Monitoring Production Equipment in Remote Locations

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1 Objectives

Within the context of Remote Equipment Monitoring, the specific customer implementation of this project has been in the area of an upstream oil and gas process. The goal was to improve the efficiency of ESP (Electric Submersible Pump) oil & gas production, by predicting (rather than just reacting to) ESP shutdown and failure and thus avoiding downtime which results in a loss of production as well as repair costs. Please see Figure 1 for an illustration of an ESP.

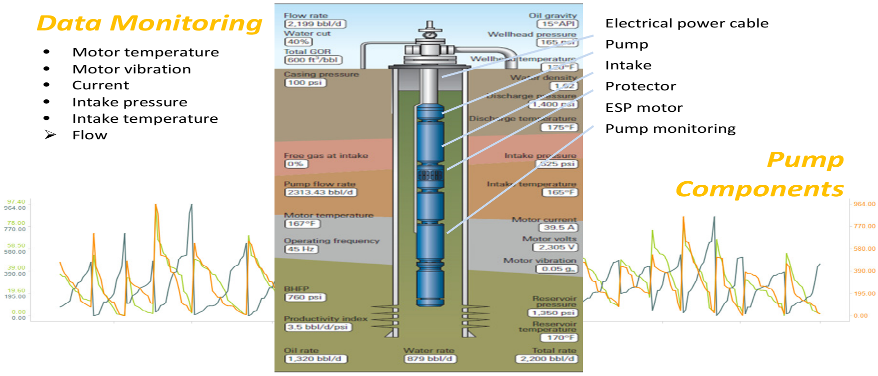

Fig. 1. Electric Submersible Pumps (ESPs)

"Replacing a single failed pump costs us more than $100K and days of production loss. We have hundreds of failures a year. Preventing even 10% of these failures represents a massive reduction in costs", well operation engineer of major Oil & Gas company.

2 Project Implementation

A methodology and solution for real-time monitoring of production equipment in remote locations is presented. The solution is developed on sensor data, transmitted from equipment to field information systems; and analyzed using visual/predictive applications connected to a central Historian data source. Resulting mathematical

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models, developed and validated on historical data, are used to monitor new sensor data as they arrive in real-time.

Our solution is illustrated using data from Electric Submersible Pumps across multiple fields. The pumps are fitted with downhole monitoring units that transmit streams of data back to surface including: motor temperature, motor frequency, motor current, pump intake pressure and intake temperature. Data is aggregated from multiple sensors with a resulting data rate of several thousand readings per minute from the Historian data source.

This data was combined with subject matter expertise to improve detection and provide event classification. Examples of this include slipping conditions indicated by pressure and flow remaining constant while energy consumption is increasing; motor temperature decrease and pressure increase indicating gas buildup; motor temperature increases at a certain rate over time leading to a motor burnout

There are several possible strategies for monitoring such variables over time, specifically a trend analysis approach, i.e. monitoring for changes in location of distribution, or changes in variability, or slope, or a statistical approach, based on statistical (e.g. Shewhart control chart) or machine learning models (y (0/1) = f (X, b) + e;where f is a logistic regression or a tree, an svm, or a neural network. In our implementation, we focus on trend changes.

Historical sensor data was imported into Spotfire to diagnose pump shutdowns and failures, enabling the creation of predictive model that could detect these leading indicators and forecast events. This model was then published to StreamBase, which monitored and scored the data in real time and generated alerts when a shutdown or failure was indicated by the model based on incoming data.

Our implemented final solution has included:

- Spotfire data discovery on ESP data: Data discovery on historical sensor data for equipment in production, and development of hierarchical mathematical models as leading indicators of equipment failure conditions (Figure 4)
- Deployment of models to real-time analytics systems, using Streambase (Figure 5)
- SDK-efficient integrations with OSI-PI historian and attribute data; and with business process management systems for management of equipment maintenance
- Understanding failure events: alerting the engineers with an email that has a picture of the variables related to root-cause of failure. (Figure 6)
- Live monitoring of real-time sensor signals using StreamBase LiveView (Figure 7)
- Comprehensive geo and location analytics mapping
- Analysis of real time alerting data for classification and prioritization, and continuous model improvements leading to reduction of false positives

3 Results

The solution performs remarkably well, identifying a variety of anomalous equipment behaviour states, and preventing multiple shutdowns and pump failures, with false positive rates close to zero.

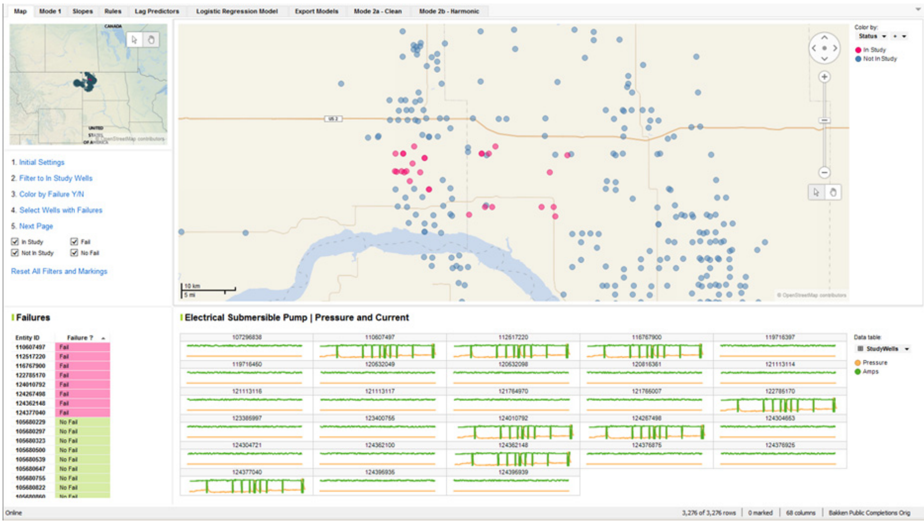

Fig. 2. Historical Data Analysis in Spotfire

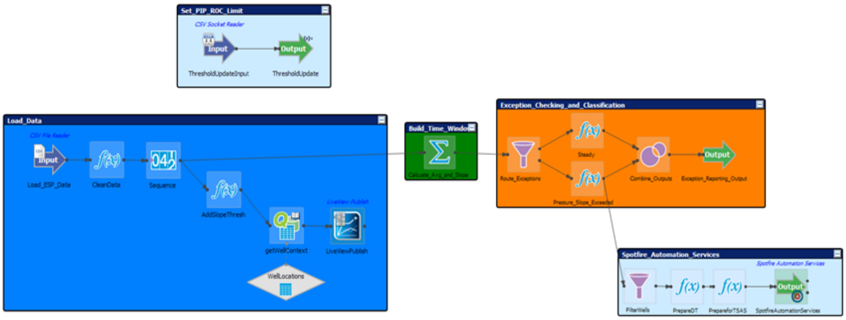

Fig. 3. Set-up for Real-Time Sensor Monitoring and Alerting in StreamBase

An ROI model for the equipment monitoring is developed as a companion to the methodology and solution. The ROI model indicates savings of up to 400 hours of production per day per thousand wells, which conservatively equates to $40M/yr regarding ESP lift alone.

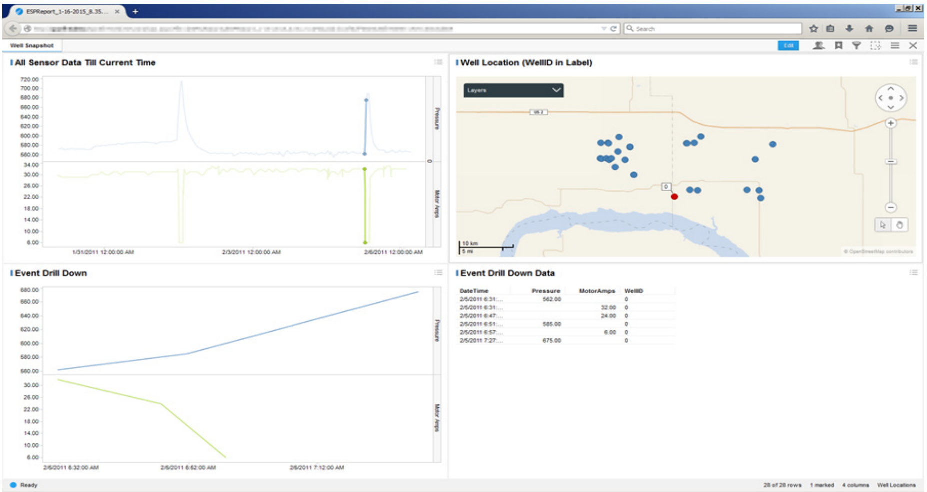

Fig. 4. Alerting View in Web Browser (via Spotfire) to Facilitate Root-Cause Analysis

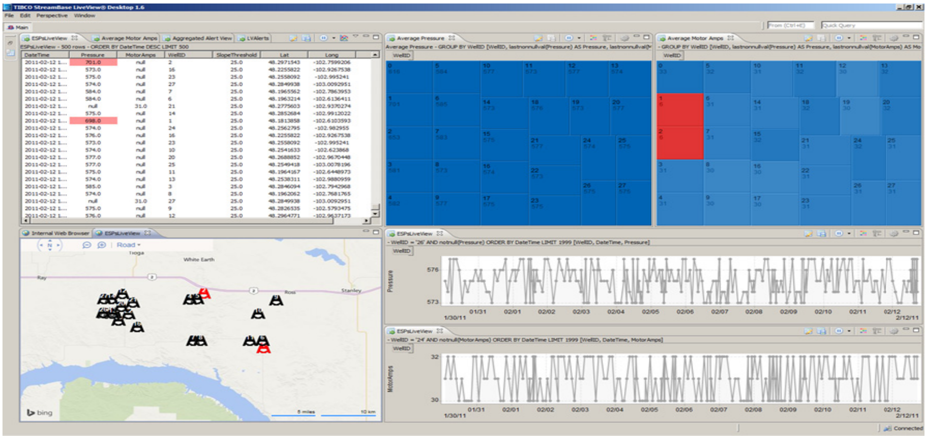

Fig. 5. Real Time Monitoring of Well Status from Sensor Data in StreamBase LiveView

4 Innovative Aspects of the Project

Data are integrated from thousands of wells across multiple plays. Data from equipment sensors are analysed and visualized. The resulting mathematical models comprise combinations of sensor data summaries, e.g. slopes and excursions beyond empirically derived thresholds set up to detect anomalous equipment behavior. The models are developed as hierarchies and back-tested on recent equipment sensor data. The models are subsequently applied to new sensor data arriving in real time.

Seamless integration of historic and real-time data, connecting big data to fast data.

Often well products are highly custom-developed, making it difficult to reapply a model or solution from one piece of equipment to another. Conversely, the products involved in our solution are highly flexible, it being easy and fast to re-implement a model or workflow onto another type of equipment, which results in very high ROI.

Actionability of the solution - alerting becomes very actionable and efficient, with human involvement only when it is required.

5 Future Work

Right now the predictive model is based on data that is selected by subject matter experts but our future state is a large scale automated back-testing framework to determine the best parameters for models.