SUCCESSFUL ESP OPTIMIZATION WITH MACHINE LEARNING DEPLOYED AT SCALE IN THE PERMIAN BASIN – A CASE STUDY

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INTRODUCTION

Many oil and gas companies rely on natural intelligence, resident knowledge, and rules-based logic to optimize production. This is especially true for fields where electric submersible pumps (ESP) make up a considerable proportion of production. The nature of ESP artificial lift systems makes them well suited for greater remote monitoring, enhanced automation, and implementation of machine learning (ML) for autonomous optimization. Extensive use of electrical surface controls integrated with downhole sensors provides an ideal operating environment to implement Artificial Intelligence (AI) through machine learning to achieve autonomous full self-pumping (FSP) operation. However, most operating companies stop short of using automation and machine learning to its full potential.

This paper will present a case study of the demonstration, refinement, and deployment of a machine learning algorithm to optimize multiple ESP wells in the Permian Basin. The paper will discuss key learning points on how to effectively implement, refine, and deploy a machine learning optimization model at scale. The overarching goal of the paper is to assist operators in their digital journey with proposed best practices and considerations for effective field implementation.

For any operator, the path to a fully mature AI-driven artificial lift solution is a long and exciting journey. The journey requires the operator and its partners to navigate numerous roadblocks and challenges as their oilfield becomes increasingly digital. The digital maturity framework presented in this paper has proved to be useful to compress timeline and resources needed for technical development and implementation change management.

The framework is a 2-variable matrix clarifying completion of important milestones for both Maturity of *Solution Capability* and *Solution Implementation* as defined below and visualized in Figure 1.

Progression of Capability Maturity

- Measure – Solution collects quality, timely, and complete data necessary for intelligent optimization

- Optimize – Solution increases quality and speed of decision making to maximize desired result(s)
- Automate – Solution provides autonomous action involving experts by exception

Progression of Implementation Maturity

- Develop – Solution is created and operates in a controlled environment meeting criteria for a Minimum Viable Product (MVP)
- Demonstrate – Solution is released to a small, real-world environment and operates under the care of domain experts
- Refine – Solution undergoes iterations of improvement with collaboration between domain end-users and developers
- Deploy – Solution is scaled and transitions into workflows of core business

A key step in the transition is implementing an ML model developed and deployed at scale (across multiple users, wells, fields, basins, etc.). For the scope of implementing a ML inference model to source setpoint recommendations to optimize a well producing with an ESP, the capability and implementation maturity paths are defined as follows:

Maturity of Solution Capability

- Measure – Predefined sensor and telemetry data are collected in a timely, consistent, and holistic manner
- Optimize – Key artificial lift tuning parameters, including ESP frequency and well flowing tubing pressure (FTP), sourced from a ML inference model
- Automate – ML model setpoint recommendations autonomously write to field control devices

Maturity of Solution Implementation (Measure & Optimize Capabilities)

- Develop – Configure field data capture, create ML inference model that autonomously generates setpoint recommendations of ESP frequency and well FTP with a User Interface (UI)
- Demonstrate – Employ ML capabilities on a subset of wells producing in the Midland Basin
- Refine – Improve ML model with reinforcement and feedback from domain experts and enhance UI
- Deploy – Distribute solution at scale across the field and transition into core business

A previous paper (SPE-214731-MS) was presented in 2023 that focused on the Develop and Demonstrate phases of the implementation process for an AI-based ESP optimization solution. This paper focuses on the subsequent Refine and Deploy phases of the implementation process.

CASE STUDY BACKGROUND

Once developed, the machine learning inference model was demonstrated in the field and produced setpoint recommendations for approximately 60 wells, roughly 25% of Vital Energy's Midland Basin ESP program. During the demonstration phase, core capabilities could be observed at scale in the field environment to be refined with feedback provided by production engineers and ESP technicians.

After approximately 9 months of refinement in the field, the ML inference model entered a deployment phase expanding utilization to over 200 wells, more than 80% of Vital's Midland Basin ESP program. From December 2022 to March 2024, the number of ESP lifted wells using the ML inference model to optimize setpoints grew from 60 to 217 wells. A deployment timeline showing well count using ML model in optimization efforts and monthly petrotechnical engagements (accepting or rejecting model recommendations) is shown in Figure 2. During this phase of deployment, tangible learnings and results were observed in well performance, field oversight, and leading indicators of operating expense.

This study focuses on the period with the highest level of petrotechnical engagement and implementation of ML sourced setpoint recommendations summarized below:

- Start Date: 12/01/2022
- End Date: 10/01/2023
- # Days: 304
- # Wells: 170

CASE STUDY RESULTS

To measure the quality of ML setpoint recommendations, next-day uplift was calculated by comparing the oil volume produced on the day after implementing a ML setpoint recommendation to the previous average production. The calculation provided a range of next-day oil gain (or loss) shown in Figure 3. The mean uplift of the program was observed to be 2% to 4% after implementation of the ML setpoint recommendation.

To understand if accepting or rejecting the ML recommendation resulted in differential performance, a subset of wells with high and consistent optimizer engagement was analyzed. The dataset consisted of 56 wells with a total of 617 engagement actions. Engagements were classified as either an "accepted" or "rejected" action, based on if a setpoint change honored (or diverted from) the ML recommendation. A total of 485 "accepted" actions were observed along with 132 "rejected" actions. Average oil uplift was observed to be ~1.8x higher when ML recommendations were accepted, occurring in 78% of engagements, as compared to instances when ML recommendations were rejected, occurring in 21% of engagements. See Figure 4.

Field Oversight Impacts (speed of decision-making)

Another way leveraging Machine Learning in Artificial Lift Optimization decision-making proves to add value is by relinquishing the time of domain experts from tedious, daily optimization evaluations – allowing them to focus their time and expertise on other challenges where it is more valuable. As digital tools evolve through the three levels of capability maturity (Measure, Optimize, Automate) operators can more efficiently leverage the knowledge of their petrotechnical domain experts.

To estimate the potential impact to field oversight, a baseline for engineering- and technician-led optimization was assumed and summarized below. For illustration purposes, if one were to assign a "pro forma" cost of petrotechnical-led optimization, say $100 / hr, the impact of automating this task can be quantified.

Baseline Assumptions for Illustration Purposes

- Evaluation frequency: 1-7 eval / well / week
- Evaluation time: 15-30 min / eval
- Petrotechnical optimizer "cost": 100 $ / hr

The machine learning model provided daily setpoint recommendations for each well in the study, equating to multiple tens of thousands of distinct setpoint recommendations for well-specific operating conditions across the field. The same level of petrotechnical oversight would have equated to more than 10,000 people-hours.

The ability to generate setpoint recommendations autonomously quickly outpaced Vital's capacity to execute changes in the field manually. The experience identified a large opportunity to unlock additional value if the ML model were given agency to safety write directly to field control devices to remove this bottleneck.

Using the previously introduced assumptions, the potential value added from fully capturing daily setpoint recommendations for a single well would equate to $25 / day. When extended to the 170 wells in this study, the annualized "size of the prize" approaches $1.5 million per annum.

Operating Expense Impacts (quality of decision-making)

In addition to improving uplift and field oversight efficiency, deploying ML-driven optimization at scale can also influence Lease Operating Expenses (LOE) by improving ESP run life. With the ability to observe petrotechnical-prescribed telemetry boundary limits, the ML model predicts which combination of operating setpoints will adhere to these limitations and dynamically confine the decision space of the model as well conditions change. This provides the operator and supplier with an additional level of proactive protection for their equipment rather than relying on reactive telemetry alarms or faults.

Though LOE saw improvement over the study's duration, this cannot be solely attributed to the deployment of the ML model across the field due to the wide range of external influences on these expenses. Rather, ESP run life data was used to determine the impact directionally on equipment reliability.

Calculated survival analysis results were completed for 2022 and 2023 ESP run life data for all Vital Energy wells produced with ESPs. This period includes a limited view of run lives from before and during the ML model deployment. Data sets were censored and filtered identically from year-to-year. Key takeaways from this analysis are as follows:

- The analysis shows ESP run lives for all wells improved year-over-year (YOY)
- There was a 138% YOY increase in the number of running ESP systems
- YOY comparisons of calculated results show improvements in:
    - % of units failed decreased: 42.7% ('22) vs. 29.6% '(23)
    - Mean time to failure (MTTF) increased: 220 days ('22) vs. 328 days ('23)
    - Probability of failure at 90, 180, and 365 days all decreased in 2023 vs. 2022
- ESP uptime increased by ~4% in 2023 vs 2022. Figure 5.

In summary, the reliability analysis showed marked improvement in several industry-standard failure KPI's from 2022 to 2023, in conjunction with the field-wide deployment of the ML model. While these improvements are not the sole result of the ML model deployment, the reliability analysis results show no negative impact to ESP run life / LOE, after deployment of the machine learning model.

KEY LEARNINGS

New Operating Skillsets

As the machine learning model is refined, the implementation focus moves to training. Training the ML model itself through feedback from domain experts is widely recognized as a key to successful implementation. However, an often overlooked but equally important training effort involves how humans oversee the ML-driven optimization program. This requires a shift in approach and the development of new skillsets necessary to supervise autonomous operations, summarized below:

- Learning how to trust the model results and recommendations
    - Becoming comfortable with "unconventional" setpoints
- Understanding when to use / not use model
    - Understanding what is within the model's core capabilities
    - Understanding what is outside of the model's core capabilities
- Learning how to confine the decision space of the model

  - Through telemetry boundary limits, human optimizers can impart external knowledge / constraints, impacting the model's recommendations (i.e. surface facility / water takeaway constraints)
- Transitioning petrotechnical optimizers to be AI-model supervisors
  - With proper petrotechnical oversight, the ML model is capable of implementing human-prescribed operating strategies (i.e. maximizing uplift, controlling drawdown, etc.) while discovering novel ways to do so
- Having greater emphasis toward field custodianship is critical (i.e. repair and maintenance, keeping valves calibrated, communications functioning, etc.)

<u>Attitude Shift</u>
The introduction of ML / AI digital solutions to workflows in the Oil and Gas Industry is too commonly met with resistance, stemming from the false narrative that petrotechnical professionals will be "replaced" with such tools. Encouraging a shift in mindset is an important responsibility in implementation change management.

Implementation success and velocity are improved significantly when the digital solution is introduced to the field / optimization technical team as an extension of their own capabilities, which will provide them the capacity to direct their time and expertise toward challenges where it is most needed.

A new perspective must also be developed regarding "failure". Throughout the refine phase of digital solution implementation, deliberate effort should be made to identify the boundaries of the core capabilities of the solution. Additionally, the nature of ML models themselves is one of continuous improvement – benefiting from feedback of both successes and failures. Successfully identifying and communicating risk tolerance prior to implementation helps to mitigate fear of failure while preserving core business.

<u>Importance of Scale</u>
Implementing the ML model into an artificial lift optimization program can provide tangible value through improving uplift, increasing petrotechnical efficiency, and reducing LOE. These benefits are often only realized when implementation is done at scale.

Though results may vary from well to well, incremental improvement (uplift, LOE, etc.) averaged across the field can serve as a powerful motivator for organizational buy-in. This can result in a compounding effect, in that improved buy-in leads to greater adoption, which in turn leads to further improved outcomes.

In addition to the importance of increasing scale in terms of well count and organizational buy-in, another valuable learning taken from this study is the need for autonomy. Implementation of ML recommendations was severely limited by the need for a human to implement each recommendation manually. The 'implementation constraint' observed when deploying ML at scale underlines the value of the 3rd phase of capability maturity: "Automate". Overcoming this hurdle will be addressed in future work.

CONCLUSIONS / SUMMARY

The journey to a fully mature and operational AI ecosystem for any operator using artificial lift is a long one. It requires the operator and its partners to navigate numerous roadblocks and challenges as their oilfield becomes increasingly digital.

The process for the successful implementation of an artificial lift ML model can be defined as follows,

- Develop the ML model
- Demonstrate its capabilities
- Refine model, user interface, and application expectations
- Deploy at scale and transition into workflows of core business

Refining the ML model, as it provides outputs and recommendations, is widely recognized as a key to successful implementation. However, an often overlooked and equally important training effort involves how humans oversee the ML optimization program. This requires a shift in perspective and the development of new skills necessary to supervise autonomous operations, as well as driving out the fear of failure of both the ML model and the humans that oversee it.

Deploying a refined machine learning algorithm at scale over multiple wells, fields, etc. can provide compelling benefits in terms of decision-making, LOE improvement, and production uplift.

REFERENCES

Hnot, T., Vasylyshyn, B., Struk, A., Benham, D., Meek, J., and N. Ferrara. "AI-Based Approach for ESP Optimization." Paper presented at the SPE Gulf Coast Section - Electric Submersible Pumps Symposium, The Woodlands, Texas, USA, October 2023. doi: https://doi.org/10.2118/214731-MS

SOURCES

- Figures 1-5, Vital Energy

FIGURES

Capability Maturity (across) → **Implementation Maturity (down)** **|** **V**	**Measure** Collecting quality, timely and complete data necessary for intelligent optimization	**Optimize** Increasing speed and quality of decision making to optimize asset value	**Automate** Autonomous action involving experts by exception
Develop: Create minimum viable product	COMPLETED	COMPLETED	COMPLETED
Demonstrate: Deploy small-scale field-trial	COMPLETED	COMPLETED	COMPLETED
Refine: Iterate with domain experts in small-scale trial(s) in prep to scale	COMPLETED	COMPLETED	IN PROGRESS
Deploy: Scale and transition into core business	COMPLETED	IN PROGRESS	IN PROGRESS

Figure 1 – Example of Capability-Implementation Maturity Matrix

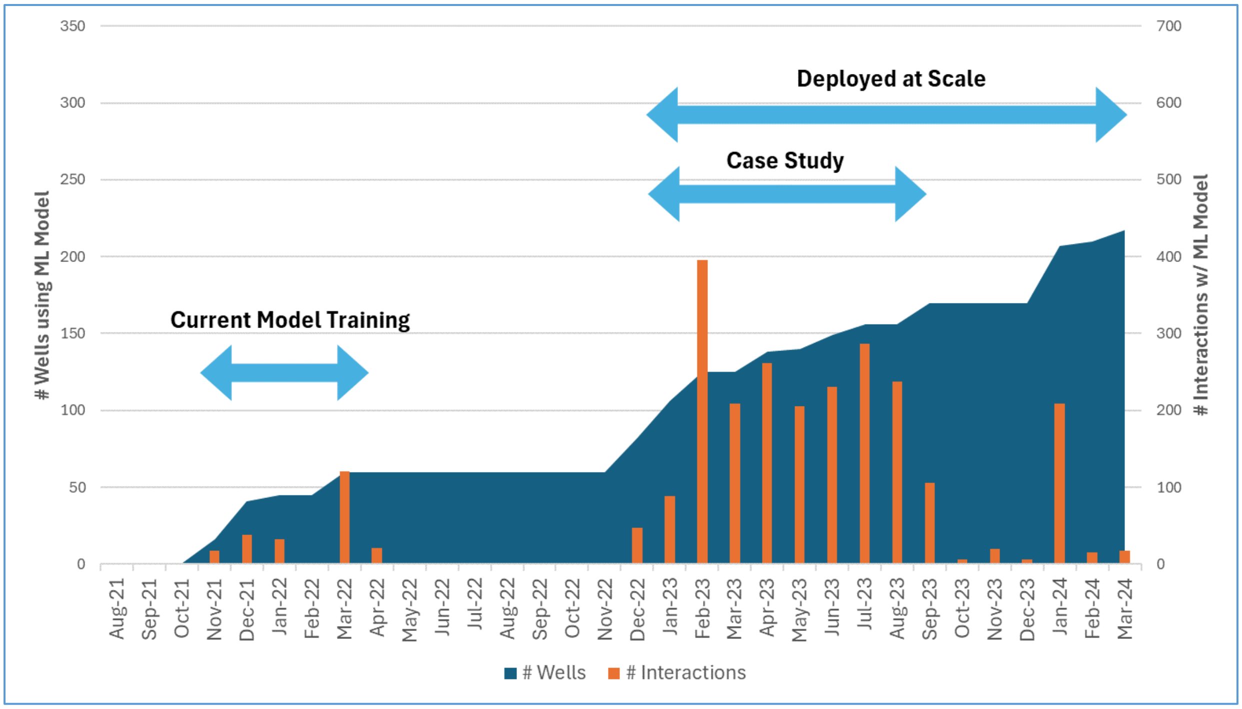

Figure 2 – ML Model Implementation Timeline

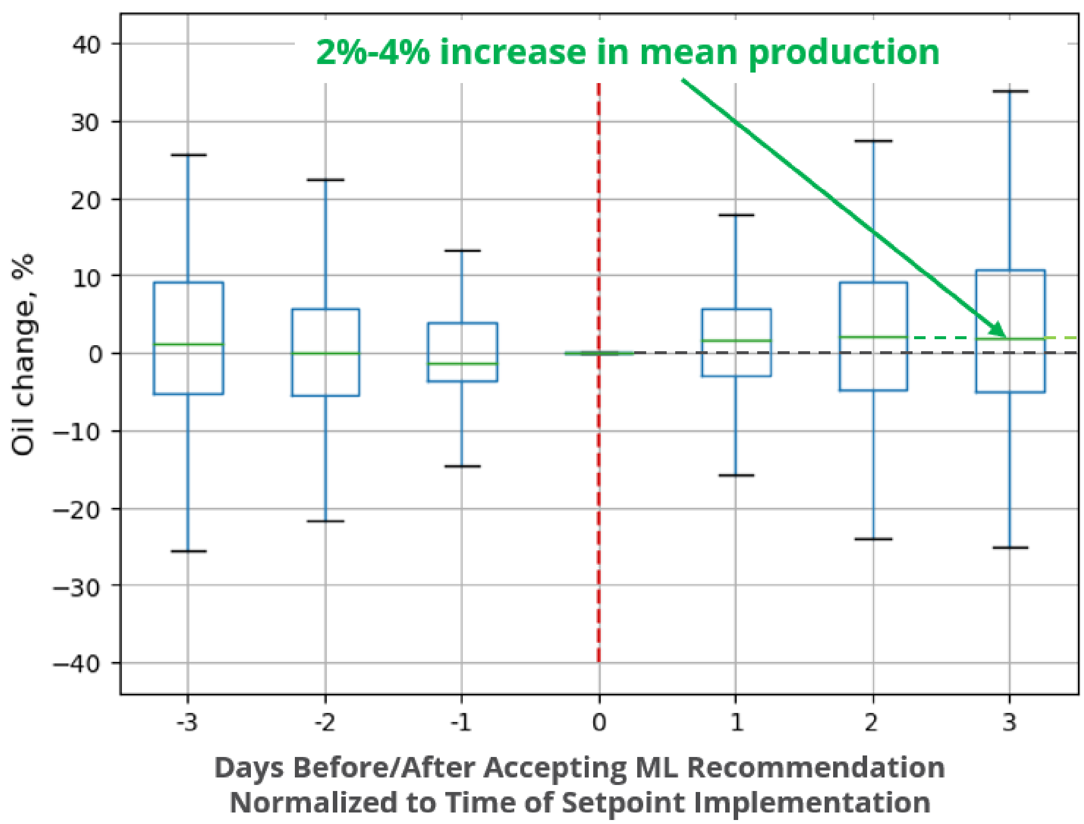

Figure 3 – % Oil Change After Implementing ML Recommendations

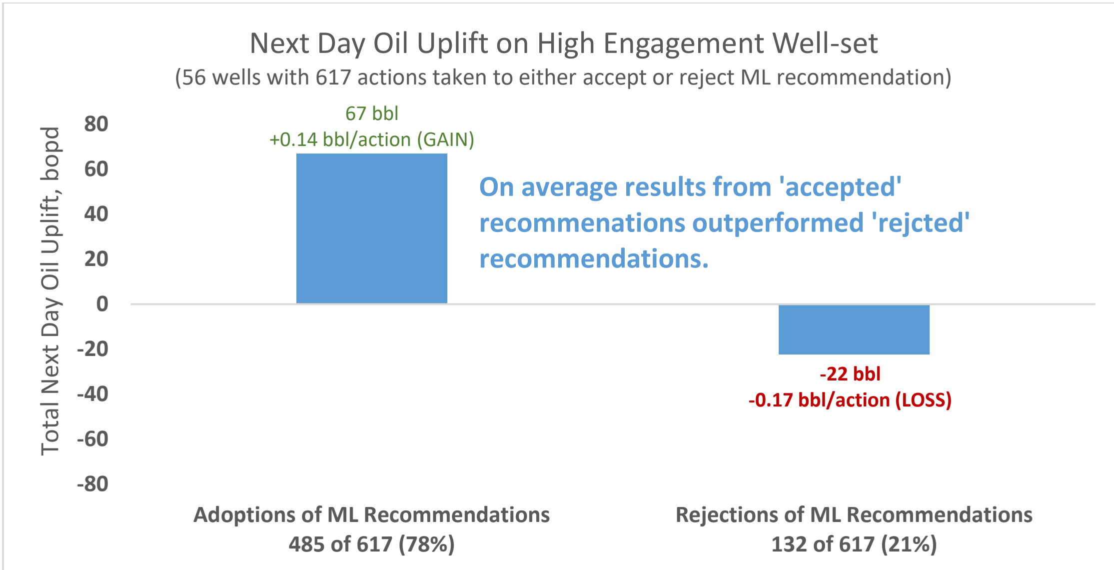

Figure 4 – Next Day Oil Uplift on High Engagement Well-set

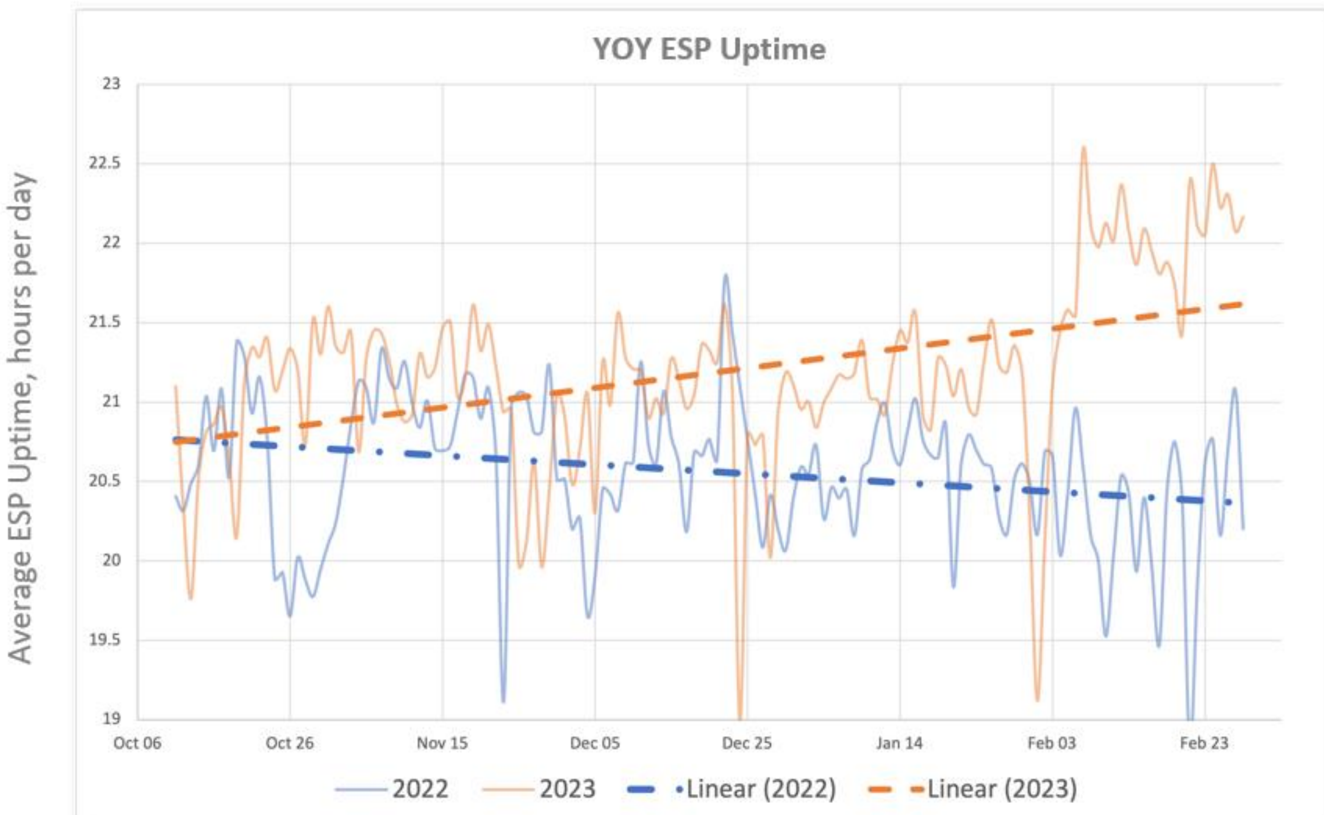

Figure 5 – Year over Year Average ESP Uptime