A DMAIC-Based Analysis of ESP Operational Performances and Their Influence on Production Stability

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Abstract *–This project applied the Define, Measure, Analyze, Improve, and Control methodology to evaluate how electrical, mechanical, and pressure-related operational variables influence the six-hour moving averages of oil, gas, and water production in a well equipped with an electric submersible pump. The analysis examined the relationships between operational conditions and production behavior to determine the extent to which these variables contribute to performance changes. Results showed low to moderate correlations, with gas production demonstrating the strongest association, while oil and water production were influenced primarily by reservoir conditions. These findings indicate that operational adjustments have limited predictive impact but contribute meaningfully to production stability. The project identified improvement opportunities focused on stabilizing pump frequency, optimizing pressure conditions, and strengthening monitoring practices. A long-term control strategy was developed using standardized procedures, performance indicators, and continuous observation to sustain improvements in well performance.*

Keywords *–Control Strategy, Electric Submersible Pump Performance, Production Analysis, Quality Improvement.*

PROBLEM STATEMENT

Electric Submersible Pumps are widely used to sustain production in wells with declining reservoir pressure, yet their performance is often affected by variations in electrical, mechanical, and pressure-related operating conditions. In mature reservoirs, production behavior is strongly influenced by reservoir dynamics, making it difficult to determine how much operational parameters truly contribute to changes in oil, gas, and water rates. This uncertainty limits the ability of operators to optimize performance, reduce variability, and implement effective control strategies. The problem addressed in this project is the lack of clarity regarding the influence of key operational variables on production behavior in an Electric Submersible Pump well and the need for a structured methodology to evaluate and improve performance.

RESEARCH DESCRIPTION

This research applied the Define, Measure, Analyze, Improve, and Control methodology to evaluate the influence of operational parameters on production behavior in an Electric Submersible Pump well. The study analyzed six-hour moving averages of electrical, mechanical, and pressure-related variables to determine their relationship with oil, gas, and water production. Statistical tools, including correlation and regression analysis, were used to quantify the strength of these relationships. The project also identified improvement opportunities and developed a long-term control strategy to enhance production stability. The research integrates quality management principles with petroleum engineering practices to provide a structured approach for understanding and improving Electric Submersible Pump performance.

RESEARCH OBJECTIVES

The objectives of this project were to assess the extent to which operational parameters of an Electric Submersible Pump influence oil, gas, and water production, acknowledging that these relationships may be weak or moderate due to reservoir-dominated behavior. The study aimed to quantify the strength and direction of these relationships using statistical tools such as correlation and regression analysis, while also identifying sources of operational variation that contribute to instability in production rates. Another objective was to develop improvement recommendations based on data-driven insights, even when the predictive power of the variables is limited. Additionally, the project sought to demonstrate the applicability of the Define, Measure, Analyze, Improve, and Control methodology for analyzing and improving Electric Submersible Pump performance in upstream oil and gas operations and to determine which operational parameters most significantly influence oil, gas, and water production.

RESEARCH CONTRIBUTIONS

This project contributes a structured Define, Measure, Analyze, Improve, and Control framework tailored to Electric Submersible Pump performance, integrating quality management principles with petroleum engineering data. It provides a statistical evaluation of how electrical and pressure-related variables relate to production rates, emphasizing that these relationships are generally low to moderate in strength. The study also offers evidence-based recommendations for operational optimization, focusing on stabilizing controllable variables and improving production consistency. Furthermore, it presents a quality management perspective applied to Electric Submersible Pump operations, demonstrating how systematic analysis can support decision-making even when statistical correlations are minimal.

LITERATURE REVIEW

Electric Submersible Pumps (ESPs) remain one of the most widely used artificial lift systems in the petroleum industry due to their ability to sustain production in wells with declining reservoir pressure. As reservoirs mature, understanding the interaction between ESP operating parameters and production behavior becomes increasingly important for optimizing performance, reducing variability, and extending equipment life. This chapter reviews the body of knowledge relevant to ESP performance modeling, operational optimization, and the role of electrical, mechanical, and pressure-related variables in influencing oil, gas, and water production.

The literature is organized into three major themes: (1) foundational background on ESP systems and their operating parameters, (2) modern optimization and data-driven approaches, and (3) predictive modeling and pressure-related dynamics. Together, these themes provide the theoretical and empirical basis for the DMAIC-based analysis conducted in this research.

Background

Electric Submersible Pumps (ESPs) are multistage centrifugal pump systems designed to lift fluids from wells where natural reservoir energy is insufficient to sustain production. Their performance is influenced by a combination of electrical, mechanical, and pressure-related variables that interact with reservoir conditions and multiphase flow behavior. Understanding these variables is essential for diagnosing performance issues, predicting production trends, and implementing optimization strategies.

Electrical and Frequency Related Parameters

Electrical parameters such as current, voltage, and motor load play a central role in ESP performance. Variations in current draw often indicate changes in pump load, gas interference, or fluid viscosity. Pump frequency, controlled through a Variable Speed Drive (VSD), directly affects pump speed and therefore influences production rates. Zhu et al. [1] demonstrated that under viscous fluid conditions, ESP performance becomes more sensitive to electrical load and frequency adjustments, making real-time monitoring essential for stable operation.

Mechanical and Thermal Behavior

Motor temperature is a key indicator of mechanical stress and equipment health. Elevated temperatures may signal inefficiencies, gas locking, or improper cooling due to low flow rates. Studies published in Geoenergy Science and Engineering [2] emphasize that thermal behavior must be considered when evaluating ESP performance, as temperature fluctuations can accelerate equipment degradation and reduce pump efficiency.

Pressure Related Variables

Tubing and casing pressures influence inflow performance, pump intake conditions, and multiphase flow stability. Pressure fluctuations can lead to gas interference, reduced pump efficiency, and unstable production. Although not always the primary focus of ESP studies, pressure dynamics are consistently identified as critical factors in understanding production behavior and diagnosing operational issues.

Collectively, the literature establishes that ESP performance is governed by a complex interplay of electrical, mechanical, and pressure-related variables. This background provides the foundation for exploring data-driven optimization and predictive modeling approaches.

ESP Optimization and Data-Driven Approaches

As ESP systems become more instrumented and data-rich, modern optimization strategies increasingly rely on analytics, machine learning, and integrated modeling. These approaches aim to improve production efficiency, reduce downtime, and enhance equipment reliability.

Historical Data Analysis and System Modeling

Sindi et al. [3] demonstrated that historical ESP data, including electrical parameters, pressures, and production rates, can be used to model the entire ESP wellbore system. Their work highlights the value of correlating operational variables such as amps, volts, frequency, and motor temperature with production outcomes. By analyzing large datasets, they were able to identify patterns that support predictive maintenance and performance optimization.

Machine Learning and Real-Time Optimization

Hnot et al. [4] introduced an artificial intelligence (AI)-based approach for real-time ESP optimization. Their model adjusts pump frequency and pressure set points dynamically, resulting in improved production efficiency and reduced operational variability. This research demonstrates the potential of machine learning to enhance ESP performance beyond traditional manual adjustments.

Integrated Optimization Frameworks

Recent studies emphasize the importance of integrating electrical, hydraulic, and reservoir data into unified optimization frameworks. These frameworks allow operators to evaluate the combined effects of operational parameters and reservoir behavior, enabling more accurate decision-making. The literature consistently supports the use of data-driven methods to refine ESP performance models and identify improvement opportunities.

Overall, data-driven optimization approaches provide a robust foundation for understanding the relationships between ESP operating conditions and production behavior, aligning closely with the analytical objectives of this research.

Predictive Modeling and Pressure-Related Dynamics

Predictive modeling plays a crucial role in quantifying how ESP operating parameters influence oil, gas, and water production. These models help operators anticipate performance changes, diagnose inefficiencies, and evaluate the impact of operational adjustments.

Artificial Neural Networks and Statistical Models

Sabaa et al. [5] developed artificial neural network (ANN) models using more than 31,000 data points, demonstrating that wellhead pressures, motor temperature, and VSD parameters are strong predictors of multiphase production rates. Their findings validate the use of machine learning and statistical models to quantify relationships between ESP operating conditions and production outcomes.

Pressure Dynamics and Multiphase Flow Behavior

Tubing and casing pressures significantly affect inflow performance and pump intake conditions. Pressure fluctuations can lead to gas interference, unstable flow regimes, and reduced pump efficiency. Although not always the primary focus of ESP modeling studies, pressure-related dynamics are consistently recognized as essential components of accurate production prediction.

PROJECT METHODOLOGY

A quantitative research design was used to evaluate the relationships between operational variables and production behavior. The Define, Measure, Analyze, Improve, and Control methodology structured the investigation and ensured systematic evaluation of performance. Historical operational and production data were collected from an Electric Submersible Pump well, and six-hour moving averages were used to reduce noise and highlight operational trends. Operational variables included pump frequency, motor current, intake pressure, discharge pressure, and tubing head pressure. Production variables included oil, gas, and water rates. Summary statistics, correlation analysis, and multiple linear regression models were used to quantify relationships between operational conditions and production behavior.

Figure 1
DMAIC Methodology

- **Define phase:** The problem was defined as the need to understand how operational variables influence production behavior in an Electric Submersible Pump well and to identify improvement opportunities that enhance production stability.
- **Measure phase:** Data exploration revealed stable operational ranges with occasional fluctuations in pressure and electrical load. Six-hour moving averages provided a clearer representation of production behavior and reduced short-term noise.
- **Analyze phase:** Correlation analysis showed low to moderate relationships between operational variables and production. Gas production exhibited the strongest association with operational changes, while oil and water production were primarily influenced by reservoir conditions. Regression models confirmed that operational variables explained only a small portion of production variability.
- **Design phase:** Improvement opportunities included stabilizing pump frequency, optimizing intake and discharge pressures, and enhancing monitoring practices to reduce operational variability and improve production consistency.
- **Verify phase:** A long-term control strategy was developed using control charts, standardized procedures, performance indicators, and continuous monitoring to sustain improvements and ensure operational stability.

RESULTS AND DISCUSSION

The results and discussion section presents the findings of the Define, Measure, Analyze, Improve, and Control methodology applied to evaluate Electric Submersible Pump well performance. The phases build on one another, moving from problem clarification to data exploration, statistical interpretation, improvement development, and long-term control. The following subsections summarize the outcomes of each phase and demonstrate how the DMAIC framework guided the investigation.

Define

The Define phase established the performance problem by identifying uncertainty regarding how operational variables influence production behavior in an Electric Submersible Pump well. This phase clarified the project scope and set the foundation for a structured evaluation of operational and production data.

Transition to Measure

With the problem clearly defined, the next step was to examine the available data to understand current performance conditions and identify potential sources of variability.

SIPOC Diagram

Suppliers	Inputs	Process	Outpute	Customers
Reservoir– provides fluids (oil,gas, water)	Pwr-Output Amps (Phase B)	1) Power Delivery – VSD controls voltage, current, rentory-motor	Ol rate (6-hour maving average)	Production engineers
ESP equipment manufacturer	Pwr-Output Volts AB	4) Surface Sepagsiation– three-phase separation (ol, gas. water)	Waterate (6-hour moving average)	Reservoir engineerees
Variable Speed Drive (VSD) / Power acquise+system	Motor temperature	5) Surface Separation– three phase separation (oil, gas, water)	ESP operaating conditions (amps. Hz, (emperature)	Operations and mainten-ance teams
Field operators and tubing pressue	Tubing pressure	6) Measurement & Monitoring– sensors measure oil rate, gas rate, tubing pressures		Arerts for abnormal conditions (pressure, cable short, voltage
Operations an maintenance teams	Wellhead pressure trends	6)Data Transmission– SCADA sends real-time data for analysis and optimization	Alerts for abnormal conditions (pressure, cable short voltage	Regulatory agencies (reporting)
Asset managers	Casing pressure			
Company leadership	Reservoir pressure			
Welthead and surface facility sngincering suppliers	Fluid composition (oil, gas, water)			
Regulatory agencies (reporting)	ESP operating guidelines Start-up/shut-down procedures			

Figure 2
SIPOC Diagram

Measure

The Measure phase focused on collecting and organizing historical operational and production data. Six-hour moving averages were used to reduce noise and highlight meaningful trends in electrical, mechanical, and pressure-related variables.

Transition to Analyze

Once the data was validated and summarized, the analysis shifted toward determining how these operational variables relate to production behavior and whether measurable patterns could be identified.

Table 1
Descriptive Statistics

	Pwr-Output Amps Ph B	Temp-Moto	Status-Hz	Tubing Pressure	Pwr-Output Volts AB	Casing Pressure	Oil Rate 6Hr MAvg	Gas Rate 6Hr Mavg	Water Rate 6Hr MAvg
Mean	284.99	235.13	54.73	174.27	265.39	178.56	82.23	1304.45	532.96
Std. Deviation	1.31	0.52	0.19	1.34	185.94	1.35	48.98	420.88	99.38
Minimum	274	233	54.1	169.37	0	173.44	0	294.6	0.31
Maximum	292	237	55.7	179.06	480	183.44	223.35	5258.58	677.63
Range	18	4	1.6	9.69	480	10	223.35	4963.98	677.32
Quartile 1	284	235	54.6	173.44	50.64	177.81	55.21	1166.37	533.27
Quartile 3	286	235	54.9	175.31	426	179.38	109.83	1335.71	571.93

Histogram, Quantile-Quantile Plot, and Run charts showing variation.

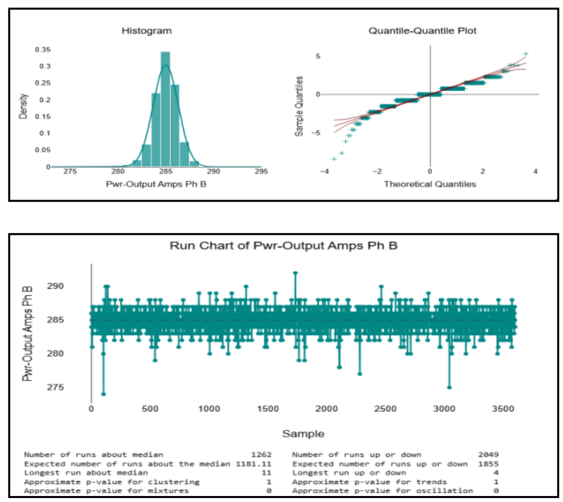
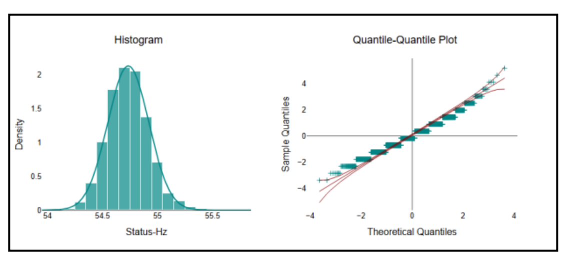


Figure 3
Histogram, Quantile-Quantile Plot and Run charts for Pwr-Outputs Amps Ph B



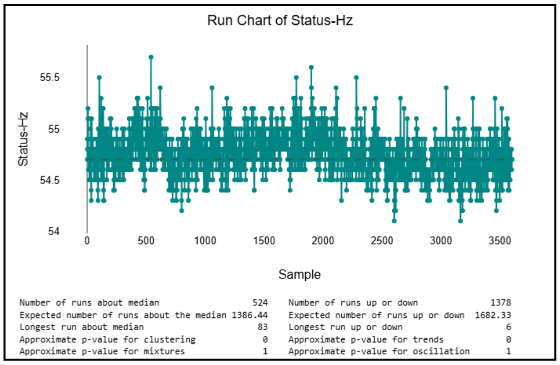
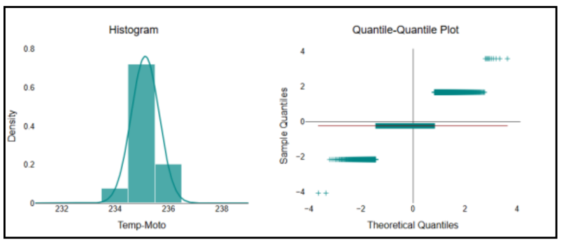


Figure 4

Histogram, Quantile-Quantile Plot and Run Charts for Status-Hz



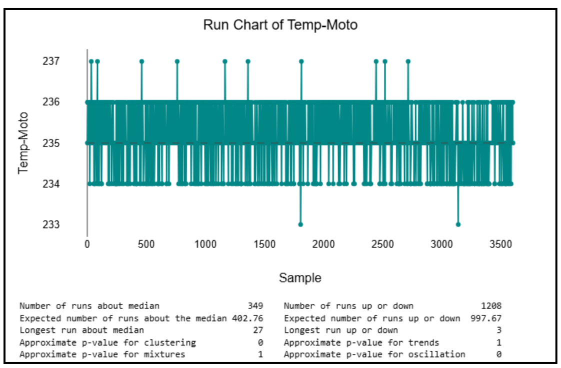
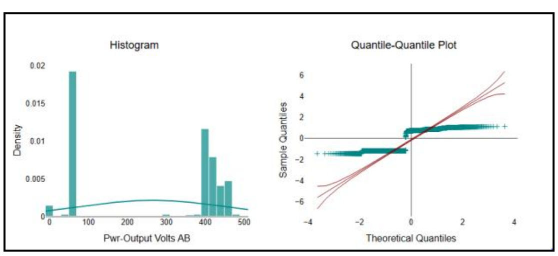


Figure 5

Histogram, Quantile-Quantile Plot and Run Charts for Temperature Motor



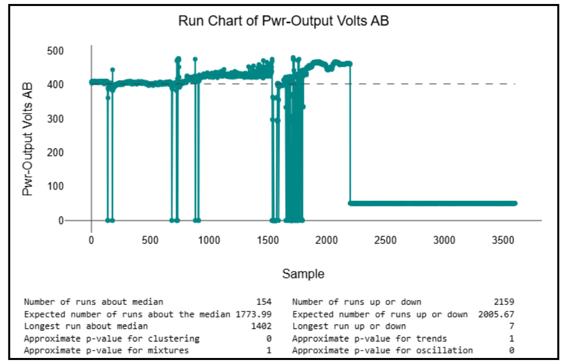
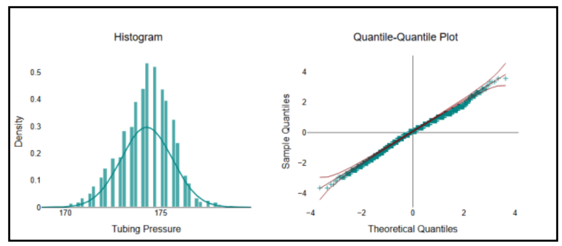


Figure 6

Histogram, Quantile-Quantile Plot and Run Charts for Pwr-Output Volts AB



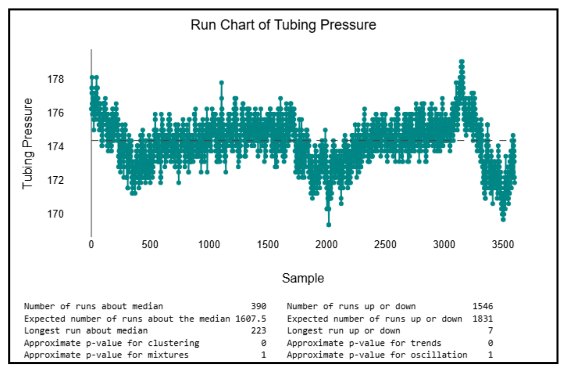
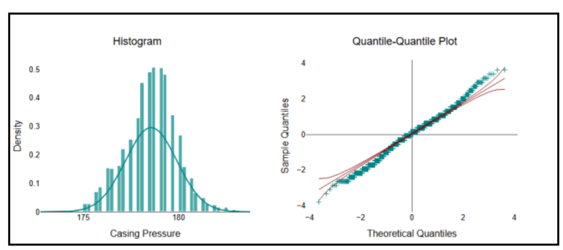


Figure 7

Histogram, Quantile-Quantile Plot and Run Charts for Tubing Pressure



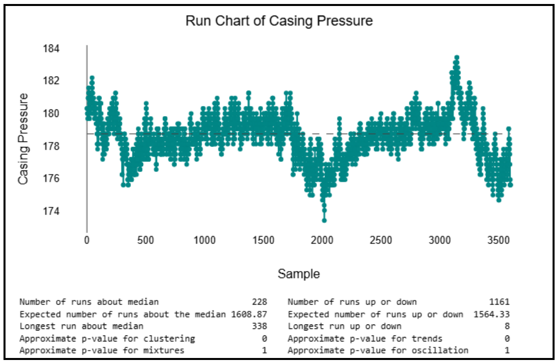
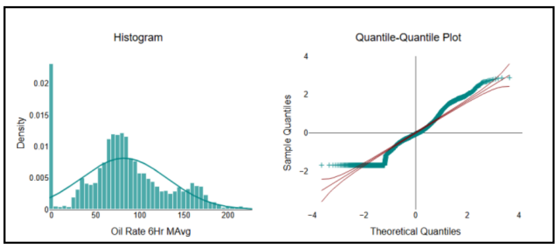


Figure 8

Histogram, Quantile-Quantile Plot and Run Charts for Casing Pressure



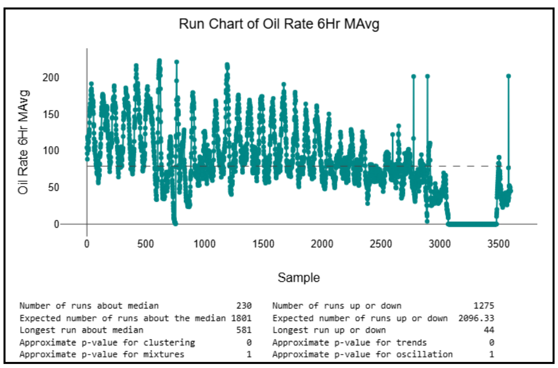
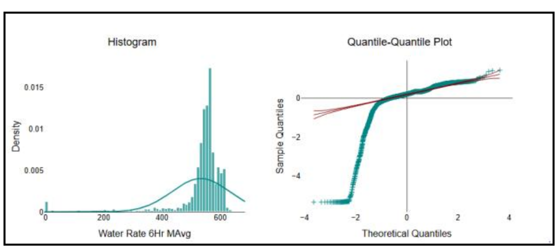


Figure 9

Histogram, Quantile-Quantile Plot and Run Charts for Oil rate 6Hr Mavg



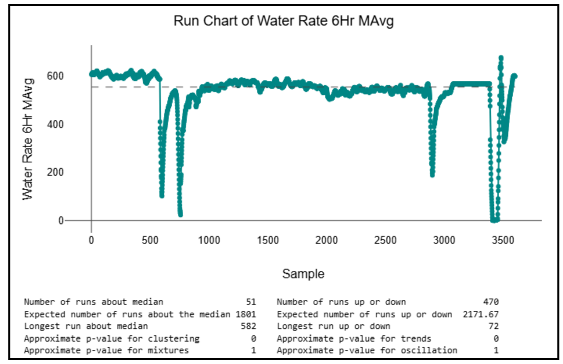
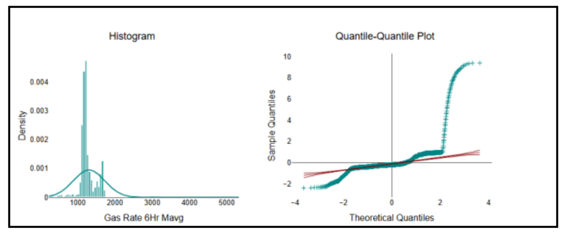


Figure 10

Histogram, Quantile-Quantile Plot and Run Charts for Water Rate 6Hr Mavg



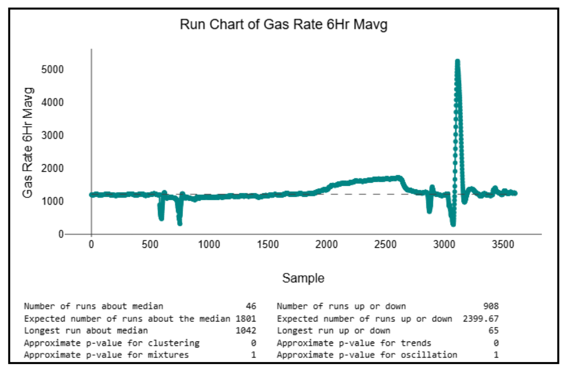


Figure 11

Histogram, Quantile-Quantile Plot and Run Charts for Gas Rate 6Hr Mavg

Analyze

The Analyze phase applied statistical tools to quantify relationships between operational conditions and production rates. Correlation and regression results showed low to moderate associations, with gas production demonstrating the strongest operational sensitivity, while oil and water production remained largely reservoir-driven.

Transition to Improve:

These analytical insights provided the basis for identifying targeted improvement opportunities aimed at stabilizing controllable variables and reducing operational variability.

Correlation and Regression Analysis between Independent Variables (X's) and Dependent Variables (Y's)

The Analyze Phase evaluates the strength and direction of the relationships between the operational variables (X's) and the production indicators (Y's). Correlation coefficients (R), coefficients of determination (R^2), adjusted R^2, and the standard error of the estimate were used to assess model performance and predictive capability.

Effect of Independent Variables on Gas Rate (6-Hour Moving Average)

The regression model for Gas Rate 6Hr MAvg produced an **R value** of **0.36**, indicating a **moderate positive correlation** between the observed values and the model predictions. The **R^2 value** of **0.13** shows that **12.81%** of the **variance** in Gas Rate is explained by the independent variables included in the model. This means that **12.81%** of the **changes in Gas Rate 6Hr MAvg can be attributed to variations in the operational parameters**.

Table 2
Gas Rate 6Hr Mavg Regression Statistics Summary (R, R^2, and Standard Error)

Metric	Value
R	0.36
R^2	0.13
Adjusted R^2	0.13
Standard Error of the Estimate	134.09

Effect of Independent Variables on Water Rate (6-Hour Moving Average)

The regression model for Water Rate 6Hr MAvg yielded an **R value of 0.21**, indicating a **low positive correlation** between predicted and observed values. The **R^2 value of 0.05** shows that **4.57% of the variance** in Water Rate is explained by the independent variables. In practical terms, **only 4.57% of the changes in Water Rate 6Hr MAvg can be predicted from the operational inputs**.

Table 3
Water Rate 6Hr MAvg Regression Statistics Summary (R, R^2, and Standard Error)

Metric	Value
R	0.21
R^2	0.05
Adjusted R^2	0.05
Standard Error of the Estimate	75.38

Effect of Independent Variables on Oil Rate (6-Hour Moving Average)

The regression model for Oil Rate 6Hr MAvg produced an **R value of 0.19**, indicating a **low positive correlation** between the observed and predicted values. The **R^2 value of 0.03** shows that **3.47% of the variance** in Oil Rate is explained by the independent variables. This means that **only 3.47% of the changes in Oil Rate 6Hr MAvg can be attributed to the operational parameters** included in the model.

Table 4
Oil Rate 6Hr MAvg Regression Statistics Summary (R, R^2, and Standard Error)

Metric	Value
R	0.19
R^2	0.03
Adjusted R^2	0.03
Standard Error of the Estimate	40.72

Multiple Linear Regression Model Results (F-values and p-values)

Gas Rate (6-Hour Moving Average) Regression Equation:

- Gas Rate 6Hr MAvg = 693.22
- 1.66(Pwr-Output Amps Ph B)
- 0.08(Pwr-Output Volts AB)
- 100.50(Status-Hz)
- 1.86(Temp-Moto)
- 5.54(Tubing Pressure) – 38.73(Casing Pressure)

Model Summary

The regression model showed that the independent variables explained 12.81% of the variance in Gas Rate 6Hr MAvg. ANOVA results indicate that the model is statistically significant, $F = 53.65$, $p < .001$, $R^2 = 0.13$.

Coefficient Interpretation

- Constant **(693.22):** Expected Gas Rate when all independent variables equal zero.
- **Pwr-Output Amps Ph B**: +1.66 per unit increase.
- **Pwr-Output Volts AB:** +0.08 per unit increase.
- **Status-Hz:** +100.50 per unit increase.
- **Temp-Moto:** +1.86 per unit increase.
- **Tubing Pressure:** +5.54 per unit increase.
- **Casing Pressure:** –38.73 per unit increase.

Interpretation:

Gas Rate is the **most responsive** of the three CTQs to the operational variables. Electrical parameters (amps, volts, Hz) and pressure conditions have a **measurable but limited** influence on gas production.

Water Rate (6-Hour Moving Average) Regression Equation:

- Water Rate 6Hr MAvg = –3044.99
- 1.42(Pwr-Output Amps Ph B)
  - 0.02(Pwr-Output Volts AB)
- 57.06(Status-Hz)
  - 7.06(Temp-Moto)
  - 1.85(Tubing Pressure)
- 11.50(Casing Pressure)

Model Summary

The independent variables explained 4.57% of the variance in Water Rate 6Hr MAvg. ANOVA results show the model is statistically significant, $F = 17.51$, $p < .001$, $R^2 = 0.05$.

Coefficient Interpretation

- Constant (–3044.99)
- Pwr-Output Amps Ph B: +1.42
- Pwr-Output Volts AB: –0.02
- Status-Hz: +57.06
- Temp-Moto: –7.06
- Tubing Pressure: –1.85
- Casing Pressure: +11.50

Interpretation

Water production is weakly influenced by the operational variables. This suggests that Water Rate is driven more by reservoir conditions (e.g., water encroachment) than by ESP operating parameters.

Oil Rate (6-Hour Moving Average) Regression Equation:

- **Oil Rate 6Hr MAvg =** –1427.86
- **0.55(Pwr-Output Amps Ph B)**
  - 0.01**(Pwr-Output Volts AB)**
- 23.36**(Status-Hz)**
  - 3.21**(Temp-Moto)**
  - 0.50**(Tubing Pressure)**
- 5.29**(Casing Pressure)**

Model Summary

The independent variables explained 3.47% of the variance in Oil Rate 6Hr MAvg. ANOVA results show the model is statistically significant, $F = 13.15$, $p < .001$, $R^2 = 0.03$.

Coefficient Interpretation

- **Constant** (–1427.86)
- **Pwr-Output Amps Ph B**: +0.55
- **Pwr-Output Volts AB:** –0.01
- **Status-Hz**: +23.36
- **Temp-Moto:** –3.21
- **Tubing Pressure:** –0.50
- **Casing Pressure**: +5.29

Interpretation

Oil Rate shows the weakest relationship with the operational variables. This suggests that oil production is influenced more by reservoir drive mechanisms than by ESP electrical or pressure settings.

Improve

The Improve phase focused on developing recommendations to enhance production stability. Key opportunities included stabilizing pump frequency, optimizing intake and discharge pressures, and strengthening monitoring practices to minimize fluctuations.

Transition to Control

To ensure that these improvements could be sustained over time, the final phase established mechanisms for ongoing monitoring and performance management.

The Improve Phase focuses on implementing targeted operational adjustments to enhance ESP performance, reduce variability, and mitigate the factors identified during the Analyze Phase. The following improvement actions are recommended based on the regression results, correlation analysis, and operational behavior of the well.

Recommended Improvement Actions

1. **Stabilize Pump Frequency (Status-Hz)**
   - Implement tighter VSD control logic to reduce frequency variability.
   - Set narrower operational bands for allowable frequency adjustments.
2. **Optimize Intake Pressure Conditions**
   - Maintain tubing and casing pressures within stable operating ranges.
   - Minimize sudden drawdown changes that may increase free gas at the pump intake.
3. **Monitor Electrical Load (Amps and Volts)**
   - Use real-time monitoring to detect early signs of gas locking or pump instability.
   - Adjust pump speed proactively when gas interference patterns are detected.
4. **Implement Water-Cut Monitoring Alerts**
   - Configure automated alerts for sudden increases in water rate.
   - Integrate water-cut trends with reservoir surveillance workflows.
5. **Maintain Stable Pressure Conditions**
   - Avoid aggressive drawdown strategies that may accelerate water breakthrough or destabilize inflow.
6. **Improve Actions for Oil Rate (Lowest Sensitivity CTQ)**
   - Maintain stable bottom-hole pressure through controlled frequency adjustments.
   - Reduce pressure oscillations that may restrict reservoir inflow.
   - Analyze available data to maintain or improve ESP reliability.
   - Define the pump’s functional behavior relative to the key variables identified in the analysis.
   - Determine the influence of each selected variable on pump reliability.
   - Calculate the probability of maintaining optimal performance or experiencing failure; Weibull probability analysis is recommended for reliability assessment.

Implementation Plan

1. **Short-Term Actions (0–30 days)**
   - Tune VSD frequency control parameters.
   - Implement real-time monitoring dashboards for key ESP variables.
   - Set alert thresholds for motor temperature, pressure deviations, and water-cut changes.
2. **Medium-Term Actions (30–90 days)**
   - Conduct controlled frequency tests to evaluate gas-handling response.
   - Optimize pressure-management strategies based on observed inflow behavior.
   - Train operators on updated control limits and monitoring procedures.
3. **Long-Term Actions (90+ days)**
   - Evaluate Weibull distributions for identified critical reliability variables.
   - Integrate predictive analytics for early detection of gas interference.
   - Reassess the ESP operating envelope using updated performance data.
   - Evaluate reservoir-driven constraints affecting oil and water production.

Control

The Control phase implemented long-term strategies to maintain operational stability, including standardized procedures, performance indicators, and continuous monitoring tools. These controls help ensure that improvements remain effective and that deviations can be detected and corrected promptly**.**

The Control Phase ensures that improvements implemented during the Improve Phase are sustained over time. Continuous monitoring, early warning indicators, and updated operational procedures are essential to maintaining stable ESP performance.

Control Objectives

- Maintain stable ESP operating parameters (frequency, amperage, voltage, pressures, and motor temperature).
- Operational deviations that negatively affect Oil, Gas, and Water production rates.
- Detect early signs of gas interference, water breakthrough, or inflow instability.
- Ensure that improvements from the Improve Phase remain effective and embedded in routine operations.

Table 5
Control Metrics (KPIs)

KPI	*Description*	*Purpose*
Pump Frequency Stability (Hz)	*Variation around target frequency*	*Prevents gas interference and unstable production*
Motor Temperature	*Continuous monitoring of thermal load*	*Avoids overheating and efficiency loss*
Tubing & Casing Pressure Stability	*Pressure fluctuations vs. control limits*	*Maintains inflow stability*
Oil Rate (6Hr MAvg)	*Primary CTQ*	*Tracks production performance*
Gas Rate (6Hr MAvg)	*Secondary CTQ*	*Detects gas interference or reservoir changes*
Water Rate (6Hr MAvg)	*Secondary CTQ*	*Detects water breakthrough*

Conclusion

The project demonstrated that operational variables influence production stability but have limited predictive impact on oil and water production due to reservoir-dominated behavior. Gas production showed the strongest operational sensitivity. The Define, Measure, Analyze, Improve, and Control methodology provided a structured and effective framework for analyzing performance, identifying improvement opportunities, and developing long-term controls. The findings support the use of quality management principles in artificial lift optimization and highlight the importance of monitoring and stabilizing key operational parameters to enhance Electric Submersible Pump well performance.

References

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