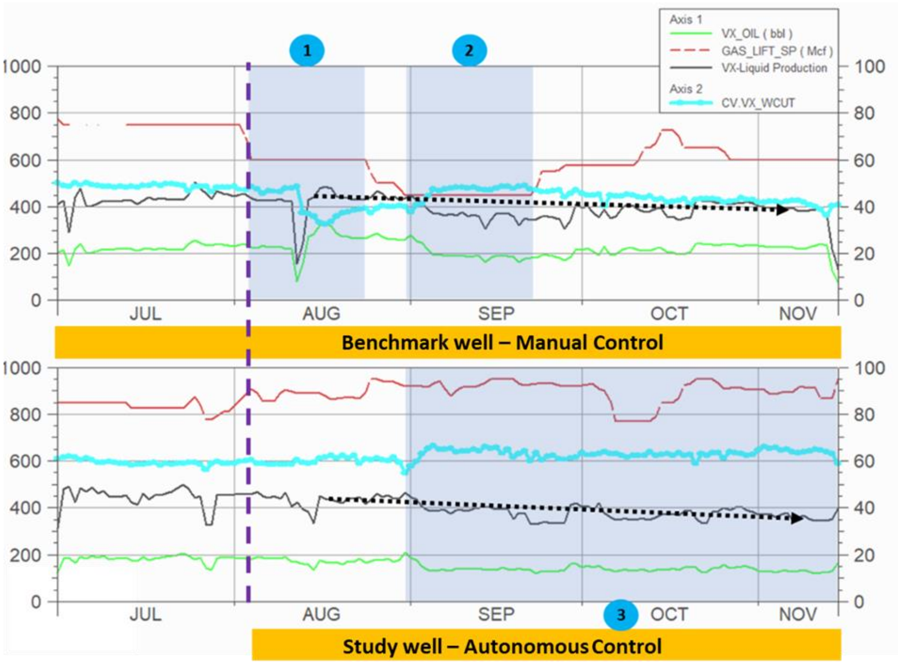


Figure 8: Application adaptation example to changes on water-cut vs manual operation.

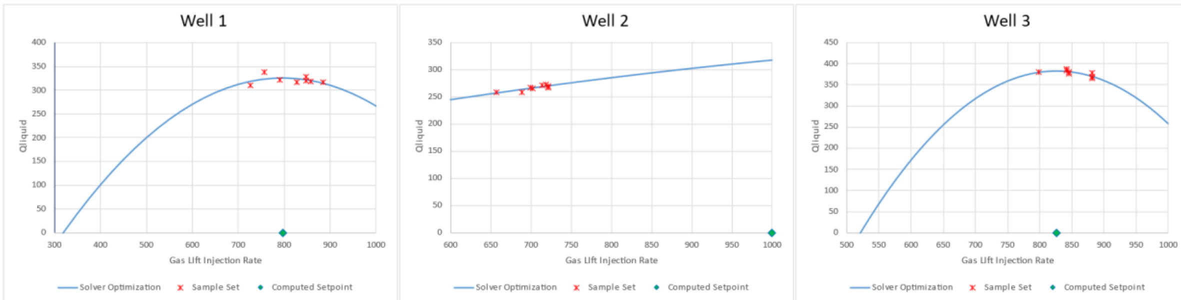
Upon analyzing the benchmark well, two instances highlight the impact of neglecting well management on production deferment:

1. In August, the benchmark well witnessed a sudden reduction in water-cut from approximately 50% to 35%, while the GLIR setpoint remained at 600 Mscfd. Following this decrease in water-cut, the well required less GLIR due to the lighter column. Despite eventually reducing the GLIR to 450 Mscfd over two weeks, this delay resulted in inefficient gas lift injection, leading to unnecessary OPEX expenditure.
2. Subsequently, after adjusting the GLIR in response to the water-cut reduction, the water-cut increased back to nearly 50%. This heavier liquid column demanded higher injection rates to maintain production. Unfortunately, the operations team overlooked this change, resulting in three weeks of no gas lift increment. Consequently, the well's performance declined, with liquid and oil production falling below optimal levels.
3. Meanwhile, the study well experienced a water-cut increase towards late August. The application consistently increased the GLIR, allowing the well to adapt to the changing conditions more effectively. Thus, while a minor production deferment occurred, it was significantly less impactful compared to the deferment experienced by the benchmark well.

Case Study 2

- Multi-Well Optimization: 3 wells
- Main Highlights:
    - Fully autonomous workflow execution
    - Production maintenance in line with natural well declination
    - Step-change for underperforming wells

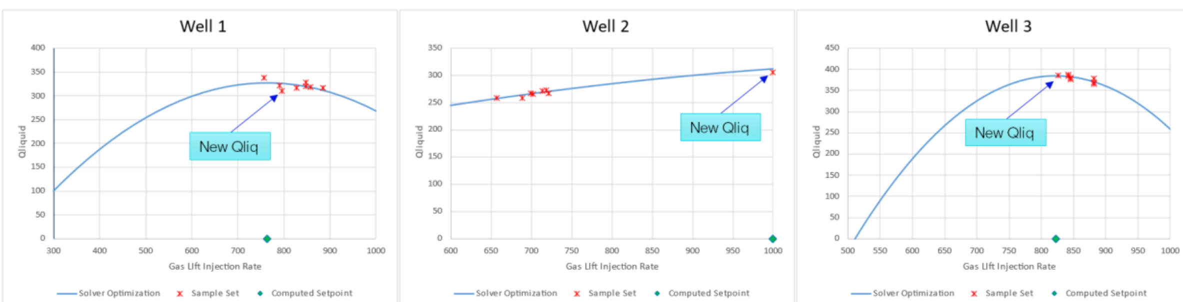
In this scenario, the solver concurrently executed the optimization process for three wells. Figure 9 illustrates the dataset generated for each well upon completing the initial data generation process outlined earlier.



Computed setpoint: 797Mscfd	Computed Setpoint: 1000Mscfd	Computed Setpoint: 826Mscfd
Output type: Optimization	Output type: Optimization	Output type: Optimization

Figure 9: Output from first optimization cycle in Case Study 2

For wells 1 and 3, the solver identified a concave trend based on the datasets, indicating that these wells were already operating near optimally. Consequently, the optimization cycle's outcome was consistent with the gathered data. However, for well 2, the solver's output differed significantly. It detected an increasing trend towards higher gas lift injection volumes. While the objective is not to replicate the Gas Lift Performance Curve (GLPC) precisely, but rather to approximate it based on the available dataset, well 2's trend did not reach its maximum within the imposed constraints (Minimum = 600 Mscfd, Maximum = 1000 Mscfd). Thus, the solver proceeded to implement the maximum allowable GLIR setpoint for well 2. Figure 10 illustrates the production rates obtained after implementing the setpoints from Figure 9.



Computed setpoint: 764Mscfd	Computed Setpoint: 1000Mscfd	Computed Setpoint: 822Mscfd
Output type: Optimization	Output type: RESAMPLE UPPER LIM.	Output type: Optimization

Figure 10: Step-Change production improvement in Case Study 2

As anticipated, wells 1 and 3 exhibited minimal changes in production output; the values recorded at the conclusion of the optimization cycle closely mirrored the existing dataset. However, well 2 presented a starkly different picture; it was evidently underperforming. Initially set at approximately ~700 Mscfd, the GLIR for well 2 was increased to 1000 Mscfd during the optimization cycle. This adjustment resulted in a notable over 20% increase in production rate within a single cycle, escalating from ~260 bopd to ~310 bopd. Figure 11 illustrates the significant shift in the production profile.

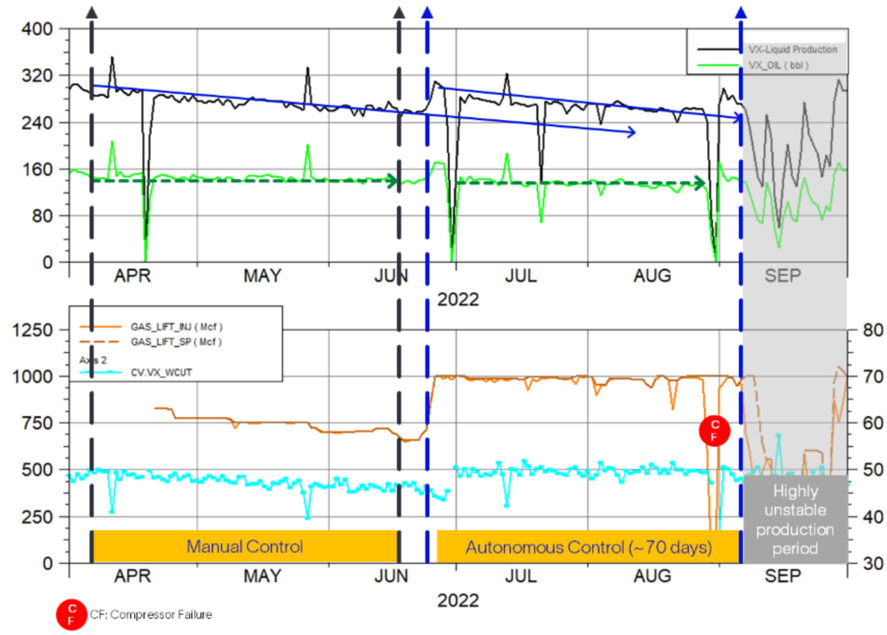


Figure 11: Well 2 production profile showing before and after DD GLO implementation.

Following the deployment of the edge application, a distinct shift in both liquid and oil production is evident. However, shortly after the production enhancement, there is a sudden increase in the well's water-cut, impacting oil production. Nevertheless, as previously mentioned, the application adeptly adapted to these new conditions, sustaining oil production levels through higher GLIR.

CONCLUSIONS

This study encompassed three phases, involving a total of eight wells. The initial phase focused on single well optimization, followed by two subsequent phases dedicated to multi-well optimization. Across the board, three wells exhibited a marked improvement in performance, averaging a production enhancement of approximately 20%. While the remaining five wells did not display a significant production boost, nonetheless these were successfully maintained at optimized conditions, aligning with natural decline patterns and ensuring maximum deliverability autonomously. Moreover, the application's ability to swiftly adapt to evolving well conditions was demonstrated, not only in response to abrupt water-cut changes but also in the consistent upkeep of production levels over time, particularly crucial given the rapid reservoir pressure depletion typical of unconventional wells. This was accomplished through an automated closed-loop process, featuring the effectiveness of the approach.

REFERENCES

- Rashid, K. and Gambaretto A. 2022. GAS-LIFT CONTROL (Patent No. WO2023039025A1). World Intellectual Property Organization.