Application of Machine Learning for Subsea Pipeline and Riser Systems Integrity Management

Technology Week 2018

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Digital Twin: A Data Driven Integrity Management Approach for Offshore Assets
Key Driver 1: IOT Sensors and Digital Inspection Technologies

New approach
DNV-RP-F101 Appendix D

Advanced Calculation
Accurate Result

Corrosion Rate & Remaining Life
Key Driver 2: Low Cost Advanced Computing Resources
Key Driver 3: Hi-Fidelity Physics Based Models
Key Driver 4: Open Source Machine Learning Tools
Case Study: Machine Learning Application Steel Catenary Risers Fatigue

- Extremely complex physics governing fatigue
- Real time damage accumulation monitoring from site motions measurements

<table>
<thead>
<tr>
<th>Failure Mode</th>
<th>Cause</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wave Fatigue</td>
<td>Vessel Motions</td>
</tr>
<tr>
<td></td>
<td>Waves</td>
</tr>
<tr>
<td>VIV Fatigue (Riser Pipe)</td>
<td>VIV due to current profile, loop / eddy current</td>
</tr>
</tbody>
</table>
Artificial Neural Network for SCR Fatigue

Time consuming FEA numerical simulations are usually performed to assess the stress range occurring in SCRs and deduce the fatigue damage.

Once trained the ANN can produce the time series of Tension and Moment at a fraction of the time taken by FEA, thus actual field measurements can be used to compute fatigue.
Case Study

- Vessel Type: Semi Submersible
- Region: GOM
- Water Depth: 4300 ft
- Pipe OD: 8.625 in
- WT: 1.13 in
- Steel Grade: X65
- SN Curve: D Curve
- Hang off: TSJ
ANN Training Methodology

1. Run Orcaflex and export time series of vessel motions and Tension and BM.
2. Import Data into Tensor Flow and compute the weights for the ANN.
3. Compare Orcaflex and ANN predictions for multiple wave seeds.
Results: Sample Time Series Comparison

<table>
<thead>
<tr>
<th></th>
<th>Orcaflex</th>
<th>ANN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>1565.5</td>
<td>1565.5</td>
</tr>
<tr>
<td>Std. dev</td>
<td>36.3</td>
<td>36.3</td>
</tr>
<tr>
<td>Min</td>
<td>1431.6</td>
<td>1431.5</td>
</tr>
<tr>
<td>Max</td>
<td>1697.6</td>
<td>1698.8</td>
</tr>
</tbody>
</table>
Results: Sample Time Series Comparison

<table>
<thead>
<tr>
<th></th>
<th>Orcaflex</th>
<th>ANN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-0.1</td>
<td>-0.1</td>
</tr>
<tr>
<td>Std. dev</td>
<td>10.0</td>
<td>10.0</td>
</tr>
<tr>
<td>Min</td>
<td>-39.8</td>
<td>-38.1</td>
</tr>
<tr>
<td>Max</td>
<td>38.7</td>
<td>37.0</td>
</tr>
</tbody>
</table>
**Results: Sample Time Series Comparison**

<table>
<thead>
<tr>
<th></th>
<th>Orcaflex</th>
<th>ANN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-3.1</td>
<td>-3.2</td>
</tr>
<tr>
<td>Std. dev</td>
<td>19.8</td>
<td>19.7</td>
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<tr>
<td>Min</td>
<td>-82.9</td>
<td>-78.3</td>
</tr>
<tr>
<td>Max</td>
<td>72.6</td>
<td>68.7</td>
</tr>
</tbody>
</table>
Fatigue Life - All Sea states (Different Seeds)
ANN Deployment Methodology

1. Collect wave measurement and vessel motions
2. Run ANN on Raspberry Pi
3. Compute fatigue and email results
Integrating with Subsea Robotic Inspection

Subsea Pipeline Inspection

- Diver and ROV Deployed tools make it possible to carry out fully automated inspections to depths of 9500ft
- ILI Verification of critical indications
- Sampling inspection of unpiggable pipelines make it possible to justify continued operation of pipelines.
  - Factors which can make lines difficult to pig: Low flow conditions, Wax buildup
  - Acquisition of high quality quantitative data allows for use of statistical methods as part of Fitness for service evaluations

Pictures Provided by Sonomatic
Integrating With Robotic Inspection
Hi- Fidelity Assessment Approaches

Data can be presented in 3D format for easy analysis.
Automated data processing and reporting.

Pictures Provided by Sonomatic

Interacting corrosion pits
# Machine Learning Application for Corrosion

<table>
<thead>
<tr>
<th>Failure Mode</th>
<th>Cause</th>
<th>Safeguards</th>
<th>ITPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Corrosion</td>
<td>MIC, CO2, H2S</td>
<td>Design to API-2RD MMS</td>
<td>Biocide Injection Availability (%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Biocide Injection</td>
<td>Corrosion Inhibitor Availability (%)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Corrosion Inhibitor</td>
<td>UT Topsides Piping (WT)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Corrosion Allowance</td>
<td>Monitor Corrosion Coupon</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Corrosion Allowance</td>
<td>Monitor WT (SS)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Topside</td>
<td>Corrosion Model</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Intelligent Pigging</td>
<td>Inline Inspection and wall thickness measurement</td>
</tr>
</tbody>
</table>

![Image of corrosion damage](image-url)
Machine learning to leverage the collected patterns

- Optimized ILI frequency
- Better Corrosion Management Predictions
- Better Corrosion Development Predictions

My Pipe

Machine Learning Techniques

Corrosion Development Patterns
Detailed Assessment Approach

**Traditional approach**

- ILI Report → List of Defects → Simplified Evaluation → Conservative Result

**New approach**

- Raw Data → Advanced Calculation → Accurate Result

*Corrosion Rate & Remaining Life*

*DNV-RP-F101 Appendix D*
Conclusion

Streamline analysis work

Utilize Big Data technology

Increase customer interaction

Combine data scientists with pipeline experts

Develop digital deliverables

Enhance customer experience