Predictive Subsea Integrity Management: Effective Tools and Techniques

The Leading Edge of Value-Based Subsea Inspection

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Background

• Low oil price having major impact on oil and gas business

• Operators need to significantly reduce OPEX
  – Looking for better strategy for managing subsea assets which will reduce costs

• Opportunities to decrease OPEX
  – Inspect less often - increase time between inspections
  – Inspect fewer items - only inspect items at risk of degradation
  – Inspect items more rapidly – less time on station
  – Remote condition monitoring rather than ROV inspection
  – Increase time between failures - improve reliability
  – Decrease time to repair or replace
  – Use lower cost vessels

• New technologies needed to reduce operating costs without compromising asset integrity
Asset Integrity Management Strategies

• **Breakdown**
  – Fix when broke
  – Expensive

• **Preventive**
  – Scheduled inspection and replacement
  – Less suitable for permanently installed subsea hardware

• **Predictive**
  – Monitor equipment and process conditions
  – Predict and prevent

- Unscheduled interventions
- Process and service disruptions
- High maintenance costs

- Regular interventions
- Equipment inspection
- Replacement before failure

- Predicted best time for intervention
- Detect & correct root causes of failure
- Deliver inherent plant reliability

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Fundamental Questions

- When will an equipment item fail?
- How soon before we need to replace or repair the item?
- How often should we inspect or test?

Important to understand
- How equipment items degrade and fail (mechanisms)
- How fast degradation progresses and leads to failure
- How much degradation can be tolerated before action needed to prevent failure

Inspection, monitoring and testing can be used to indicate:
- Actual state/condition of equipment to support decision making
- Changes of state/condition over time (if monitored)

Currently industry approach
- Mainly to detect current state/condition
- Not making best use of this data to forecast asset life
Predicting Time of Failure

- Conventional reliability based on two states: working and failed
- Historically simple reliability models used to forecast probability of failure with time
  - \( \lambda \) is the asset failure rate \( \text{MTTF} = \frac{1}{\lambda} \)
  - \( t \) is the age of the asset

\[ P = 1 - \exp(-\lambda t) \]

How do we move forward?

- Fundamentally 2 states not enough to manage asset reliability and integrity
- Need additional states - working, degraded, failed
Advanced Predictive Analytics and Tools

- **Forward prediction methods**
  - Markov chains - state space models
  - Damage accumulation and limit state models
  - Reliability growth analysis

- **Predictive models must be realistic representation of the degradation and failure mechanisms of monitored equipment**

- **Monitored data must be relevant to the actual degradation/failure mechanisms of monitored equipment**

- **Tools for using and analysing observed data**
  - Hidden Markov models with Bayesian updating
  - Bayesian updating of damage accumulation and limit state models
  - Machine learning from observed data
    - Supervised and unsupervised learning
Hidden Markov Model

- State is hidden
- State revealed by observable $Y_i$
  - Monitored data
  - Inspection data
- $Y$ indicates if state is
  - N (working as good as new)
  - D (degraded) or
  - F (failed)

- Forward forecast by state space Markov model
- State probability updated using advanced analytics e.g. Bayes or ML algorithm
- Time to next action = time to reach maximum allowable probability for that action e.g.
  - Time to next inspection
  - Time before need to replace or repair
- Predicts time to reach unacceptable damage state
Damage Accumulation - Limit State Models

- Damage accumulates from time $t=0$ until failure
- Damage rate varies with time (e.g. corrosion, erosion, wear, fatigue)
- Failure occurs when damage $D$ exceeds allowable damage $D^*$
- For example: $D^*$ can be corrosion allowance or wall thickness

- Can be used where there is a well understood failure mechanism e.g. corrosion
- Predictions based on historical degradation rate data and equipment design
- Can be updated given actual measurements of degradation rate
• Machine Learning - a powerful tool for analysing data
• Applicable to analysis of monitored data or inspection data
• A number of different algorithms available e.g.
  – Supervised learning commonly used
  – Train the model using classification algorithm to recognise which observables indicate when state is working, degraded or failed

Machine Learning Techniques

Machine Learning

Unsupervised Learning

Clustering

Supervised Learning

Classification

Regression

Note: machine learning will be in 6D space if there are 6 observables relevant to equipment state
Practical Application Examples

Subsea Valves
- Signature test data
  - Time to close/open
  - Actuated hydraulic volume
- Predictive Models
  - Use of observed test data to update and forecast degraded and failed states
  - Integration of individual valve forecasts into system isolation model

Pipelines
- Typical external observables from ROV inspection
  - Coating condition
  - Anode wastage
  - Visible corrosion
  - Leaks
- Predictive Models to update and forecast degraded and failed states
  - Include equipment states and barrier states
Summary and Conclusions

- Currently not enough use made of existing data collected as part of the Operators Integrity Management
-Existing IM data are limited in scope and quality
- Significant amount of subsea integrity data based on inspection
- Operators looking to make more use of remote condition monitoring approaches that rely less on expensive vessels
- Advanced Predictive Analytics applicable to any subsea asset or asset barrier (e.g. CP, coatings, inhibition systems) that can be monitored or inspected
  - Valves (trees, manifolds, down hole safety, chokes)
  -Jumpers, pipelines, flow lines
  - Control system and umbilicals
  - Pumps and subsea processing