Assessing Offshore Infrastructure Reuse Potential for Carbon Storage
An Award-Winning AI Model to Forecast Resiliency

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NETL Support Contractor

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AIIM: Advanced Infrastructure Integrity Modeling

Overview

AIIM applies big data, big data computing, and multiple predictive machine learning (ML), spatio-temporal, and advanced analyses to evaluate infrastructure integrity and forecast remaining useful lifespan and risk likelihood.

Values Delivered

- Evaluates the current state of offshore infrastructure for reuse potential
- Informs lifespan extension, remediation, and safe-use strategies
- Cross-compares with social and environmental data to identify potential vulnerabilities, and supports risk prevention
The **AIIM** Approach:

**Big data, big data computing, and multiple machine learning/advanced analytical models to evaluate infrastructure integrity**

1. Remaining lifespan
2. Risk likelihood

### Machine Learning Models (Dyer et al. 2022)
- Gradient Boosted Decision Trees (2 models)
- Artificial Neural Network (2 models)
- Bayesian Network

### Advanced Analytics
- Geographically Weighted Regression
- Causality/Time Series Analytics

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**The Approach:**

ML models capable of predicting removal age < 3 years

**Identified connections among biochemical and metocean variables and incidents**

**Corroborated results with news and reports**

**AI/ML & Advanced Modeling**

**Structural information**

**Metocean & biochemical variables**

**Geohazard data**

**Incident reports**

**Production information**

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Using the Whole to Inform Local Trends & Predictions

- 11k+ platform records
- 26k+ miles of pipelines
- 68k+ well records
- 51k+ environmental layers
- Geohazard layers
  - Landslide prediction surface from NETL’s Ocean and Geohazard Analysis smart tool
- 46GB+ biochemical data
- Spatio-temporal production data at the well, platform, and lease block level
- 70+ years of platform incidents
- 30+ years of pipeline incidents
- 50.6GB of monthly ship trackline data

**Approach: Big Data & Big Data Computing-Driven Insights**

- Data representing the natural-engineered offshore system

**Ages of Existing Platforms as of November, 2022**

**Pipelines by Status**

**Status** | **Miles**
---|---
Abandoned or Removed | 23,838
Active | 19,731
Cancelled, Proposed Abandon or Remove | 3,914
Proposed | 109

*Deepwater (1,000m+)*
**Ultra deepwater (5,000m+)*
Examining Risk Cause and Effect

Currently building a Bayesian Network to map cascading events

**Causes**
- Structure type, age, location
- Preventative maintenance
- Operations and activities
- Past incidents
- Environment conditions
- Other external factors

**Consequences**
- Severity (e.g., cost, damage)
- Environmental impact
- Fatalities or injuries
- Monetary cost
- Corrective actions

**Reported Incident**
- Fire
- Explosion
- Collision
- Leak

Answer questions:
- What factors contribute to high-severity events?
- At what age are platforms most prone to incidents?
Evaluating Platform Incidents

Reported Incidents Per Year from 1952 – 2021

Trend can be attributed to the **integrity of aging structures** and the **improved incident reporting**

Sources:
- Bureau of Safety and Environmental Enforcement (BSEE) and past agencies
- 292 incidents from Hurricane Reports
- 239 incidents from the Pipeline and Hazardous Materials Safety Administration (PHMSA)
Time Series Analytics

Biochemical Variables → Reported Platform Incidents

• Aggregated incidents and biochemical time series to estimate transfer of information
  • 26 years of biochemical data (1990—2015)
• Causal relationship was not found
  • Biochemical variables → incident time series
• Identified a causal relationship
  • Biochemical variables → rate of change of incident time series

Example of biochemical time series

Biochemical properties cause incidents over two main periods:
  10 years and 20 years

<table>
<thead>
<tr>
<th>Model</th>
<th>Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medusa/Orca (U.K. NOC)</td>
<td>Alkaline, diatom chlorophyll, nondiatom chlorophyll, detritus, inorganic carbon, inorganic nitrogen, detritic carbon, dissolved iron, dissolved oxygen, biologenic silicon, silicon, diatom phytoplankton, non-diatom phytoplankton, silicate, meso zooplankton, micro zooplankton</td>
</tr>
</tbody>
</table>
More Time Series Analytics

Estimating Transfer of Information

Metocean Variables → Platform Incidents

- Maximum wave height → rate of change of incident time series
  - 41 years of wave height data (1979–2019)
- Peaks in transfers of information at ~7 years (see red box)
  - Violent nature of extreme waves
  - Correlations did not appear meaningful

Next steps include testing alternative aggregations

<table>
<thead>
<tr>
<th>Model</th>
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<tbody>
<tr>
<td>Wavewatch III</td>
<td>Wave height, period, direction, and power; Wind direction and magnitude</td>
</tr>
<tr>
<td>Hybrid Coordinate Model</td>
<td>Floor current direction and magnitude; Surface current magnitude and direction</td>
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</table>
Understanding 30+ Years of PHMSA Incidents

• Compiled, cleaned, and mapped 970 PHMSA incidents
  (Pipeline and Hazardous Materials Safety Administration)

• 30+ years of incidents (1986 – 2021)

• Spatially mapped more than 80% to lease blocks

• Calculated impact-based severity

Incidents per lease block

Total incident severity per lease block

Reported incidents over time
Evaluating Incident Consequences Over Time

Incident Cost
Costs based on 2021 USD value

Incident Severity

Highlights

- Majority of platforms are past design life and predicted lifespan

- Extreme weather events relate to incidents and are a key variable in forecasting lifespan

- Biochemical properties (corrosion) cause incidents at 10- and 20-year intervals

Next Steps

- Apply analytics to pipeline and well reported incidents

- Share insights and information through AIIM spatial visualization dashboard

**Pipeline Incident Causes**

- Corrosion Failure, 42.03%
- Outside Force Damage, 16.79%
- Natural Forces, 12.30%
- Other, 9.95%
- Material Failure, 8.45%
- Equipment Failure, 6.74%
- Incorrect Operation, 3.74%

**Corrosion Type**

- INTERNAL - 79.25%
- EXTERNAL - 16.32%
- BOTH - 4.43%
Overview Map: Spatial Filtering – Protraction Areas

AIIM Dashboard for Offshore Infrastructure
Overview Map: Spatial Filtering – Lease Blocks

AIIM Dashboard for Offshore Infrastructure
Overview Map: Spatial Filtering – Pipeline Status

AIIM Dashboard for Offshore Infrastructure
Overview Map: Pipeline Segment

AIIM Dashboard for Offshore Infrastructure
Pipeline Map: Machine Learning Predictions

AIIM Dashboard for Offshore Infrastructure
Pipeline Map: Variable Selections

AIIM Dashboard for Offshore Infrastructure
References


Acknowledgments

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Pocket Slides
Project Overview

**Objective**

- Evaluate current state of **platform**, **pipeline**, and **wells** in the U.S. Federal Gulf of Mexico

- Identify relationships or **causality** among key **stressors**, **incidents**, and **structural integrity** to inform **reuse** and **repurposing operations**

**AIIM**: **Advanced Infrastructure Integrity Modeling**

AIIM applies big data, big data computing, and multiple predictive machine learning (ML), spatio-temporal, and advanced analyses
Enhanced Environmental Factors

Integrating 46GB+ BioChemical Data and Seafloor Data

- Developed visualization to support Metaocean Big Data Processing Program quality control
- Time series processing option
- At-depth data extraction to better support pipelines and wells analytics

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<tr>
<td>International Best Track Archive for Climate Stewardship</td>
<td>Storm category, max sustained wind speed, sea height, max gust, minimum central pressure</td>
</tr>
<tr>
<td>Medusa/Orca</td>
<td>Alkaline, diatom chlorophyll, nondiatom chlorophyll, detritus, inorganic carbon, inorganic nitrogen, detritic carbon, dissolved iron, dissolved oxygen, biogenic silicon, silicon, diatom phytoplankton, non-diatom phytoplankton, silicate, meso-zooplankton, micro-zooplankton</td>
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<td>Floor current direction and magnitude</td>
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Multiple Machine Learning (ML) and Advanced Modeling

Machine Learning Models (Dyer et al. 2022)
- Gradient Boosted Decision Trees (2 models)
- Artificial Neural Network (2 models)
- Bayesian Network

Advanced Analytics
- Geographically Weighted Regression (Nelson et al. 2021)
- Causality/Time Series Analytics

Identified connections among biochemical and metocean variables and incidents

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ML models capable of predicting removal age < 3 years

Structural information

Metocean & biochemical variables

Geohazard data

Incident reports

Production information
Expanding Analytics: Predicting Platform Age at Removal

- Integrated 70+ years of data
- 11k+ structure records
- 1,700+ features

- Calculated incident severity based on incident impact (i.e., damage, cost)

- Applied ML models to updated data

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<thead>
<tr>
<th>Model</th>
<th>RMSE* (years)</th>
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<tbody>
<tr>
<td>Gradient Boosted Decision Tree (CatBoost)</td>
<td>3.1</td>
</tr>
<tr>
<td>Gradient Boosted Decision Tree (XGBoost)</td>
<td>3.4</td>
</tr>
<tr>
<td>Artificial Neural Network</td>
<td>5.3</td>
</tr>
</tbody>
</table>

*Root Mean Square Error

Feature engineering to identify key stressors impacting integrity and risk
Ex. Reduced 100s of production features to less than 10 (i.e., peak production years, water-oil production)
More Time Series Analytics

Estimating Transfer of Information
Metocean Variables → Platform Incidents

- **Maximum current velocity → rate of change** of incident time series
  - 29 years of maximum current velocity data (1993–2021)

- Peaks at 19 years, but...
  - **Strong signal and noise relative contributions**
  - Correlations not meaningful

Next steps include testing alternative aggregations

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Integrating Well Infrastructure

Utilizing Past Research to Inform New Insights

- Leveraging data and insights from onshore well integrity testing
- Evaluating well integrity for reuse potential

Ages of Active Wells as of Oct. 27, 2022

Source: Enverus

**Stressors Identified**

- **Age** (Dilmore et al., 2015)
- **Type** (Kiran et al., 2017)
- **Concrete type and installation** (Wang et al., 2016; Kiran et al., 2017; Wise et al., 2019; Rocha-Valadez et al., 2014)
- **Water depth** (Wise et al., 2019)
- **Corrosion** (Kiran et al., 2017)
- **Direction** (Lackey et al., 2021)
- **Pressure and temperature** (Rocha-Valadez et al., 2014; Wang et al., 2016; Kiran et al., 2017)
- **Seismic/tectonic activity** (Kiran et al., 2017)
- **Geology** (Dilmore et al., 2015; Kiran et al., 2017)
Examining Risk Cause and Effect

- Began development of Bayesian Network to correlate incident attributes and causes with incident severity.

- Evaluating trends across structure type, depth, installation age, and more.

Average Severity by Structure Type

- Low
  - Mini tension-leg platform
  - Steel tower
  - Mobile offshore drilling unit
  - Drillship
  - Caisson
  - Compliant tower
  - Tension-leg platform
  - Fixed platform
  - Semi-submersible
  - Mobile offshore production unit
  - Unknown

- High
  - Spar
  - Jackup
  - Floating production storage and offloading
  - Well protector