ESP shutdown prediction using hybrid support vector machine and improved parallel particle swarm optimization

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Outline

• Introduction and current challenges
• Current challenges in why predict ESP shutdown?
• Objectives
• Methodology
• Field examples - results and discussion
• Conclusions
Background and motivation for ESP-based well operations management

- Big data technologies are now being used to address many industrial problems & challenges related to high volume, high velocity, high variety.

- Digitization using advanced sensors in intelligent oilfield solutions has resulted in the generation of huge amount of data that can be used to enhance the performance, operational health surveillance & management of ESP.

- Need to use powerful analytics to estimate inexpensively and accurately equipment performance degradation, equipment failures, or detrimental interactions among subsystems.

- Enhanced monitorability to reduce downtime and improve hydrocarbon recovery.

![Diagram of data flow and benefits](image-url)
Current challenges in smart ESP-based well operations management

- Overwhelming downhole & surface sensor data has become too large and complex to be effectively processed by traditional approaches

- Acquiring, cleansing, processing & analyzing data has to be done in shorter time frames

- Downhole big data analytics requires a range of technologies (big data platforms – Spark; data warehouses and databases; data ingestion, pipeline, integration; virtualization and containerization of workloads; servers, storage and networking infrastructure; analytics model tuning, visualization and reporting applications;

- Current upscaling of online ESP surveillance practices, are largely determined by the size of the training data and the limited computational infrastructure for storing, managing, analyzing and visualizing big datasets
Objectives

• Develop a general purpose system architecture for predicting ESP shut-down focusing on low-cost cloud–based computing platform

• Explore the feasibility of using real-time data collected by downhole sensors as the only source of information about the normal and abnormal operating conditions of a ESP system

• Investigate the potential of using data-driven artificial intelligence and statistical techniques for efficiently extracting and capturing information about the expected patterns of the signals coming from the ESP sensors, controller data, power data, surface data during the normal operating conditions of an ESP (normal operating patterns)
Methodology: proposed solution framework

- No guess work on data - Fuzzy logic based analysis for finding whether data is increasing, decreasing or constant
- Easy to recognize ESPs with issues – exception based surveillance (Exceptions are cross verified with the Prescriptive rules)
- Once the analyzed data and rules/pattern matches, alarms are triggered based on the prescription

ESP Operation Expertise
- Subject Matter Expert experienced on operating ESPs in different application
- Support model institutional learning and continuous model calibration

Data Access
- Right data is transmitted in the right time - reliably
- Data is available to people, tools, model calibrator where it can be use

Pattern detection, alarm, model and Prescriptive recommendation
- Easy to recognize ESPs with issues – exception based surveillance (Exceptions are cross verified with the Prescriptive rules)
Methodology: proposed deployment service platform

Data Aggregation System
- Data Sources
  - MODBUS
  - CSV/LAB Files
  - PI
  - OPC/UA
- Aggregators
  - TSD Adapter
  - CSV IN
  - PI Data Miner
  - OPC/UA

Data Store/Stream
- PDH
- Streaming powered by Apache Kafka

Analytics Engine
- Batch Process/Historical
- Streaming/Realtime Data

Results/Alerts
- Push Alerts to AMBIT through Kafka Notification System

AMBIT Notification Manager powered by Apache Flink

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Methodology: proposed system architecture

**Data Acquisition**
- DTS Datamining
- Demand Trac
- DSS Datamining
- DNP3
- SCPI
- CSV-Time Series

**Data Streaming (RT/HA) and Storage**
- Cassandra
- Energistics
- PRODML
  - 1.2, 1.3, 2.0 (DAS)
- Kafka

**Data Computation**
- Real Time Data
- History Data
- Configuration parameters
- Training Data from Gateway

**Data Visualization**
- Gateway UI
- Visual alerts

**Shutdown Prediction Engine**
- Rule based
- ML Apache Spark

**Apache Spark Cluster**

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Methodology: proposed spark computational cluster architecture
Methodology: ESP shutdown prediction model

Identify Problem Domain → ESP Data Selection → ESP Investigate Data Set

Classification

- Normal ESP Conditions
- ESP Shutdown Conditions

Clustering Algorithm

- Low
- Medium
- High

Pattern Recognition Algorithm for Anomaly Detection

ESP Shutdown Prediction
### Dataset for the case study

<table>
<thead>
<tr>
<th>TOTAL NUMBER OF WELLS</th>
<th>~350</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of shutdown</td>
<td>3,984</td>
</tr>
<tr>
<td>Maximum shutdowns per month</td>
<td>597</td>
</tr>
<tr>
<td>Minimum shutdowns per month</td>
<td>111</td>
</tr>
<tr>
<td>Average shutdowns per month</td>
<td>332</td>
</tr>
<tr>
<td>Total SCADA shutdowns</td>
<td>1,751</td>
</tr>
<tr>
<td>Total input power quality</td>
<td>1,516</td>
</tr>
<tr>
<td>Total operations/downhole</td>
<td>635</td>
</tr>
<tr>
<td>Total external signal shutdown</td>
<td>46</td>
</tr>
<tr>
<td>Total internal drive component</td>
<td>36</td>
</tr>
</tbody>
</table>

### Distribution of dataset

- **Training set**
  - Normal Conditions
  - Shutdown Conditions

- **Testing set**
  - Normal Conditions
  - Shutdown Conditions
Applications – case studies

Important operating parameters that is typically monitored include ...

- Frequency
- Pump intake pressure and temperature
- Pump discharge pressure and temperature
- Internal motor operating temperature
- Flow rate
- Surface current and voltage
- Voltage imbalance
- Tubing pressure and casing pressure
- Current leakage
- Unit vibration

Important operating parameters that may be Inferred include ...

- Seal section oil expansion
- Driveline torque
- Thrust bearing loading
- Motor terminal voltage
- Motor terminal current
- Motor load factor
- Pump operating range
- Stator temperature
- Seal oil temperature
Applications – case studies

<table>
<thead>
<tr>
<th>OPERATIONAL/DOWNHOLE</th>
<th>TOTAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trip (non-ESP trip)</td>
<td>151</td>
</tr>
<tr>
<td>Underload</td>
<td>148</td>
</tr>
<tr>
<td>Low intake pressure</td>
<td>136</td>
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<tr>
<td>High motor temp.</td>
<td>57</td>
</tr>
<tr>
<td>High intake temp.</td>
<td>41</td>
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<tr>
<td>High discharge pressure</td>
<td>38</td>
</tr>
<tr>
<td>Motor stall</td>
<td>33</td>
</tr>
<tr>
<td>Overload</td>
<td>12</td>
</tr>
<tr>
<td>High downstream pressure</td>
<td>6</td>
</tr>
<tr>
<td>Troubleshooting</td>
<td>5</td>
</tr>
<tr>
<td>Leak</td>
<td>1</td>
</tr>
<tr>
<td>Low speed trip</td>
<td>6</td>
</tr>
<tr>
<td>Over current</td>
<td>1</td>
</tr>
</tbody>
</table>
Applications – case studies

Shutdown Category Breakdown

- SCADA Shutdown: 44.0%
- Input Power Quality: 38.1%
- Operations/Downhole Issues: 15.9%
- Internal Drive Component Issues: 0.9%
- External Signal Intervention: 1.2%

Monthly Num. of Shutdowns per Category

<table>
<thead>
<tr>
<th>Category</th>
<th>JAN</th>
<th>FEB</th>
<th>MAR</th>
<th>APR</th>
<th>MAY</th>
<th>JUN</th>
<th>JUL</th>
<th>AUG</th>
<th>SEP</th>
<th>OCT</th>
<th>NOV</th>
<th>DEC</th>
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</thead>
<tbody>
<tr>
<td>SCADA Shutdown</td>
<td>197</td>
<td>51</td>
<td>90</td>
<td>110</td>
<td>130</td>
<td>110</td>
<td>242</td>
<td>223</td>
<td>150</td>
<td>101</td>
<td>104</td>
<td>134</td>
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<tr>
<td>Input Power Quality</td>
<td>4146</td>
<td>51</td>
<td>16</td>
<td>41</td>
<td>54</td>
<td>53</td>
<td>130</td>
<td>114</td>
<td>136</td>
<td>107</td>
<td>64</td>
<td>70</td>
</tr>
<tr>
<td>Operations/Downhole</td>
<td>332</td>
<td>68</td>
<td>24</td>
<td>26</td>
<td>37</td>
<td>30</td>
<td>42</td>
<td>47</td>
<td>46</td>
<td>118</td>
<td>53</td>
<td>53</td>
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<tr>
<td>Internal Issues</td>
<td>67</td>
<td>21</td>
<td>26</td>
<td>37</td>
<td>47</td>
<td>30</td>
<td>73</td>
<td>64</td>
<td>50</td>
<td>3</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Intervention</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>0</td>
<td>3</td>
<td>2</td>
<td>7</td>
<td>6</td>
<td>2</td>
<td>4</td>
<td>7</td>
</tr>
</tbody>
</table>

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Applications – case studies

Operations/downhole issues breakdown

- Trip (Non-ESP trip) 23.78%
- Underload 23.31%
- Low Intake Pressure 21.42%
- High Motor Temp. 15.49%
- High Intake Temp. 11.41%
- High Discharge Pressure 10.48%
- Motor Stall 5.20%
- Overload 1.89%
- High Downstream Pressure 0.94%
- Troubleshooting 0.79%
- Leak 0.16%
- Low Speed Trip 0.94%
- Over Current 0.16%
- Over Current 0.16%
- Over Current 0.16%

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Conclusions

• An automated detection and prediction of shutdown has been designed and implemented for real-time Electrical Submersible Pumps (ESP) performance monitoring and diagnostics.

• The main novelties are that the proposed approach extracts features from operating conditions based on clustering analysis and predict via data classification.

• Test, verify and demonstrate the effectiveness and efficiency of the novel methodology for ESP shutdown prediction on a number of real-life case studies from the field.

• Robust performance is guaranteed and versatile to various ESP applications – onshore, offshore, SAGD, etc.

• Future directions – more sophisticated anomaly detection algorithms for online self-learning on cloud-based distributed clusters.