An Advanced Analytic Solution for ESP Monitoring in Upstream Oil Production

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Thank you!
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SPARTAN CONTROLS

- Western Canada’s Leading provider of
  - Industrial automation
  - Valves
  - Measurement and
  - Process control solutions
- Emerson Impact Partner
- > 900 employees
- Operational excellence
Solutions group > 40 employees
RESEARCH COLLABORATION

• NSERC Senior Industrial Research Chair in Control of Oil Sands Processes
  - Chair holder: Biao Huang, Ph. D., P. Eng., Professor, Dept. Chemical and Materials Engineering, University of Alberta
  - Industrial Partners
AGENDA

• Introduction
  - Process: Steam assisted gravity drainage process
  - Equipment: Electric submersible pumps (ESPs)
  - ESP reliability issues

• Monitoring Solutions
  - Monitoring based on performance curves
  - Data-driven models for failure prediction
  - Pattern recognition techniques

• Emerson’s Analytics Platform

• Business Results Achieved

• Summary
STEAM ASSISTED GRAVITY DRAINAGE (SAGD) WELLS

- Alberta’s SAGD production capacity: ~ 1.28 million bbl./day
- Amount of steam injected per day: ~ 3.59 million bbl./day
ELECTRIC SUBMERSIBLE PUMPS IN SAGD APPLICATION

- ESP run life in SAGD: 2 months to 3 years
- Workover and replacement in case of a failure costs half a million to a million dollars
## ELECTRIC SUBMERSIBLE PUMPS IN SAGD APPLICATION

<table>
<thead>
<tr>
<th>Facility</th>
<th>Production (bbl./day)</th>
<th>SOR</th>
<th>Number of Wells (Inj+Prod)</th>
<th>Steam (bbl./day)</th>
<th>ESP wells</th>
</tr>
</thead>
<tbody>
<tr>
<td>AOC Hangingstone</td>
<td>12,000</td>
<td>4.66</td>
<td>46</td>
<td>55920</td>
<td>19</td>
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<td>CNRL Kirby South</td>
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<td>543</td>
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<td>3.72</td>
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<td>Connacher Great Divide</td>
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<td>4.34</td>
<td>89</td>
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<tr>
<td>Conoco Surmont</td>
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<td>355</td>
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<td>Devon Jackfish</td>
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<td>Husky Sunrise</td>
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<td>4.25</td>
<td>124</td>
<td>255000</td>
<td>45</td>
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<tr>
<td>Husky Tucker Lake</td>
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<td>3.49</td>
<td>179</td>
<td>104700</td>
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<td>MEG Christina Lake</td>
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<td>373</td>
<td>176800</td>
<td>149</td>
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<tr>
<td>OSUM Orion</td>
<td>10,000</td>
<td>3.59</td>
<td>50</td>
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<td>1</td>
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<td>Pengrowth Lindbergh</td>
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<td>39125</td>
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<td>Suncor Firebag</td>
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<td>2.63</td>
<td>373</td>
<td>533890</td>
<td>~106</td>
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<td>Suncor MacKay River</td>
<td>38,000</td>
<td>3.1</td>
<td>208</td>
<td>117800</td>
<td>2</td>
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</table>

| Total Production          | ~1.3 (million bbl/day)| SOR Average | ~3.28 | Number of well pairs | ~1820 | SOR (weighted average) | ~2.81 | Number of ESP wells | ~1138 |

Data from [https://www.oilsandsmagazine.com/projects/thermal-in-situ](https://www.oilsandsmagazine.com/projects/thermal-in-situ) (as of September 2018)
ESP RELIABILITY ISSUES

- Completion failures
  - Wellbore and liner damages
  - Sand control system failure, etc.
- Manufacturing
  - Material selection
  - Assembly
- Installation
  - Well cleanout
  - System assembly
- Operation
  - Poor operating procedure
  - Inadequate condition monitoring
- Reservoir fluids
  - Sanding
  - Gas &/steam breakthrough
- Design
  - Wrong selection of equipment
- Wear & Tear

Source of failure:
- Completion
- Installation
- Manufacturing
- Wear & tear
- Operation
- Reservoir fluids
- Design

Failing components:
- Pump
- Pump intake
- Seal
- Cable
- Motor
EQUIPMENT MONITORING

- **Fault detection**: Detect incipient fault that may lead to equipment failure
- **Fault diagnosis**: Identify the root cause, recommend/implement corrective measures, etc.
- **Fault prognostics**: Failure prediction, predict remaining useful life, etc.
REQUIREMENTS OF AN ESP MONITORING SOLUTION

- Data-driven models from real-time measurements to monitor pump performance and predict failure
- Detect and diagnose conditions that will lead to pump failure
- Communicate actionable suggestions
- Facilitate decision making
- Closed-loop control

Facility-wide Surveillance Solution
PERFORMANCE MONITORING ALGORITHMS

- Characteristic curves reconstructed using data-driven models
- Online operating conditions are compared against the characteristic curves
PERFORMANCE MONITORING ALGORITHMS: EXAMPLE

- Performance monitoring using Torque vs Speed characteristics of a 3-phase squirrel cage motor

Ideal curves reconstructed from data

- Online monitoring using pattern recognition
- Detect and track time spent on abnormal operating conditions and alert operations

Table 1: Summary of the fault conditions and actionable suggestions

<table>
<thead>
<tr>
<th>Type of fault</th>
<th>Reason</th>
<th>Conditions it could represent</th>
<th>Actionable suggestions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive bias</td>
<td>The pump is producing more and/or against a higher head at the given speed</td>
<td>High torque/load, thrust failure</td>
<td>Increase the pump speed. This does not affect production</td>
</tr>
<tr>
<td>Negative bias</td>
<td>The pump is producing less and/or against a lesser head at the given speed</td>
<td>Low torque/load, thrust failure, gas lock, pump off</td>
<td>Decrease the pump speed. This also does not affect production as the pump is already running in a low inventory state</td>
</tr>
<tr>
<td>High variance</td>
<td>Producing more gas</td>
<td>High gas production</td>
<td>Decrease pump speed if desirable. This can affect production</td>
</tr>
</tbody>
</table>
CASE STUDY

Start up 3 weeks of abnormal operation

Significant deviation from the ideal characteristics

Time of failure

Alarms generated by the monitoring application

GRAPHIC: Torque over time with predicted ideal torque, upper and lower bounds, and actual torque. Alarms are indicated by symbols at specific time points. The period of abnormal operation is highlighted with a shaded area.
CASE STUDY - ROOT CAUSE ANALYSIS

- Frequency is ramped up to a new state
- BHP decreases initially and then starts to increase
- Production rate is not sustained in the new state
- Effect of decrease in head and decrease in flow can be seen in motor current

Significant deviation from the ideal characteristics, Indicating low load torque and pump-off conditions

Time of failure

Alarms generated by the monitoring application

Start up
## PERFORMANCE MONITORING OF MULTIPLE ASSETS

- **R. I:** Reliability index – Calculated based on the time spent on an abnormal operating condition
- **1** – Least amount of time spent on an abnormal operating condition, **0** – Most amount of time spent on an abnormal operating condition

<table>
<thead>
<tr>
<th>Asset#</th>
<th>R.I 1</th>
<th>R.I 2</th>
<th>R.I 3</th>
<th>Status</th>
<th>Runlife (days)</th>
<th>Asset#</th>
<th>R.I 1</th>
<th>R.I 2</th>
<th>R.I 3</th>
<th>Status</th>
<th>Runlife (days)</th>
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<tbody>
<tr>
<td>Asset 1</td>
<td>1</td>
<td>1</td>
<td>0.94</td>
<td>Running</td>
<td>710</td>
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<td>0</td>
<td>0.679</td>
<td>0.882</td>
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<tr>
<td>Asset 2</td>
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<td>0.961</td>
<td>1</td>
<td>Running</td>
<td>274</td>
<td>Asset 17</td>
<td>0.867</td>
<td>1</td>
<td>0.951</td>
<td>Failed</td>
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<tr>
<td>Asset 3</td>
<td>1</td>
<td>0.999</td>
<td>0.892</td>
<td>Running</td>
<td>477</td>
<td>Asset 18</td>
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<td>0</td>
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<td>0</td>
<td>About to fail</td>
<td>1142</td>
<td>Asset 19</td>
<td>1</td>
<td>1</td>
<td>0.952</td>
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<td>Asset 5</td>
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<td>Asset 6</td>
<td>1</td>
<td>0.945</td>
<td>0.703</td>
<td>Running</td>
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<td>Asset 8</td>
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<td>0.964</td>
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<td>Asset 23</td>
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<td>1</td>
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<td>Asset 24</td>
<td>0.873</td>
<td>0.695</td>
<td>0.893</td>
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<td>Asset 10</td>
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<td>Asset 11</td>
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<td>0.977</td>
<td>Failed</td>
<td>211</td>
<td>Asset 29</td>
<td>1</td>
<td>0.312</td>
<td>0</td>
<td>Failed</td>
<td>991</td>
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<td>Asset 15</td>
<td>1</td>
<td>1</td>
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<td>Failed</td>
<td>411</td>
<td>Asset 30</td>
<td>0</td>
<td>0.999</td>
<td>0.976</td>
<td>Failed</td>
<td>734</td>
</tr>
</tbody>
</table>
MONITORING ALGORITHMS BASED ON VFD DATA: CASE STUDIES
CASE STUDY 1: PHASE CURRENTS, VOLTAGES AND POWER
CASE STUDY 2: SPECIFIC VFD TAGS FOR FAILURE PREDICTION
NODAL ANALYSIS APPROACH

Oil well with an ESP

Node point Description
1. Formation
2. Well bottom
3. Pump intake
4. Pump discharge
5. Wellhead
6. Surface separator
7. Fluid level
8. Casinghead

\[ \Delta p_2 = p_{\text{下游}} - p_{\text{下游}} \]

\[ \Delta p_3 = p_{\text{下游}} - p_{\text{下游}} \]

\[ \Delta p_4 = p_{\text{下游}} - p_{\text{下游}} \]

\[ \Delta p_5 = p_{\text{下游}} - p_{\text{下游}} \]

\[ \Delta p_6 = p_{\text{下游}} - p_{\text{下游}} \]

Loss in reservoir
Loss in completion
Loss in tubing
Loss in flowline
Total pressure loss
MONITORING BASED ON DATA-DRIVEN NODAL ANALYSIS

- Grey-box models trained adaptively.
- Model prediction picks up the heat transfer and hydraulics anomalies and sensor anomalies.

Predict the surface temperature from the bottom hole parameters and surface pressure and compare against the measured temperature

Predict the bottom hole pressure from the surface parameters and bottom hole temperatures and compare against the measured pressure
CASE STUDY: DATA-DRIVEN NODAL ANALYSIS

- Start up
- Time of failure
- Increase in prediction error before the failure
- Alarms issued by the monitoring application
MACHINE LEARNING APPROACH

- Create a data-driven model that reduces high-dimension data to one or two process health indicators using data from normal operating conditions
- Determine statistical control limits from the data-driven model
- Detect process drifts online by monitoring the health indicators extracted from data
**MACHINE LEARNING APPROACH**

- **Available process data**
  - **Feature extraction**
    - Group 1 PVs
    - Group 2 PVs
    - Group N PVs
  - **Detection metric**
    - Composite detection metric
  - **Higher level feature extraction**

- **Monitor the process and equipment based on one or two indicators**
- **Fuse features from different groups and perform dimension reduction**
- **Perform dimension reduction and capture features that explain the variability in the data**
- **Combine process knowledge and high-dimension data to group process variables**

**Detect**

**Diagnose**
MACHINE LEARNING APPROACH: CASE STUDY

The PCA-SFA performance

Model training
One month before ESP failure
Shutdowns
Feature before the failure
Control limit
MONITORING ABNORMAL OPERATING CONDITIONS

- Low SOR
- Equipment reliability
- Increased oil mobility

- Steam breakthrough
- Equipment failure

- High SOR
- Reduced oil mobility

Eroded liner

Pump cavitation
MACHINE LEARNING TO PREDICT STEAM BREAKTHROUGH

Correlation matrix of the temperatures measured along the wellbore during normal operation

Correlation matrix of the temperatures measured along the wellbore just before the incidents

- Patterns in temperature measurements along the wellbore used to predict some of the abnormal incidents
- When steam breaks through some parts of the well, measured temperatures in those parts tend to have distinct trends compared to the rest of the well
Trends of temperatures measured along the wellbore

Temperature measurements reduced to a single monitoring statistic

Alarms issued by the monitoring tool

STEAM BREAKTHROUGH PREDICTION RESULTS
EMERSON’S DATA ANALYTICS PLATFORM

▪ Platform developed by Integration Objects, Tunisia-based company
▪ Acquired by Emerson in April, 2019
▪ To be integrated with Emerson’s Plantweb digital ecosystem

KnowledgeNet
A Unique Platform for Your Digital Transformation

KnowledgeNet (KNet) platform is primarily used to empower operations in the chemical, oil and gas, power, and utilities Industries in making timely business decisions to increase production uptime, profitability, and safety. KNet supports cloud platforms and offers to end users a cutting edge technology to migrate to Industry 4.0. Users may include operators, shift supervisors, engineers, and plant managers.

KnowledgeNet helps you digitize your plant to future proof your operations and improve your assets performance and reliability.
KNET SOFTWARE FEATURES

- Includes a number of in-built tools for data connectivity, preprocessing and data analytics, automated root cause analysis, alarm analytics, etc.
- Easy to compile and drop custom-built algorithms for monitoring and prediction applications
KNET: MAIN COMPONENTS AND DETAILED ARCHITECTURE
ESP MONITORING IN EMERSON’S ANALYTICS PLATFORM

- All our algorithms are built, deployed and tested in KNET online
- Research to deployment – A fast route
BUSINESS RESULTS ACHIEVED

• Field Trial:
  - The performance monitoring application is currently being field tested with one of the producers in the province to assess the financial benefits.

• Joint Industrial Project:
  - A JIP to study data from multiple ESP installs at multiple producer sites has been initiated in collaboration with Canadian Oil Sands Innovation Alliance (COSIA)

• Potential benefits:
  - There are about 1100 thermal oil wells equipped with ESPs in Alberta
  - One less rig over per well on an average can provide over 300 million dollars savings to the industry
SUMMARY

• Electric submersible pumps (ESPs) are widely preferred artificial lift systems in upstream oil production

• Keeping the ESPs operational is one of the important challenges faced by the operators

• Under the Industrial Research Chair, we have been investigating a number of different data-driven algorithms for fault detection, diagnosis and failure prediction of ESPs

• Emerson’s analytics platform with its data connectivity and analytics capability allows taking the research results to the field in a quick and easy manner

• Field tests are being conducted to properly assess the financial benefits
WHERE TO GET MORE INFORMATION

• Industrial research chair program:
  - https://www.ualberta.ca/engineering/research/groups/oil-sands-process-control

• Spartan Controls
  - https://www.spartancontrols.com/

• ESP Resources:
  - http://jip.esprifts.com/
  - https://www.onepetro.org/conference-paper/SPE-56663-MS
  - https://www.onepetro.org/conference-paper/IPTC-17413-MS

• Analytics platform
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