Managing offshore disruptions with AI

Justin Lacko

Structured validation approach

Case question:

How might we use AI to reduce disruptions to planned maintenance schedules?

Key considerations:

- Buy vs. build
- Partnering
- Strategic alignment
- Proof of concept/MVP before pilot
- Defining value early

Step 1: Define the problem and baseline

- Map the decision-making process: Who decides what, when, and using what information?
- How big is the problem? What is the baseline for disruptions? (Frequency, types, duration, costs)
- Identify key pain points in the decision-making process

Step 2: Explore opportunity space and propose ideas

- Look at trends: What are competitors doing? What's happening across the industry?
- Refine hypothesis with quantitative data to understand potential business value early
- Map opportunities to identify quick wins vs. big bets

Step 3: Evaluate feasibility and define business case for pilot

- Audit data: Identify gaps and map data availability, assess complexity (technical risk, skills and capabilities, change management, capacity)
- Build business case: Potential savings vs. investment, ROI threshold for leadership buy-in
- Pilot: Determine suitable site, timeline, and key success criteria (savings, feasibility, adoption)

AI-powered intelligent offshore operations

PHASE 1 Quick wins/foundation building	PHASE 2 Advanced planning capabilities	PHASE 3 Intelligence layer enhancement	PHASE 4 Portfolio optimisation	PHASE 5 Integration and scale
Virtual engineer (Large language models)	Dynamic scheduler (Neural networks)	Predictive digital twin (Generative AI)	Wake-aware scheduling (Deep reinforcement learning)	Intelligent offshore operations platform

QUICK WIN (0-3 months)

Virtual engineer for maintenance operation

What if understanding complex datasets didn't require technical expertise, and AI was accessible to all team members, not just data scientists?

Idea: A ChatGPT-like interface that allows maintenance planners, operations managers, and field technicians to interact with complex operational data using natural language.

Advantages

- Democratisation of data access
- Real-time data synthesis
- Contextual intelligence
- Continuous learning
- Integration ready via APIs

Potential value

- Reduction from hours to minutes for decision-making time
- 8m DKK/GW annual savings for accessibility optimisation[1]
- 30m DKK/year savings detecting new performance losses[2]

1: https://www.sciencedirect.com/science/article/abs/pii/S0306261924022980
2: https://ore.catapult.org.uk/resource-hub/projects/cognitive-business

BIG BET (8-12 months)

Generative digital twin for scenario planning

What if it was possible to synthesize realistic "what-if" operational scenarios without waiting for them to happen in real life?

Idea: A physics-informed generative AI system that creates a living virtual replica of each offshore wind turbine and learns to simulate realistic operational scenarios - including rare events that haven't occurred yet.

Advantages

- Synthesize future scenarios without only relying on historical data
- Predict equipment behaviour under edge-case conditions
- Test maintenance strategies virtually before executing

Potential value

- Lower than predicted wear and tear on turbines[1]
- 60% reduction in field inspections and 85% reduction in repair lead time[2]

1: https://group.vattenfall.com/press-and-media/newsroom/2024/digital-twins--a-road-to-more-profitable-offshore-wind
2: https://www.vhive.ai/understanding-digital-twin-technology-in-wind-energy/

Data requirements

Virtual engineer for maintenance operation

Internal data:
- Turbine operational data
- Maintenance records
- Asset configuration data: Turbine models, specs, age and operational hours of major components
- Resource availability: vessel schedules, specifications, technician rosters, parts inventories, warehouse locations
- Financial data: Downtime revenue loss calculations, maintenance cost breakdowns, contractual penalties for unavailability

External data:
- Weather & marine forecasts
- Electricity market data
- Vessel tracking, port congestion/availability
- Industry benchmark data: Component failure rate statistics, best practice maintenance intervals

Bottom line: Not all data sources are required for this solution to be successfully implemented - a virtual engineer can work with available data sources and expand its capabilities as more sources become available. Consider the sensitivity levels of data sources and ensure they are safe to expose to an AI.

Generative digital twin for scenario planning

Internal data:
- Turbine operational data
- Real-time sensor data: Accelerometers, strain gauges, tilt sensors, etc.
- Historical performance data, including fault logs and degradation curves
- Condition Monitoring System data: Vibration analysis, oil quality, acoustic emission, thermal imaging

External data:
- Environmental loading data: Ocean conditions/wind speed and direction, seabed conditions, water depth (available from Ørsted?)
- Extreme weather forecasts, including climate models and ensemble weather predictions (standard products)
- Physics simulation tools and validation data for turbines and wake calculation (from open-source/academic collaboration)
- Industry failure statistics for training (using Ørsted's own fleet data?)

Bottom line: Ørsted likely already has the majority of this data available for ingestion into a Gen AI solution. Minimal infrastructure investment may be required to retrofit older turbines to collect real-time sensor data, but initial focus should start with newer turbines to reduce investment.