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An Artificial Intelligent Cutting-Edge Technology for Automated Field Production Optimization & ESP Failures Prediction

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Abstract

Unpredicted an Electrical Submersible Pump (ESP) failure can have a serious impact on well production and overall field economics; therefore, it is important to reliably predict the starting time of damaging operating conditions and take proactive action to prevent early failure of an ESP. Most operators rely mainly on production engineers to monitor and optimize equipment performance with remote monitoring and surveillance technologies that provide threshold-based diagnostics to detect electrical or mechanical problems. Due to fundamental constraints in exception-based monitoring, it is extremely difficult to reliably predict the root cause of equipment failure and remaining useful life (RUL) of an ESP.

Methods, Procedures, Process: Predictive Failure Analysis (PFA) leverages artificial intelligence (AI), statistical and physics-based models to constantly predict Remaining Useful Life (RUL) and possible failure cause. The models are qualified and validated using historical sensor time-series from both running and failed ESPs. The validated models are deployed to predict short-term events that may lead to sudden failure, such as a broken shaft, short-circuit, grounded downhole failure; as well as long-term events which build up over time, such as pump low efficiency, sand, scale deposition and gassy conditions.

Results, Observations, Conclusions: The paper presents a case history for a major operator that was experiencing similar operational challenges in three of its producing assets. unpredicted failures happen frequently since they are hard to predict ahead of time with the data available to production engineers. This case study demonstrates how Advanced ESP Predictive Failure Analytics (PFA) technology has helped this operator to detect such events and extend ESP run life. For one ESP, PFA detected scale deposition and predicted a sharp decline in RUL. After confirming the decrease in production fluid, and other surface and downhole sensor trends indicating scale deposition in the ESP, the production engineer applied chemical injection and avoided the failure. For a second ESP in this case study, PFA detected a grounding condition and predicted sudden decline in RUL. The production engineer noticed motor amps increased beyond the recommended threshold and performed electrical optimization to reduce motor amps. The ESP ran for another year and eventually failed due to grounded downhole sensor failure, which PFA had detected two weeks prior to the failure.

Novel/Additive Information: PFA is a unique approach that combines AI, physics-based, and expert knowledge-based approaches to provide interpretable predictions of ESP failure. Unlike traditional CBM approaches, PFA generates fewer alarms with longer lead times, enabling the operator to take preventive measures to avoid sudden failure. In addition, PFA ranks ESPs based on criticality, which enables effective surveillance of large number of wells.

Introduction

In artificial lift operations, an ESP must be replaced when it reaches the end of its useful life or when it fails prematurely. In either event, the cost of replacing an ESP and the deferred oil production due to downtime amounts to a meaningful economic impact. A major E&P operator in the Americas was experiencing shorter ESP run life in three of its highest producing assets. The expected run life in these assets is two years, but 43% of the ESPs had failed within the first six months, and 93% in less than two years as shown in (Fig.1). Both the operator and the ESP manufacturer were struggling with the obvious questions, for example: Which ESPs have a high risk of failure? When will an ESP fail? What is the reason for failure, and could a preventive maintenance or optimization prevent it? How to plan workovers and backup inventory?

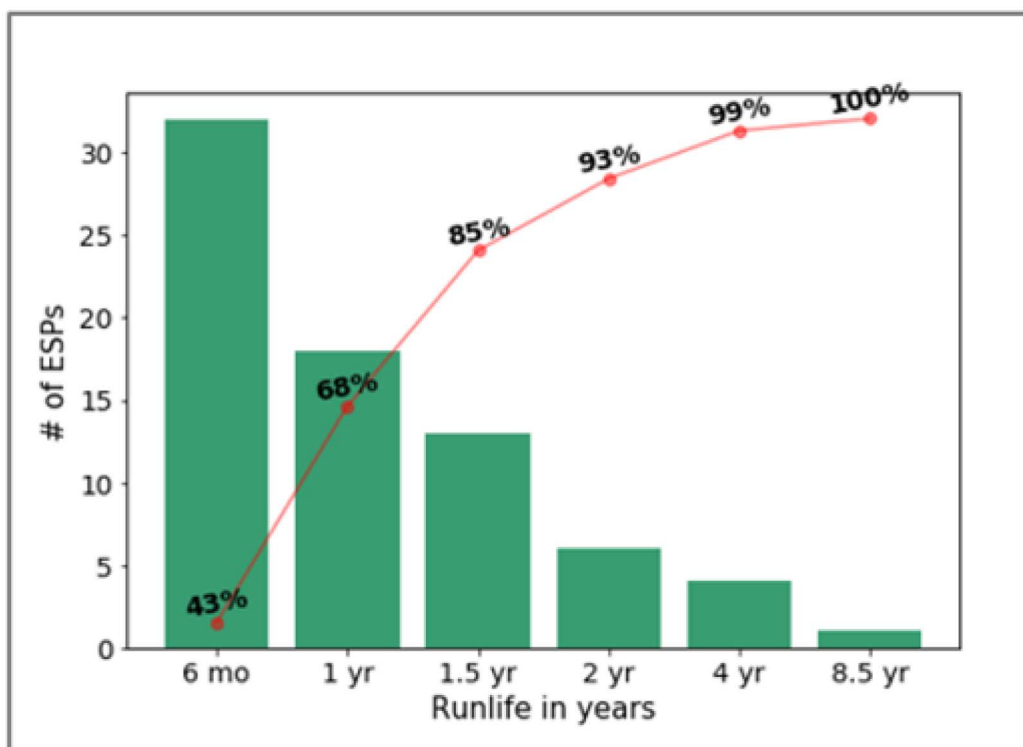


Figure 1—Run life distribution of 101 failed pumps from three producing assets in Americas.

Previous Studies

Previously, operators and ESP manufacturers have used knowledge- and physics-based methods to generate alarms in the event of sensor trend changes associated with potential ESP failures. In addition, they have detected short- and long-term damage events, such as motor overload and underload, imminent shutdown, pump wear, broken shaft, gas interference, tubing leak, plugged pump, plugged tubing etc. (Gagner et. al. 2010, Awaid et. al. 2014, Bermudez 2014, El Gindy 2015, Adesanwo et. al. 2016 and Grassian et. al. 2017). Moreover, a list of remedial recommendations for each damage event was proposed (Bermudez 2014 and Adesanwo et. al. 2016). However, the use of fixed thresholds for trend detection and overlapping expert

rules for event detection in the proposed methods are prone to generate overwhelming alarms, and do not generalize well.

Other approaches include the use of an enhanced Cox Proportional Hazard Method (CPH) to predict ESP failure based on data from previous ESP pulls (Bailey et. al. 2018), or the use of high fluctuations in Fourier and Wavelet transformation of motor current to predict ESP failures due to scale build up (Noui-Mehidi et. al. 2019).

Another approach used to address ESP failures used Machine Learning (ML) models to predict the probability of ESP failure. More specifically, a semi-supervised ML model was used to classify the sensor timeseries from historical failures as normal, pre-failure and failure followed by an SVM classifier to predict probability of each class in the historical failures. However, despite this proposed method being able to capture 80% of the actual failures (80% recall) it also raised a false failure alarm 50% of the time (50% precision) (Liu et. al. 2011). Therefore, it would be unrealistic to make any key decisions to optimize an ESP operation based on a model that produces too many false alarms.

Other ML approaches include Principal Component Analysis (PCA) applied on surface and downhole sensor data to distinguish stable operation, and unstable ESP operation indicating a failure (Mohannad et. al. 2017 and Bhardwaj et. al. 2019). Deep learning models were applied to extract latent features from surface and downhole sensors data during stable and abnormal ESP operation. The latent features from abnormal events were used to train an ML classifier to predict failure due to broken shaft, pump wear or other different root causes (Nguyen et. al. 2020). Finally, an eXtreme Gradient Boosting (XGBoost) and Natural Language Processing (NLP) ensemble model was trained to predict root cause of failure, after the ESP has failed, based on the static data available from historical Dismantle, Inspection, and Failure Analysis (DIFA) reports. In this last approach the aim was to automate the DIFA process and reduce human effort to perform this analysis after the ESP fails. However, predicting a failure or the root cause of a failure before the ESP fails was out of scope (Karnik et. al. 2021).

All the approaches listed above answer one or more of the six questions, however, to the best of our knowledge none of the existing literature answers all questions within one application. See Table 1 for a summary of existing approaches used by operators and ESP suppliers/service providers for ESP predictive failure analysis.

Table 1—Data collected to develop Predictive Failure Analytics (PFA)

	Source	Type of Data	Data
(a)	ESP Tracking Spreadsheet	ESP Operations and Manufacturing	ESP specifications, run number, installation date, start date, pull date, failure date, field name, well name, event log
(b)	DIFA Reports	ESP Reliability Data	ESP pull reason, failure description, root cause, failure component, comments from teardown
(c)	SCADA/ Historian	Surface and Downhole Sensor Data, Well Test Data	Drive frequency, motor current, voltage, intake pressure, discharge pressure, wellhead pressure intake temperature, motor temperature, current leakage, vibration, total fluid production rate, water-cut, GOR

The above cited literatures describe various aspects of ESP run life, but there is no practical solution available to comprehensively and precisely answer the questions noted in the Introduction section.

PFA was developed to address all these questions within a single application. PFA predicts the ESP failure probability, estimates the remaining useful life, identifies damage events that may lead to a failure and provides remedial recommendations using industry best practices.

In this case study we will demonstrate PFA's capabilities using 36 running ESPs in three producing assets in the Americas.

Data Auditing and Inventory

For this case study, data from 137 ESPs in three different fields was analyzed. It includes 101 ESPs that had failed and 36 pumps that were still running. The failed pumps display a run life distribution that ranges between 1 day (infant mortality) to approximately 8.5 years (see Figure 1).

More specifically, ESPs that operated in fields 1 and 3 show a narrower run life range of 1 day to 2 years, whereas the ESPs that operated in field 2 had an overall longer life range with life up to 8.5 years. Most ESPs failures (56%) are classified as electrical failures and failure cause is associated with either grounded downhole sensor failure, or electrical short-circuit or current unbalance. The second most frequent failure category is mechanical failure, which is seen in 33% of the failures, associated with a broken or fractured shaft.

The rest of the failures are due to reservoir issues, nevertheless in this case study we focused on predicting mechanical and electrical failures only Figure 2.

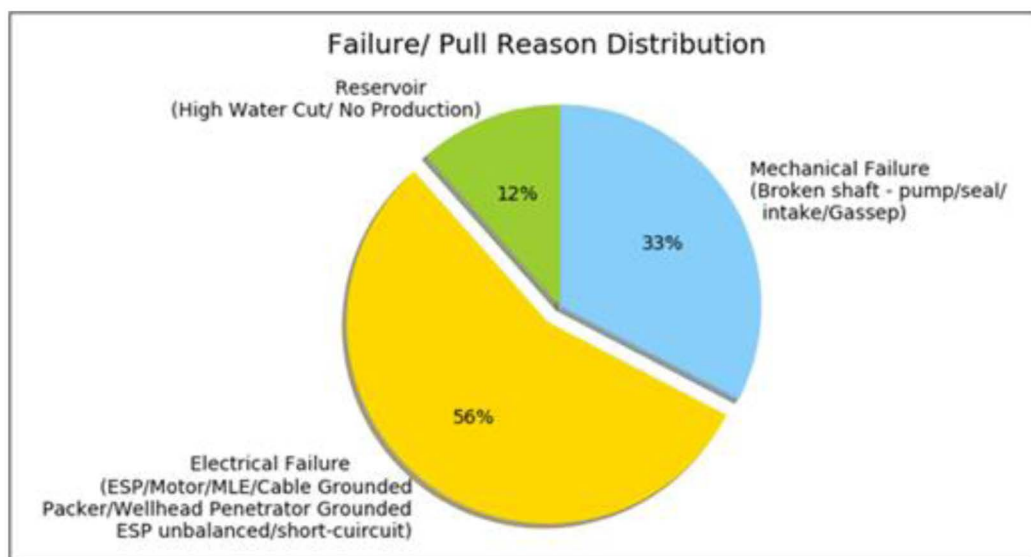


Figure 2—Failure reasons distributions

Failure/Pull reason distribution of 101 failed pumps from three producing assets in the Americas.

A list of data sources and information collected from the ESP manufacturer and the operator in the Americas to develop PFA is presented in Table 1. Data from ESP tracking spreadsheets (as listed in Table 1a) for the 101 failed ESPs was matched with the DIFA reports (Table 1b) to create ground truth labels.

The installation/start date and pull/failure dates of the 137 running and failed ESPs were used to collect historical surface and downhole sensor timeseries from the operator's SCADA (Table 1c). The surface and downhole sensor tags were collected at a 10-minute sampling rate for all 137 ESPs. For failed ESPs, the pulled data was between the first day the ESP was started and up to the reported failure date. For running ESPs, the data was collected up to the current date.

The data quality of input data greatly affects any subsequent model training; hence, the ESP's timeseries data must be evaluated and curated prior to model training. The data preprocessing steps include dealing with missing data as well as evaluating and scoring available data. Advanced interpolation techniques were applied to deal with missing data points. Data scores consider data gaps, sensor error as well as constant

values. The quality scores range between 0 (low quality) and 1 (high quality). Data quality is further used to weight input data while training failure predictive models.

PFA Methodology

Our predictive failure analysis package includes reliability models, data-based AI/ML models, and knowledge-based methods which are all combined together to predict electrical or mechanical events that may lead to an ESP failure. The models are also used to estimate the RUL of individual ESPs. See [Figure 3](#) for a schematic view of PFA architecture.

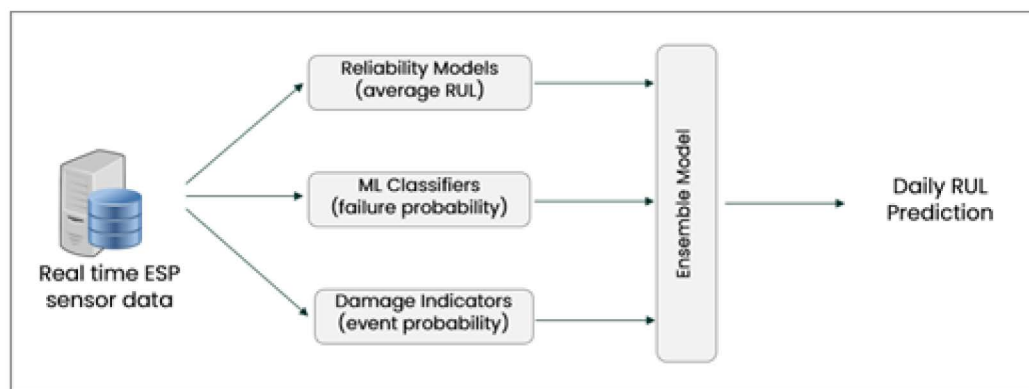


Figure 3—High level diagram of PFA algorithm

Three main steps are included while training a failure predictive model. First the Weibull distribution is used to generate reliability models using ESP life cycle information from the three different fields. The reliability models are used to set a base line for the ESP's remaining useful life (RULbase). Weibull distribution models were trained using all ESPs available.

Second, an ensemble of decision tree-based gradient boosting ML classifiers (XGBoost) was trained to predict ESP failure in different lead times, i.e., 30, 60, and 90 days to failure. Surface and downhole sensor timeseries from both failed and running ESPs were used to train and evaluate the performance of these models. The ML models were trained using 83 of the 101 failed pumps. The rest of the pumps were used for testing the models' performance.

Lastly, knowledge-based engineering rules which identify damage to the ESPs are used together with ML models to quantify the probability of short- and long-term damage events that may lead to an ESP failure.

The outputs from all these three steps are combined to create one ensemble model which will output the predicted accelerated RUL, RULpred at any given time. The performance of the ensemble model is then evaluated, and models are fine tuned to improve the performance.

Results and Discussion

As a first step in evaluating the data that was pulled for all 137 pumps, a completeness analysis was performed on the raw data. Overall, ten tags were considered for the completeness analysis, including both downhole and surface sensors. On average, 45% of the data was missing while considering these ten sensors. After preprocessing the data, which included data interpolation and quality scoring, only 5% of the data remained missing. See the heat maps in [Figure 4](#) for comparison between data completeness before data processing and after.

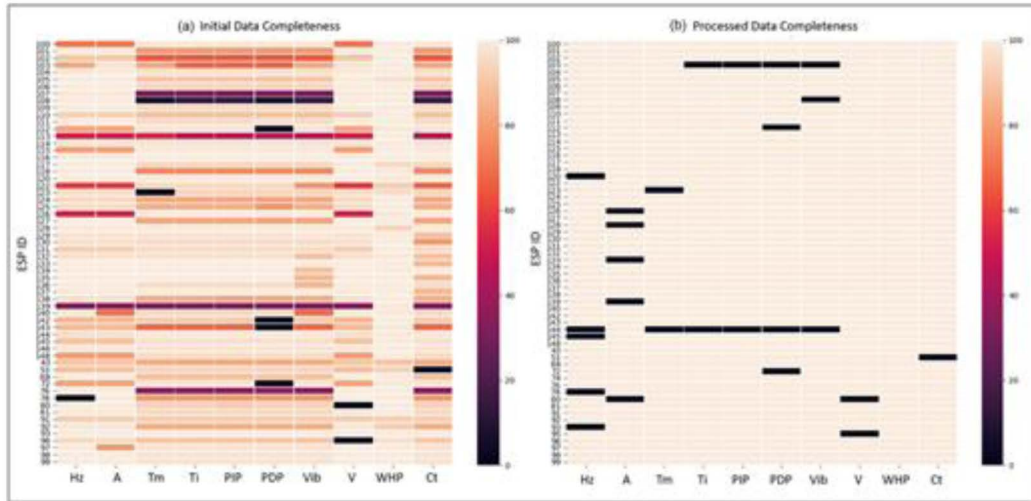


Figure 4—Data completeness comparison. (a) Data completeness prior to data interpolation. (b) Data completeness after data interpolation. Y-axis represents different ESPs in our dataset.

Each row stands for a different ESP. X-axis has ten columns one for each sensor being evaluated. Data completeness is represented using a color scheme, the darker the cell is the more data is missing. More specifically, when all the data is available for a specific ESP and tag, the corresponding cell will be colored in light orange (has a value of 100% completeness) whereas when all the data is missing for a specific ESP and tag the corresponding cell will be colored in black (has a value of 0% completeness)

Once the data was preprocessed and scored, it was used as an input to the ML models to predict ESP failures. The key performance indicator (KPI) used to evaluate the ensemble model's performance is balanced accuracy. Balanced accuracy is widely used when evaluating the performance of classification models and it is especially useful when the classes are imbalanced. Balanced accuracy is based on sensitivity (also known as true positive rate, TPR) and specificity (also known as true negative rate, TNR). As a first step a confusion matrix is defined (See [Table 2](#)).

Table 2—Confusion matrix for PFA performance

		Actual	
		Pump Running	Pump Failed
Prediction	Pump Running	28 (TN)	9 (FN)
	Pump Failed	8 (FP)	9 (TP)

True positive (TP) are cases where PFA correctly predicted a failure. We consider a TP as an event where the RUL predicted by PFA, RUL_{pred} , is within 60 days of the ground truth RUL, RUL_{actual} , this scenario is defined as a correct alarm. False negative (FN) are cases where PFA did not raise an alarm for a failed pump (a missed alarm). We consider a FN as event where $RUL_{pred} > RUL_{actual} + 60$ days, and this scenario is defined as a missed alarm. True negative (TN) are cases where PFA did not raise an alarm for a running pump. We consider a TN as an event where RUL_{pred} is close in value to the RUL calculated from the Weibull distribution, which is our baseline, RUL_{base} . False positive (FP) are cases where PFA raised an alarm for a running pump (a false alarm). We consider a FP as an event where RUL_{pred} is ~ 30 days, but the ESP continued to run for ~ 90 days past the alarm date. However, if any scheduled maintenance or optimization was performed on the ESP, it's not considered as a false alarm and the pump is considered a TN.

Using this confusion matrix, we calculated a TPR of 0.5 and a TNR of 0.78. The overall balance accuracy is 0.64. Based on these values, PFA is performing very well on running pumps and is not raising too many false alarms. As for the failed pumps there is room for improvement. The performance of the model can be significantly improved by improving the quality of the data received from the SCADA system. Moreover, five out of the nine ESPs missed failures are ESPs that failed due to a short circuit. Higher data resolution than what is available in this particular SCADA system will enable PFA to detect certain electrical failure with a higher precision and accuracy. Upgrading the SCADA system or the use of edge devices can lead to higher data resolution.

Overall, the ensemble model (PFA) performed reasonably well on both failed and running ESPs from the three fields. After the client's approval, the model is deployed and used to predict RUL for ESPs that are currently running.

Operationalizing PFA

When PFA was deployed using a web application, the models produced daily predictions for remaining useful life as well as damage indicator alarms for each of the running ESPs. To visualize the daily outputs from PFA, interactive web-based user interfaces were designed, consisting of two main pages - the Field View page and Well View page, as shown in Figures 5 and 6 respectively. These web pages allow the production engineers to identify ESPs that are running under critical condition and perform remedial actions to extend the ESPs run life.

The Field View webpage includes two main areas – the chart area (Figure 5a) and the ESP list (Figure 5b). The chart area groups the ESPs based on their days to failure, specifically ESPs with ~30, ~60, ~90 and >90 (labeled as Early Warning) days to failure (Figure 5d–g). Any ESP with an estimated RUL of more than two years is not included in the Early Warning bin (Figure 5g). The resolved (Figure 5h) bin includes the number of ESPs for which estimated RUL has increased after the operator performed some optimization or maintenance action. The moon chart (Figure 5c) displays the distribution of ESPs with $RUL_{pred} \leq$ two years.

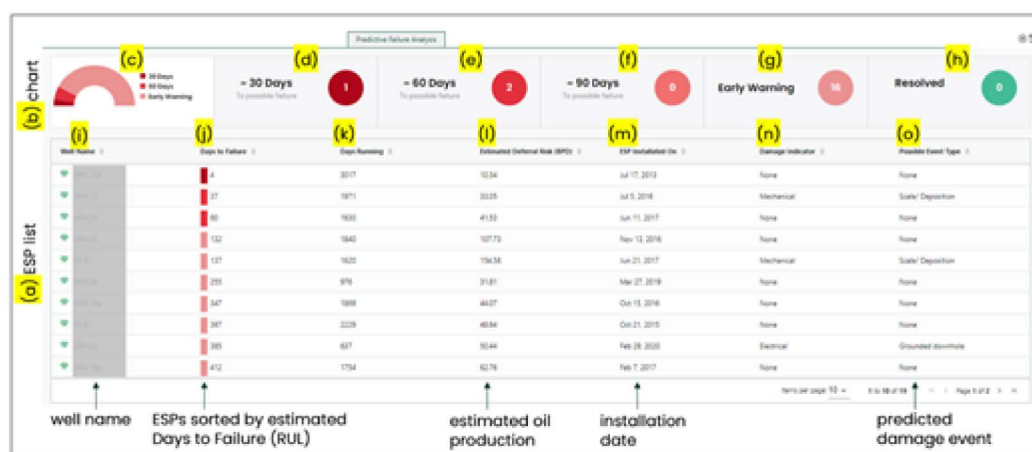


Figure 5—PFA Field View webpage for 36 running ESPs in the Americas fields

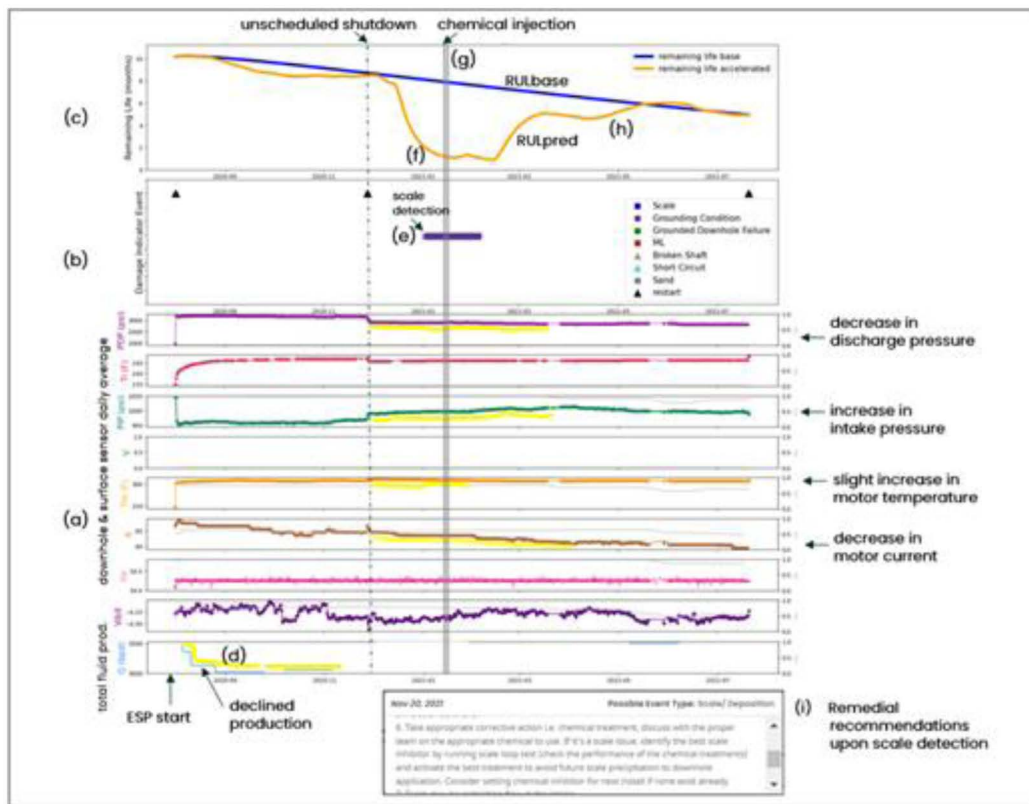


Figure 6—PFA Well View webpage for the ESP-1 operating in Well-1

The ESP list on the Field View webpage lists all 36 ESPs, sorted in an ascending RULpred or ‘days to failure’ order (Figure 5j). Each row in the ESP list contains information of the individual ESP - the well name, estimated days to failure (RULpred), total days running, estimated oil production rate (BPD), ESP installation date, predicted damage event (electrical or mechanical) and, damage event type (such as scale, grounded downhole sensor failure, short circuit etc.) as shown in Figure 5i–o.

The chart area and the ESP list are interactive.

Selecting any item on the chart updates the ESP list accordingly. For example, selecting the ~30 days circle (Figure 5d) will update the ESP list with the list of ESPs with RULpred ≤ 30 days. In addition, clicking any row on the ESP list would lead the user to the PFA Well View (Figure 5) to show PFA results in more detail.

Using the PFA's user interface, the production engineers are able to prioritize wells that are bound to develop unfavorable conditions such as scale and make operational and maintenance decisions to optimize the ESP's operation. In the next section we will discuss in more detail the PFA output for two ESPs, operating in two separate wells, and the decision the production engineers made based on these results.

Optimizing ESP Operation in Well-1 with Scale Issue

Well-1, in which ESP 1 is operating produces an average of 5500 BPD total fluid, with 12°API (heavy oil). Looking at the Well View webpage (Figure 6) provides the production engineer with a deeper insight into the ESP operating conditions. The Well View webpage consists of four main areas, the daily average of surface and downhole sensor data (Figure 6a), the total fluid production collected from monthly well tests (Figure 6d), along with PFA output which includes daily RUL predictions (Figure 6c), and daily damage indicator events (Figure 6b).

ESP-1 was installed in well-1 in July 2020. By November 2020, the total fluid production declined to 5000 BPD (Figure 6d). After an unscheduled shutdown in November 2020, the discharge pressure (PDP)

started decreasing, the intake pressure (PIP) started increasing and operating current (A) slowly started decreasing (see highlighted in yellow areas in Figure 6a). PFA's damage indicator algorithm assigned a high probability for a scale event during this time period (Figure 6e) based on these sensor trends.

After detection, remedial recommendations were provided based on the industry's best practices (Figure 6i). Accelerated remaining useful life estimation, RULpred (orange curve in Figure 6c) rapidly declined from ~8 months to ~1 month due to this event (Figure 6f). This decline in RUL led the ESP's listing to move to the top of the ESP list on the PFA Field View webpage, which caught the attention of the production engineers. Once the engineers saw the scale detection alarm and the remedial recommendations from PFA, they executed a chemical injection procedure in which acid was injected through production tubing to remove the scale buildup (Figure 6g), recover the production, and avoid the imminent failure. After the chemical treatment, the scale alarm resolved over time and the sensor trends slowly went back to normal trends, as well as the fluid production rate which went back up to ~5500 BPD. The accelerated remaining useful life, RULpred also gradually increased to ~6 months, close to remaining useful life baseline, RULbase from field average (blue curve in Figure 6c), showing an extension of the ESP run life. The ESP was then added to the Resolved category in PFA Field View (Figure 5h) so that the production engineers no longer view it on the list of priority wells.

Predicting ESP Grounded in Well-2 with High Current Issue

Well-2 in which ESP-2 is operating produces an average of 5400 BPD total fluid, with 27°API (light oil). As in the previous case, the Well View webpage has the same sections, total fluid production from monthly well tests (Figure 7 last panel), the daily average values for surface and downhole sensor data (Figure 7a) of the ESP installed in this well, and the daily RUL predictions (Figure 7c) as well as the damage indicator events (Figure 7b).

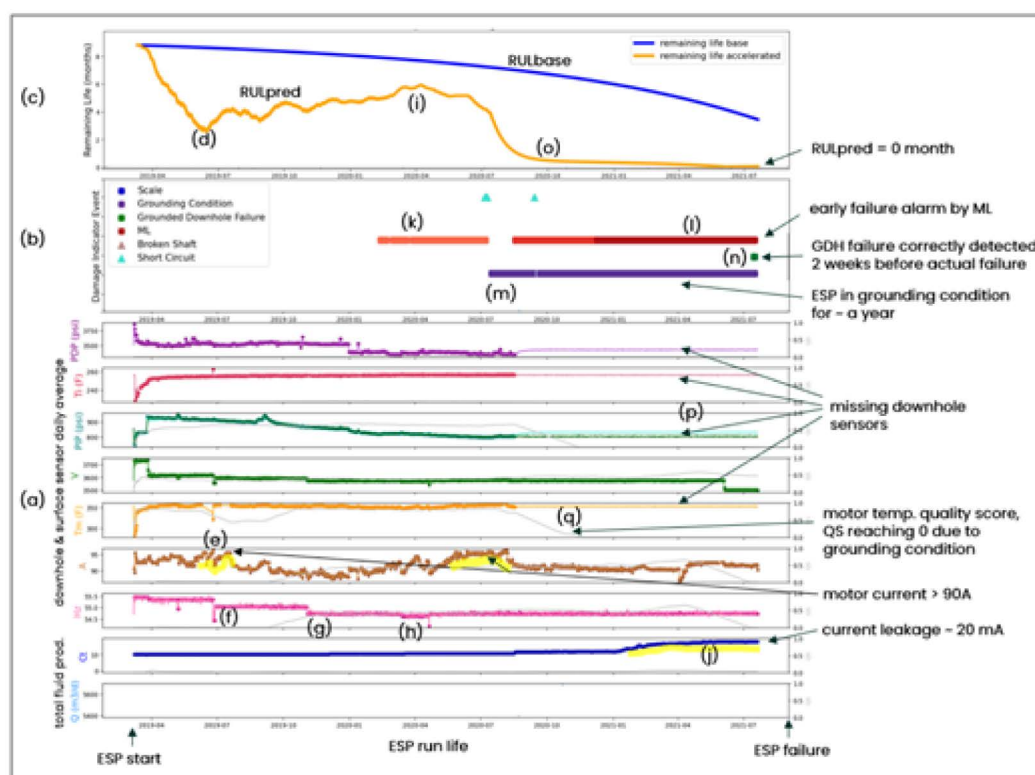


Figure 7—PFA Well View webpage for the ESP-2 operating in Well-2

ESP-2 was installed in well-2 in March 2022 and failed in August 2021 due to a grounded downhole sensor (GDH) failure. By June 2019, the predicted accelerated RUL, RULpred has declined from ~8 months to ~2 months (Figure 7d), which is a significant decline from the remaining life base, RULbase. Due to this substantial change, the production engineers noticed the ESP has moved to the top of the ESP list on PFA Field View webpage. Looking at the Well View webpage for this ESP (Figure 7), the production engineers identified that the motor current increased beyond 90A, which is the recommended threshold for operating ESPs in their field (figure 7e). To solve this issue, they performed an electrical optimization procedure through VSD to reduce the motor current. Despite their efforts the motor current remained above the recommended threshold.

As an alternative, the production engineer gradually reduced the drive frequency from 55.5 Hz to 54.5 Hz, between July 2020 through April 2020 (Figure 7f–g). As a result, motor current decreased to below the 90A threshold, and the RULpred increased from ~2 months to ~6 months over this time, indicating a successful extension of the ESP run life due to optimization performed by the production engineers. Starting February 2020, ML models were predicting an increase in failure probability (Figure 7k - the darker the red color is the higher the probability is). In addition to that, in September 2020, the downhole sensor readings were lost, this situation can be identified by looking at the surface and downhole daily average data (Figure 7a). In this section of the webpage actual sensor values are represented by solid dots, however when the data is missing and there was a need to interpolate, that data is plotted using a line (see Figure 7p). Besides, the light gray lines in each sensor plot in Figure 7a indicate data quality scores, QS ranging from 0-1, where 0 means the worst quality and 1 means the best quality. In September 2020, QS dropped to 0 for all downhole sensors (see Figure 7q), showing downhole sensor readings were lost.

Moreover, starting Jan 2021 current leakage gradually increased beyond the 10.5 mA threshold for normal ESP operation. Based on all these sensor trends, PFA generated a grounding condition alarm (as shown in Figure 7m in purple). Due to these alarms, RULpred declined to less than one-month lifetime (see Figure 7o). Eventually, in August 2021 the ESP failed due to grounded downhole sensor failure, which PFA detected two weeks prior to the actual failure (as shown Figure 7n in green). The ESP was grounded due to motor contaminated by the well fluid. This case demonstrates a TP case for PFA output.

Conclusion

In this case study, Predictive Failure Analytics (PFA) was trained and deployed for a major operator in the Americas, who was experiencing short ESP run life in three of its high producing assets. Based on the outcomes, the production engineers could rely on the failure alarms, and the RUL estimation generated by PFA, to take preventive actions. Using the PFA Field View webpage, production engineers were able to identify two wells, well-1 and well-2, which had ESPs with a high risk of failure. The Field View page indicated these ESPs have a RUL of less than two months, due to scale and grounded downhole sensor (GDH) damage alarms, respectively.

The production engineers were able to execute preventive actions to optimize the ESPs' operation and mitigate indicated damages root causes, based on PFA outputs and recommendations. For Well-1, the production engineer applied chemical injection as recommended by PFA, to resolve the scale issue, which extend the ESP run life and recovered the production. To this date, the ESP is still running without any further issue. For Well-2, the production engineer analyzed PFA results and sensor trends and performed electrical optimization and slight speed reduction three times to optimize ESP operation. Despite these actions, the ESP failed due to GDH sensor failure. However, PFA detected the GDH alarm two weeks prior to the actual failure, which enabled the operator to schedule the workover in a timely manner, reducing downtime by two weeks. This helped the operator save \$4.3M from reduced deferred production, in addition to saving other costs associated with emergency workover.

In addition, the sorted ESP list using estimated RUL in the Field View page helped the operator perform long term planning for its assets, based on the overall number of expected failures within the next two years.

In summary, operators try to manage production and workover logistics, while also holding down costs - both OPEX and CAPEX. Production and facility engineers have many roles to play in a developing field. It is very difficult to glance briefly at a SCADA display and derive insights in a timely manner, while also selecting and qualifying new pumps and completion technologies. Using PFA, the production and facility engineers can prioritize their workload to streamline their operations, plan for workovers and backup inventory.

Acknowledgments

The authors would like to thank Baker Hughes for the permission to publish this work.

Nomenclatures

ESP	: Electrical Submersible Pump
PFA	: Predictive Failure Analytics
DIFA	: Dismantle, Inspection, and Failure Analysis
RUL	: Remaining useful life
RULpred	: Predicted RUL
RULbase	: Baseline Rule
RULactual	: Actual RUL
AI	: Artificial Intelligence
ML	: Machine Learning
CPH	: Cox Proportional Hazard Method
PCA	: Principal Component Analysis
NLP	: Natural Language Processing
SVM	: Support Vector Machine
XGBoost	: eXtreme Gradient Boosting
KPI	: key performance indicator
BPD	: Barrel Per Day
PSI	: Pound Per Square Inch
SCADA	: Supervisory Control and Data Acquisition
PDP	: Pump Discharge Pressure
PIP	: Pump Intake Pressure
Ti	: Intake Temperature
Tm	: Motor Temperature
V	: Volts
A	: Motor Current
Hz	: Drive Frequency
Ct	: Current Leakage
Q	: Total Fluid
API	: American Petroleum Institute
MLE	: Motor Lead Extension
GDH	: Grounded Downhole
TPR	: True Positive Rate
TP	: True Positive
TNR	: True Negative Rate
TN	: True Negative

CAPEX : Capital Expenditures
 OPEX : Operating Expenditures

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