ESP TREND ANALYTICS: MERGING DATA SCIENCE WITH APPLICATION ENGINEERING KNOWLEDGE TO IMPROVE OPERATIONAL STATE IDENTIFICATION

Dylan Bucanek and Nathan Mayer
ChampionX – Theta Automation and Optimization

OBJECTIVE

Historical electrical submersible pump (ESP) analyses have been completed with daily ammeter circular charts drawn on the surface. From these charts, operators were able to diagnose low fluid levels, gas interference, and power quality issues among other operational issues (Takacs, G). Over the last two to three decades, variable speed drives (VSDs) and downhole sensors became available and allowed ESP operators to control their wells based on more variables than solely motor current. Around the same time period, monitoring and control systems connected the wellsite to the office, making remote surveillance and optimization the standard in the oil industry.

Over time, the amount of people looking at ESP variables trends has grown exponentially. This had led to a vast amount of knowledge gained on understanding operating conditions with ESPs previously held in the minds of few field-dedicated operators. What made the knowledge leap possible was the enormous amount of data collected from the field. The subject matter experts (SMEs) from the 1960s to the 1980s were able to take their prior knowledge of ammeter charts and apply more variables to confirm once suspected issues and learn new operational conditions previously out of their reach. The historical limiting factor with this vast knowledge base was the lack of sharing this knowledge with younger engineers and operators of ESPs.

The process described in this paper merges statistical analysis applied to the data of multiple ESP parameters simultaneously with the guidance from industry expertise of how to diagnose ESP operating conditions. The results will provide the operator with current operational states and potential failure anomalies in an easy-to-use and interactive environment. Not only will this facilitate quicker decision making, but also enable operators to increase the number of wells under management. This paper will explain how we are closing the knowledge gap and sharing ESP knowledge with younger operators as the traditional SMEs are retiring from the industry. Thus, the transfer of ESP knowledge has moved from minds into software with the potential to impact many operators in very little time, while reducing the burden of trying to figure out how ESPs operate without an SME as a mentor.

PROCEDURE

Data Acquisition

In order to build a reliable model for trend analytics, a large sample of realistic data must be acquired to develop and tune the model. This ESP trend model is based on data obtained from over 1400 live production ESP wells from across the United States. The wells present in this data set represent a variety of well depths, pump sizes, configurations, and operational states. The ESPs had varying data frequency, availability, and quality. The volume and diversity of this data set allowed the model to be applied to a variety of reservoir characteristics and well designs.

The development of this model was also based on hundreds of ESP system dismantle inspection failure analysis (DIFA) reports generated for these field assets. By connecting trend patterns seen in the ESP systems prior to failure with the results of the ESP teardowns, deeper engineering insight has been applied to the classification of trend patterns than would have not been possible through simple trend analysis.

Because this model was designed to be run in a host system that monitors many wells simultaneously, the model had to be able to process wells with differing data frequencies and levels of data quality. Also, because ESPs have diverse downhole sensor configurations based on the manufacturer, the model was built to support any available configuration of sensors. Some level of analysis can be performed if any sensor data is present, but accuracy improves as more sensor data is made available for a given well.

The model will use the following data if available:

1. Motor Frequency (Hz)
2. Surface (Drive) Motor Current or Downhole Motor Current (Amps)
3. Motor Temperature (ºF)
4. Pump Intake Pressure (psig)
5. Pump Discharge Pressure (psig)
6. Tubing Pressure (psig)
7. Casing Pressure (psig)

Trend Analysis
A general model for ESP trend analytics must be able to handle variation in data frequency, data quality, and data availability. Several steps must be taken in order to produce trends that can be analyzed by a general model. The general model must be equipment-agnostic to ensure valid results regardless of surface and downhole manufacturers used.

Validation
Data must meet minimum thresholds of quality in order to be considered for trend analytics. In this model, thresholds are minimal to allow as many wells as possible to be considered for analysis. At minimum, the well must have:

1. Sufficient data frequency, at least one scan value per hour recorded in the host system
2. A minimum of Motor Frequency or Surface Motor Current available for most classifications
3. Data falling within acceptable ranges (positive, nonzero)

Cleansing
Once data has met minimum quality thresholds, data must be cleansed in order to produce a stable trend signal. Data that can be attributed to temporary failure of sensors or communications equipment is discarded so that analysis can be performed on data considered to be reliable. Examples of data that should be discarded are:

1. Extreme single-point deviations from the mean of the sample data
2. Zero or negative values for sensors measuring most pressures, temperatures, and other environmental conditions

Standardization
A general model for ESP trend analytics must be applicable to wells with a variety of designs and reservoir characteristics. Where possible, data must be considered not according to absolute values, but normalized relative to the mean of those values. Trend analysis will be less vulnerable to sensor noise and insignificant variations in data if trends are normalized to a rolling average of the sensor values, where an average of the last hour (or other time frame) of data becomes the base trend from which analysis is performed.

Anomaly Detection
Electrical Submersible Pumps are applied in a wide range of reservoir and well conditions, meaning that the normal operating dynamics of these systems will vary significantly between wells and fields. An unconventional, high Gas-Liquid-Ratio (GLR) ESP installation in the Permian Basin has very different “characteristic” operating conditions than a high water-cut well in California. Because of the diversity of well conditions possible with ESPs, an analytical model cannot simply alert operators to trends that fall outside of a “rule of thumb” range. A general system for analyzing ESP trend data must be based on anomaly detection, in which deviation from a flexible baseline established for each well is used to determine when well conditions have changed.

In order to detect anomalies in an ESP system, a standard for what qualifies as anomalous must be developed based on engineering insight and experience. Some examples of possibly anomalous behavior for an ESP are:

1. An increase in pump intake pressure by 10%
2. An increase in motor temperature of 5%
3. An increase or decrease in motor current by 20%

However, change in operating frequency is the most significant input for each of these three trends. In order to detect changes in operating condition that are not caused by frequency changes, the model must rule out changes to these trends immediately following shutdowns and remove the variation caused by changes to frequency setpoints made manually or automatically in PID control loops. By removing the variation caused by frequency, true changes in well operating conditions can be detected and flagged as anomalies.

Anomaly Classification

Once an anomaly has been detected in an ESP system, it is helpful to operators to classify the anomaly both as an educational tool for less experienced ESP analysts and as a starting point for experienced analysts who must focus their attention on the highest priority wells. A model for classifying changes to ESP operating conditions must use the same trend signals that experienced ESP analysts rely on for determining the cause of an anomaly.

Some of these trend signals are:

1. Trend absolute values (low pump intake pressure, high motor temperature)
2. Trend slope (increasing temperatures or pressures)
3. Trend standard deviation (increase or decrease in the variability of motor current)
4. Trend covariance (An increase in the spread of pump intake and discharge pressures)

While none of these trend signals contains enough information to accurately classify the operational condition of the ESP system, combining these signals from all available sensor data can give us enough information to produce a classification.

Based on normalized trend data from over 1400 ESP systems, characteristic profiles of trend signals were built for the following operating conditions as shown in **Table 1**.

Each of these classifications can be diagnosed using the following process:

1. An anomalous condition is detected in the trends for an ESP.
2. The profile of each trend (slope, variance, absolute value, covariance) is compared with each signature trend for each classification.
3. The distance of each trend from its characteristic pattern for that anomaly is weighted and added together.
4. The condition profile that has the lowest “distance” from the observed trend profile is selected as the most likely cause of the trends observed.

This system is advantageous in that:

- It allows for varying sensor configurations, as distances are only computed for available sensors.
- It can be easily extended to include new sensors or trend signals as the system improves.
- It is easily explainable in the conclusions it produces because the scoring is based on a linear combination of the inputs.
- It can be computed quickly and frequently without requiring advanced hardware configurations.

Some of the disadvantages are:

- Lower potential accuracy than less explainable “black box” machine learning methods.
- Any additional tuning must be done manually.

These anomalies can then be prioritized based on the severity of the predicted classification and saved in a time series data format and displayed to the user as a starting point for their exception management process. The top three most likely classifications are recorded so that possible alternative classifications can also be displayed and considered.

RESULTS

As the concept of data analytics was proven in an external database using the data of 1400 ESP wells, including failure data from DIFA reports, the next task was reducing the sample size to 130 randomly selected ESP wells. The reason for the reduction in sample size was to enable manual investigation on each classification or lack of classification while increasing the turnaround time after tuning the algorithms.

After the first iteration, the trend analytics was around 65% accurate in the classification of operating conditions. This original model was trying to classify a reservoir pressure increase based on pump intake pressure. Unfortunately, a pump intake pressure increase can be linked to many other possibilities, such as a backpressure increase on surface or an ESP speed reduction. Therefore, instead of trying to identify the exact issue, the model now gives the user valuable information based on a change from the ESP’s normal operation. Accuracy can be increased with fewer false positives.

Upon sequential iterations, the accuracy improved to about 80%, and eventually achieved 90% accuracy after multiple validation cycles on the 130 test wells. As stated above, it was determined that the algorithms being used to classify operating conditions limits the accuracy but increases the meaning to the end user by the way it is presented. There are more advanced algorithms available with the potential of achieving higher accuracy but at a cost of understanding and explaining the results to the user. There is more value in understanding and learning from the trends rather than trusting results without evidence to support such claims as seen in other algorithms.

The design of the system was critical to the end user because we needed to provide the classification information in a meaningful way without data overload consequences. The first step was to develop a dashboard that serves as the landing page for the analytics. Five pie charts across the top of the screen present the application type, run status, communication status, controller alarms, and the trend analytics classifications as shown in **Figure 1**. The grid view under the pie charts begins with the left-most column of priority ranking mentioned previously. Moving to the right, the columns headers display the same data in the pie charts above but are now tied to the asset (well) name rather than the application (artificial lift type).

The dashboard allows for more than just visual representation. The user can filter based on multiple variables in each pie chart along with the column headers below. Each column has the ability to limit how much data is shown to further reduce the well count to only the wells the user is interested in. The priority ranking based on the severity of the classification is also adaptable, giving the user the option to change priorities which conform to their company’s operating standards and procedures. After the filtering and sorting has been completed the user may double-click the asset name and a new window is launched revealing the trends and associated classifications as shown in **Figure 2.**

The layout of the screen in Figure 2 is concise and displays the information needed to illustrate the classifications documented on the previous dashboard screen. The top left of the screen displays the asset name and beneath is the classifications. Date ranges are organized by five presets ranging from 1 to 30 days along with a custom date range feature. The two sections labeled Events and States are shown with the respective classifications and the color key. Events are described as short-term anomalies while States are classifications which have shown persistence in the trends over an extended period. By hovering over the classifications, a description will show in a tool tip, giving a possible explanation for the occurrence. The first row of information displays the corresponding color keys related to the classifications over the flagged length of time. Beneath the color bands are the main four variables used in the analysis which are frequency, pump intake pressure, motor temperature, and motor current. Any additional variables such as tubing and casing pressure and pump discharge pressure can also be added to this screen.

The user will then have the ability to return to classification dashboard shown in Figure 1 and make a decision about the classification presented for a well. By right-clicking on the classification, the user can acknowledge the primary classification, acknowledge all classifications for that well, or suppress the classifications. Upon acknowledging the classification, the well will disappear from the view. Meaning the user has reviewed the classifications with the trends. Suppressing a classification will generate a pop-up for the user to enter how many days the classification should be suppressed. This prevents the classification from being presented on the dashboard when the user understands a potential problem exists and does not need to be alerted while the problem is being resolved. If the user wishes to see which classifications have been acknowledged, suppressed, or left unacknowledged, the respective filter can be chosen.

Case Studies

As the ESP trend analytics were running on live data, the classifications were studied in real time to validate the accuracy of anomaly and failure detection. Anomaly detection was verified by engineer's and ESP operator's independent interpretation of the trends and comparing their results to the trend analytics classifications. Failures were verified in the ESP failure database by reviewing the detailed DIFAs to determine the cause of the failure and cross-referencing the report's findings with the final classifications identified prior to the ESP failure.

In Figure 2 a broken shaft was identified on 08/25/2019 by analyzing the rise in motor temperature. Motor temperature alone may have many causes, so the pump intake pressure data was also analyzed to make a connection between the rise in both variables. Then the motor current displayed a sudden large drop in amperage that was followed by multiple restarts without a return to normal amperage loads. Finally, the frequency was analyzed to make sure the changes in the other three variables were not caused by a change in frequency. Compiling the slope changes, magnitude of change and the time span of those changes, a broken shaft was determined to be the most likely cause. Understanding the physics behind the classification can be done once all variables are taken into account. The motor temperature rose due to a lack of fluid flowing past the motor in order to keep it cool. The pump intake pressure began to rise because no fluid was reaching the surface, allowing fluid to build up in the casing-tubing annulus. Finally, the motor current dropped close to idle amps which means the motor was no longer required to pull the same amperage as before due to a shortened shaft length to turn. This information was checked against the DIFA report for this ESP and the findings confirmed a broken shaft in the third pump.

A second example from live ESP data is shown in **Figure 3**. The classifications shown are periodic but consistent gas pockets seen by the downhole sensor at the base of the ESP unit. The classifications display a high gas ingestion state for most of the window of time shown on the trend. The analytics have established this is a gassy well and because it has experienced gas for so long, it has essentially become a new normal operating state. Furthermore, the interesting events captured by the analytics show repetitive trend signals of gas increases lasting at least one day during each occurrence. First, the pump intake pressure rises each time followed by a meaningful rise in motor temperature. These two variables need to be checked against the motor current which dropped and sustained lower amperage during the high pump intake pressure interval. The tubing pressure also showed lower values. The varying frequency confirmed the ESP was running in a PID loop to help against gas ingestion. By using the five variables available, the classification of a gas increase was given for the first three intervals, but the fourth interval was given a gas slugging classification due to the shortened time frame in which the same variable signatures manifested and resolved. From the consistent nature of the gas increases, one explanation may be peaks in the well's lateral section that collected gas pockets before the pressure was high enough to unload and the process continues to repeat itself.

The third and final example is shown in **Figure 4**. The trend analytics identified a rise in the motor temperature and drive current while the pump intake pressure continued to decline at a steady rate. After about 12 hours, the pump intake pressure began to rise while the motor temperature and drive current peak and plateau thereafter. Meanwhile the tubing pressure begins to decline as the ESP continues to run. The increased motor temperature and drive current indicate inadequate motor cooling and an increased working load on the shaft. Rising pump intake pressure and a declining tubing pressure indicate fluid is no longer moving through the ESP, allowing fluid to build on the backside. Individually all of these trends tell a different story but when combined, we have a much better understanding of the system from a holistic point of view with the most likely classification being blocked pump stages.

CONCLUSIONS

The ESP community is adapting to new ways of analyzing trends over time. For many years, circular ammeter charts were the only piece of information available that could be extrapolated to downhole conditions. As downhole sensors became standard in the industry, new variables became available, creating a steep learning curve overnight. The multi-variable trend analytics presented in this paper demonstrate a logical and interactive way to close the knowledge gap our industry faces in our current decade. New information is presented in a clear and easy-to-follow visualization to help operators learn more about ESPs, while also helping to understand possible inflow and surface constraints that impact the ESP system. Being able to manage more assets with an automated system allows operators to devote more time to higher priority wells without feeling like the other wells are neglected. ESP trend analytics empowers operators by providing valuable feedback on current operating conditions, probable failure points, and expansion of “sight” to cover a larger area of ESPs.

The work presented in this paper will continue to expand into more classifications over time. Further work is required to build out recommendations based on the classifications presented. This will help the operator understand why the anomaly is occurring the steps to be taken to resolve the problem or mitigate the current condition to prevent a premature system failure.

REFERENCES

Takacs, G. 2009. Electrical Submersible Pumps Manual: Design, Operations, and Maintenance, first edition. Burlington, Massachusetts: Gulf Professional Publishing/Elsevier.

ACKNOWLEDGMENTS

We would like to thank ChampionX Unbridled ESP Systems for providing the live ESP data, along with the DIFA reports used in the development of this work. Collaboration across operating companies has proven to be an invaluable source of knowledge and expertise. Thank you to Doug Rauenzahn and Terry Treiberg for their support and the opportunity to develop the ESP trend analytics in the XSPOC production optimization software. We are also grateful for Sebastian Spivey, Ian Nickell, and Kari Bathe for peer reviewing and offering comments on this work.

Table 1 – Examples of operating conditions based on trend signals.

Broken Shaft	Hole in Tubing	Solids in Pump
Increase in Gas Ingestion	Gas Slugging	Wearing Stages
Blocked Pump Intake	Reduced Well Inflow	Increased Well Inflow
Water Cut Increase	Intake Pressure Increase	Motor Temperature Increase
Surface Shut In	Malfunctioning Intake Pressure sensor	Malfunctioning Motor Temperature sensor
Extended Shut Down	Cycling	Backpressure Decrease

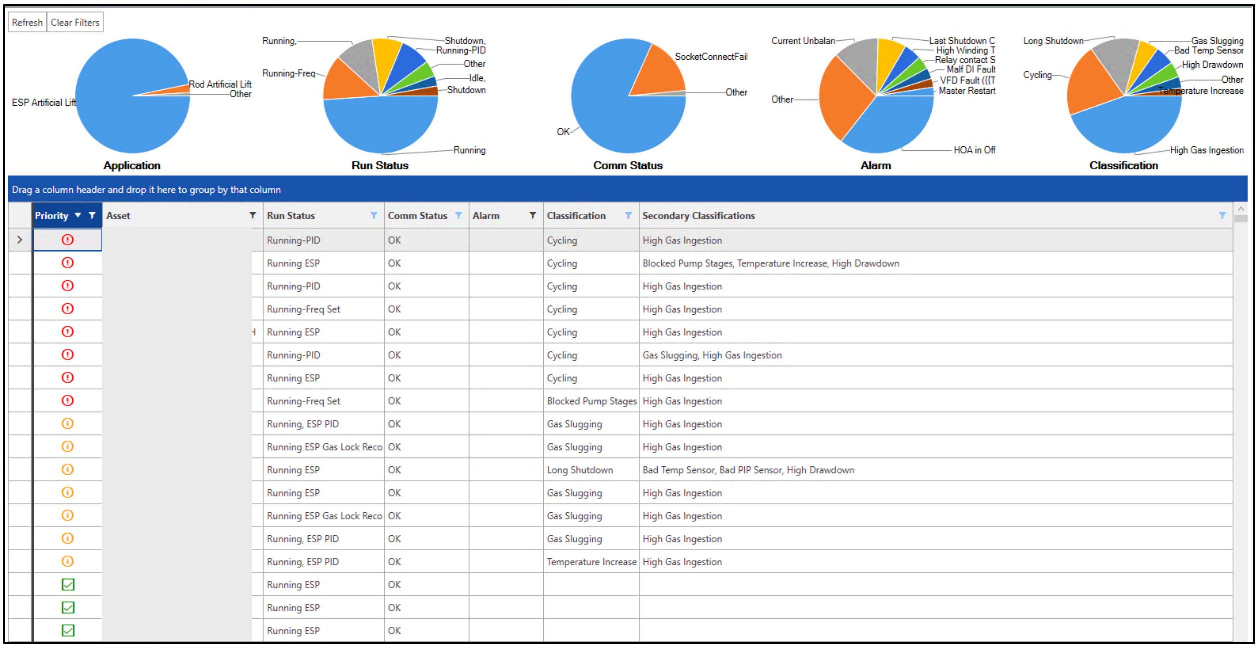

Figure 1 – Example of trend analytics Dashboard.

Figure 2 – Example of trend analytics output on one ESP well classifying a broken shaft.

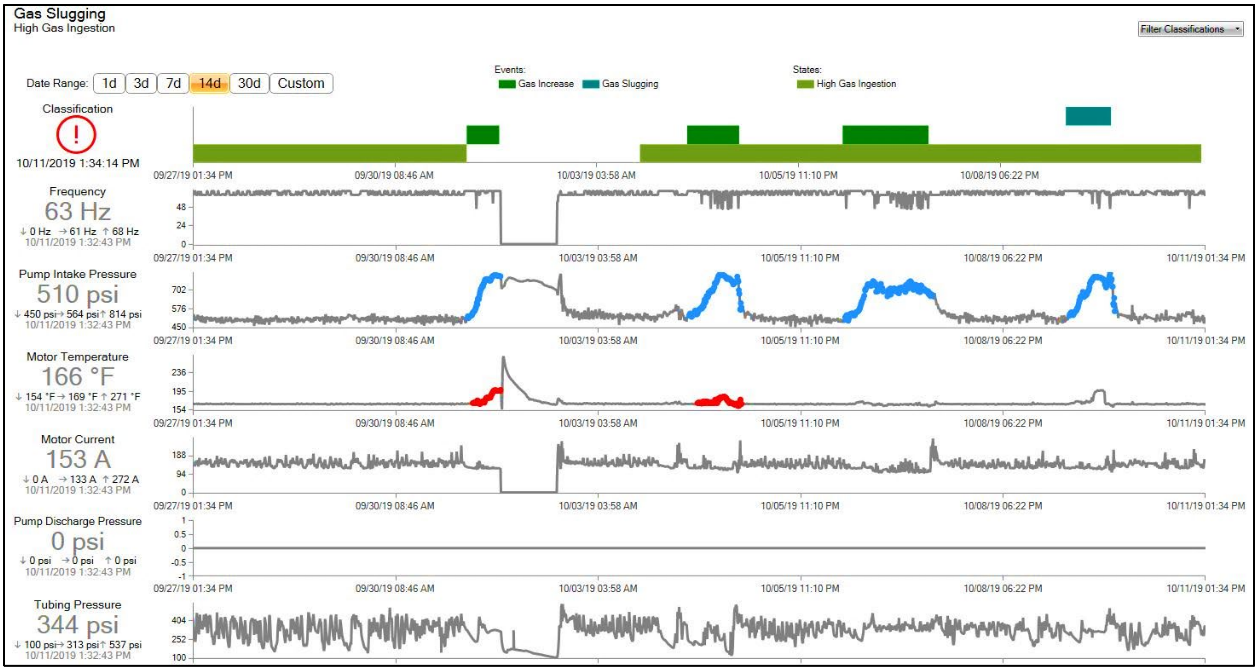

Figure 3 – Examples of high gas ingestion of an ESP well.

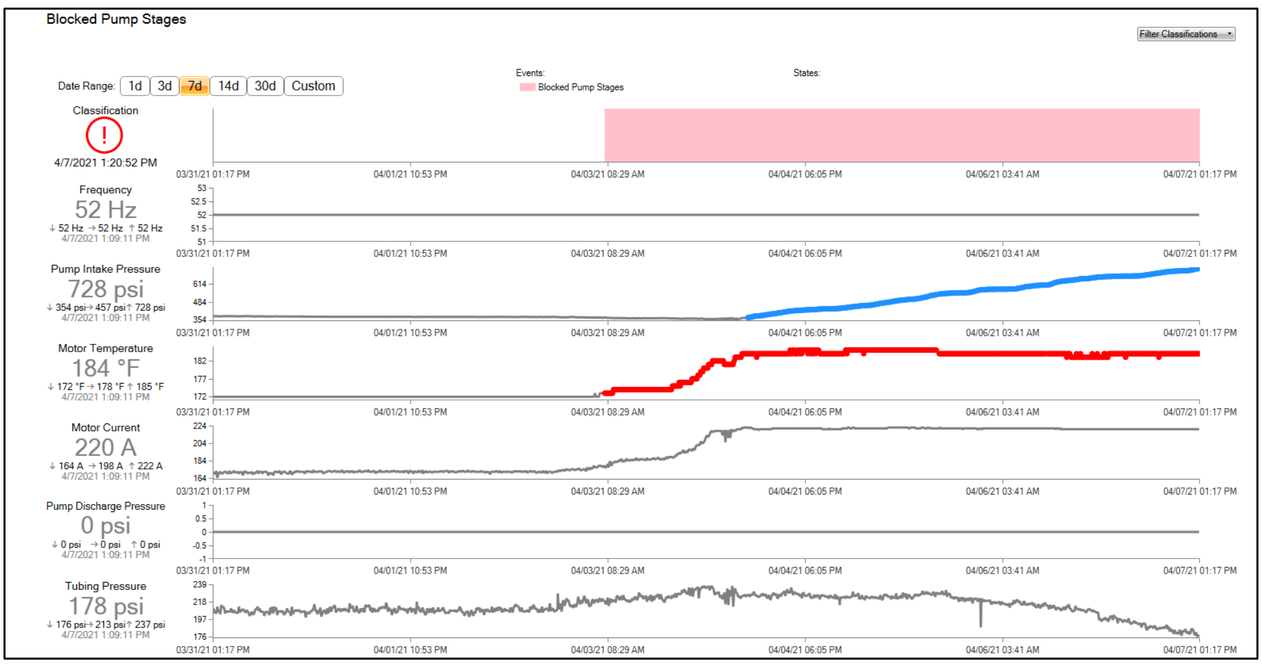

Figure 4 – Example of blocked pump stages in an ESP.