



ENERGY RESEARCH AND DEVELOPMENT DIVISION

FINAL PROJECT REPORT

NextWind: Advancing Wind Energy Technology Using Real-Time Monitoring Systems in a Digital Twin Application

February 2024 | CEC-500-2024-007



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ACKNOWLEDGEMENTS

This project was funded through the Electric Program Investment Charge program and supports a critical research need for the developing offshore wind industry to aid in developing this renewable energy source in a sustainable manner and with the aim of providing affordable renewable energy to Californian constituents with the lowest possible environmental footprint. We are grateful to the California Energy Commission for trusting the NextWind project team with this important task of developing a next-generation wind energy technology.

Sharon Kramer and Stephanie Schneider of H. T. Harvey & Associates for their expertise in the field of ecology, where their expertise was instrumental in identifying information gaps regarding potential marine environment interactions, best practices and methods for environmental monitoring such as key areas for monitoring, and environmental use-case development and data analysis.

Maria Bulakh of Aker Solutions for her continued support of the NextWind project team throughout the duration of project activities.

Shari Matzner from Pacific Northwest National Laboratory for providing seabird data from the ThermalTracker-3D, deployed in the Humboldt Wind Energy Area and used to develop the seabird Digital Twin demonstration.

James Joslin of Marine Situ for his support in identifying environmental use-cases and sensor technologies and for providing underwater monitoring footage and data from an adaptable monitoring package deployment at the Wave Energy Test Site, Kaneohe, Hawaii.

The Technical Advisory Committee members for their guidance: Arne Jacobson, Director of the Schatz Energy Research Center at Cal Poly Humboldt; Garry George, Director of the Clean Energy Initiative at the National Audubon Society; Walt Musial, Principal Engineer at National Renewable Energy Laboratories; Knut Erik Stein at Norwegian Energy Partners; and Francine Kershaw at the Natural Resources Defense Council.

PREFACE

The California Energy Commission's (CEC) Energy Research and Development Division supports energy research and development programs to spur innovation in energy efficiency, renewable energy and advanced clean generation, energy-related environmental protection, energy transmission, and distribution and transportation.

In 2012, the Electric Program Investment Charge (EPIC) was established by the California Public Utilities Commission to fund public investments in research to create and advance new energy solutions, foster regional innovation, and bring ideas from the lab to the marketplace. The EPIC Program is funded by California utility customers under the auspices of the California Public Utilities Commission. The CEC and the state's three largest investor-owned utilities— Pacific Gas and Electric Company, San Diego Gas and Electric Company, and Southern California Edison Company—were selected to administer the EPIC funds and advance novel technologies, tools, and strategies that provide benefits to their electric ratepayers.

The CEC is committed to ensuring public participation in its research and development programs that promote greater reliability, lower costs, and increase safety for the California electric ratepayer and include:

- Providing societal benefits.
- Reducing greenhouse gas emission in the electricity sector at the lowest possible cost.
- Supporting California's loading order to meet energy needs first with energy efficiency and demand response, next with renewable energy (distributed generation and utility scale), and finally with clean, conventional electricity supply.
- Supporting low-emission vehicles and transportation.
- Providing economic development.
- Using ratepayer funds efficiently.

For more information about the Energy Research and Development Division, please visit the <u>CEC's research website</u> (<u>www.energy.ca.gov/research/</u>) or contact the Energy Research and Development Division at <u>ERDD@energy.ca.gov</u>.

ABSTRACT

In support of California's Renewable Portfolio Standard (Senate Bill 100, De León, 2018) target of 100 percent renewable retail electricity by 2045, the California Energy Commission, as required by Assembly Bill 525 (Chiu, 2021), established planning goals of 10 gigawatts of offshore wind energy capacity by 2040, with an interim target of 3 gigawatts by 2030. Environmental conditions at installation sites far offshore pose adverse fiscal and operational challenges. Additionally, potential interactions between the installations and marine life are uncertain. Aker Offshore Wind (a Mainstream Renewable Power company), in partnership with Cognite and H. T. Harvey & Associates, developed an architecture for the digital representation, or digital twin, of an offshore wind asset in an industrial DataOps platform to explore how a digital twin application, or virtual representation, can help to reduce operational expenditures and increase understanding of how a floating offshore wind installation interacts with the surrounding environment. The project used available data for overall wind farm integrity management and condition monitoring in real time, as well as wildlife interactions, culminating in the identification of 24 use-cases for reducing operational expenditures, identifying tools that enable regulatory governance to address likely monitoring needs, and aiding in understanding environmental interactions between the installations and marine life.

Keywords: Offshore wind, planning, digital twin application, environmental interactions, monitoring

Please use the following citation for this report:

Siddiqi, Kamil, Sharon Kramer, Stephanie Schneider, Mariah Bulakh, and Elise Buck. 2024. *NextWind: Advancing Wind Energy Technology Using Real-Time Monitoring Systems in a Digital Twin Application.* California Energy Commission. Publication Number: CEC-500-2024-007.

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Executive Summary

In this project, the NextWind project team, comprising Aker Offshore Wind (a Mainstream Renewable Power company), the industrial data firm Cognite, and ecological consultants H. T. Harvey & Associates, explored the methods and tools to establish a digital twin, or virtual representation, enabled through data and simulators, of a floating offshore wind asset. Using real-time and representative data from offshore assets and the surrounding environment, the project team explored how to tackle two of the major challenges facing a burgeoning offshore wind industry in the United States: high costs and a lack of understanding about environmental interactions.

Background

California has shown leadership in tackling the climate crisis through its ambitious clean energy targets and by embracing carbon-free sources of energy, from solar, to onshore wind, to hydropower and now, offshore wind.

Senate Bill 100 (De León, 2018) established targets accelerating California's Renewable Portfolio Standard to 100 percent clean, carbon-neutral, and renewable energy powering all retail electricity sold by 2045. Achieving the 2045 target will require significant amounts of new renewable energy sources deployed at commercial scale, including an estimated 10 gigawatts of offshore wind. Rising to the challenge, the California Energy Commission, as required by Assembly Bill 525 (Chiu, 2021), established industry-leading offshore wind targets of up to 5 gigawatts by 2030 and 25 gigawatts by 2045. In December 2022, the Bureau of Ocean Energy Management (BOEM) held the first West Coast offshore wind leasing auction off Humboldt Bay on the North Coast and off Morro Bay on the Central Coast.

The deep waters of the Pacific Ocean off California's coast will require floating offshore wind technology where wind turbine generators are connected to floating platforms tethered to the ocean floor — often more than 20 miles from shore — rather than traditional fixed-bottom offshore wind installations. Deep-water installations raise several challenges and opportunities, including increased operational expenditures where project costs are impacted by the operations and maintenance for planned and unplanned corrective repairs. There is also a lack of high-resolution data available to assess how floating offshore wind installations interact with the surrounding environment due to their deep-water locations. However, these challenges provide an opportunity for data and environmental research in areas of the ocean that may have previously been under-researched.

Due to the uncertainty on types of interactions, regulatory agencies will be expected to maintain thorough data requirements that traditional monitoring methods would struggle to provide throughout the permitting process.

Project Purpose and Approach

The purpose of the NextWind project was to explore how a digital twin application can be applied to a floating offshore wind installation to address the challenges of managing large quantities of data to optimize environmental and systems integrity monitoring. The analysis will inform the potential for a digital twin application to reduce operational expenditures and increase awareness of how these installations interact with the surrounding environment. In the floating offshore wind industry, these benefits would translate to savings for ratepayers through a reduced levelized cost of energy and would increase the industry's awareness about the benefits of using configurable digital solutions that allow operators to make data-driven decisions about operations and the surrounding environment.

A digital twin is a virtual representation of an asset or system, allowing an operator to understand the asset or system's operational performance using remote technologies. The benefits of digital twins have already been observed in other industries (e.g., manufacturing and construction) where they have been used for condition monitoring and predictive maintenance of entire systems or parts of a system. They have been proven to optimize operations, revise maintenance philosophies, increase worker safety, and provide on-demand accessibility to data.

The NextWind project aimed to establish a digital twin application for use by the offshore wind industry, regulatory entities, academia, and others that uses real-time and representative data from offshore wind assets to provide:

- Data collection, analysis and visualization;
- Risk analysis, reliability and integrity;
- Maintenance prediction and modifications;
- Maintenance optimization and inspection programs; and
- Environmental information integration and user availability.

In addition, the NextWind project will lead to technological advancement and breakthroughs to help California meet its required energy goals by liberating data from traditional data silos and, at scale, translating data into actionable information.

To achieve the goals of the project, the NextWind project team organized the scope around a set of tasks:

- Task 1: General project tasks and project coordination activities;
- Task 2: Platform architecture of Internet of Things, and integrity data collection for contextualization;
- Task 3: Digital solution configuration for offshore wind diagnostics and integrity management;
- Task 4: Evaluation of systems diagnostics data for environmental monitoring;
- Task 5: Evaluation of project benefits;
- Task 6: Technology/Knowledge transfer; and
- Task 7: Production readiness.

This report focuses on the three primary technical tasks: tasks 2, 3, and 4.

Key Results

Over the course of this project, the NextWind project team identified 24 potential use-cases based on historical applications for remote monitoring for existing offshore wind and other industrial project applications and applied these to floating offshore wind installations. The use-cases covered categories for production optimization, condition monitoring, maintenance, and the environment. The NextWind project team assessed primary challenges for stakeholders and developed prioritization metrics related to minimizing operation and maintenance costs and evaluated use-cases based on each case's viability and value to the overall solution.

The team identified and prioritized six use-cases that supported the project goals of exploring cost reduction solutions, such as improving production efficiency and maintaining asset integrity, and understanding environmental interactions. The available datasets were contextualized within Cognite Data Fusion, an industrial DataOps platform that uses a combination of pre-trained machine-learning-based models, custom machine-learning-based models, rules engine, and manual/expert-sourced mappings with built-in continuous learning. DataOps applies to the entire data lifecycle from data preparation to reporting and recognizes the interconnected nature of the data analytics team and information technology operations.

Cost Reduction

The National Renewable Energy Laboratory (NREL) published the *2020 Cost of Wind Energy Review* (Stehly and Duffy, 2022) estimating the levelized cost of energy for land-based and offshore wind energy projects in the United States. Using the reference case defined in the NREL's report, the NextWind project team estimated an operational expenditure reduction in the range of 9.1 percent to 12.3 percent and levelized cost of energy reduction in the range of 4.7 percent to 8.9 percent over a 25-year operating period for a 600-megawatt floating off-shore wind project. With the implementation of environmental monitoring solutions in addition to the operational expenditure reduction, the net operational expenditure reduction was estimated to be in the range of 8.7 percent to 11.7 percent and the estimated levelized cost of energy reduction in the range of 4.3 percent to 8.2 percent over a 25-year operating period.

Environmental Interactions

One example of an environmental use-case, Seabird Collision and Avoidance, was simulated on the data platform. The interactive dashboards were produced with an objective of understanding the presence of seabirds within and near floating offshore wind sites and obtaining information on birds flying in the rotor-swept zone.

The project team used data collected from the ThermalTracker 3D deployed on a LiDAR buoy in the Humboldt Wind Energy Area off the coast of Northern California that used functional algorithms to detect and track birds within the field of view. This information was made available on a dashboard that contextualizes bird tracking data in near real time and can alert an operator to high bird activity.

Knowledge Transfer and Next Steps

The NextWind project team has been engaged and publicly sharing information about the NextWind project and the solutions being developed at many industry events and conferences, including CeraWeek 2022 and American Clean Power 2022. NextWind is also in touch with other relevant stakeholders such as regulatory authorities, entities focused on sustainable renewable energy development, and educational institutions. Other notable documented means for knowledge sharing include publications in the National Ocean Industries Association's annual Environmental Social & Governance reports and BOEM OCS 2021-030, *Floating Offshore Wind Turbine Development Assessment, Final Report and Technical Summary*.

The NextWind project team defined several use-cases in reports which can be requested from the California Energy Commission. The *Production Optimization Report* and the *Condition Monitoring Evaluation Report* showcase how installations can potentially improve operations and minimize maintenance costs. The *Environmental Interactions Metrics Report* defines several use-cases that address the key metrics and identification principles for distinct environments that will interact with floating offshore wind installations.

The next phase of this project will be to digitize relevant available data streams and extract information needed to support understanding of seabird collision and avoidance, marine mammal use, and upper-water column/artificial structure as habitat resulting from floating offshore wind structures.

CHAPTER 1: Introduction

Background

Senate Bill (SB) 100 (De León, 2018) established bold and ambitious targets accelerating California's Renewable Portfolio Standard (RPS) to 50 percent by 2025 and 60 percent by 2030. In addition, SB 100 calls for 100 percent clean, carbon-neutral, and renewable energy powering all retail electricity sold by 2045. California is on track to exceed its 2025 RPS target with large-scale renewables already implemented as part of its resource planning. Achieving the 2045 target will require California to diversify its energy portfolio by adding significant amounts of new renewable energy sources deployed at commercial scale.

Floating offshore wind (FOSW) technology is expected to perform an important role in California's effort to address the issues of decarbonizing energy sources, grid reliability, growing load profile and use, and energy resilience. The California Energy Commission, as required by Assembly Bill 525 (Chiu, 2021), has set a target of deploying up to 5 gigawatts (GW) of offshore wind by 2030 and 25 GW by 2045. The deep waters off the Pacific Coast will require the state to rely on FOSW technology instead of traditional fixed-bottom offshore wind turbine generators (WTGs).

Deep-water Challenges

With the expectation that FOSW installations will be sited in deep waters located far from shore, the challenging environmental conditions limit personnel access for regular operations and maintenance (O&M), thus adversely affecting the up time/availability of installations and the O&M costs over the project lifecycle. Also, with a lack of high-resolution site-specific marine species data for the California wind energy areas (WEAs) and with FOSW being a novel renewable energy resource, there is uncertainty about the type of interactions between FOSW installations and the surrounding environment.

Due to this uncertainty, federal and state regulatory agencies may adopt rigorous monitoring requirements seeking significant amounts of data to address uncertainties and potentially rare interactions. Traditional monitoring methods using boat-based surveys are expensive and time-consuming and provide relatively infrequent or a low magnitude of data, prolonging the permitting process for projects. Examples of interactions that would likely require monitoring include interactions between birds and bats and WTG rotors, and cetaceans with floating structures, moorings, and dynamic power cables, which are not well understood. Currently, efforts to model these types of interactions are being funded by the Bureau of Ocean Energy Management (BOEM) and the California Energy Commission (CEC), but model results will need to be verified and validated. For many types of interactions, the technology and instrumentation to conduct assessments is not available commercially off-the-shelf or is in research and development stages, making it difficult to implement and requiring a high level of specialized expertise.

Project Objectives

The NextWind project team set out to use operational data from offshore wind assets and the surrounding environment to develop an application for a digital twin of an FOSW project. That application can be used by wind farm operators, wind power consultancies, and authorities. The creation of a digital twin application will convert reams of data into actionable information and will aid in lowering the levelized cost of energy (LCOE) of offshore floating wind by optimizing energy production, decreasing maintenance costs, and improving the industry's understanding of environmental interactions and potential mitigations. These three factors will contribute to the acceptance of the developed application.

Project Approach

Figure 1 depicts a digital twin, or virtual representation of a physical asset, of an FOSW. Digital twins are defined as "a virtual representation of a physical asset enabled through data and simulators for real-time prediction, optimization, monitoring, controlling, and improved decision making," (Rasheed et al., 2020) which can play a transformative role throughout the life cycle of various cyber-physical assets. The digital twin will: make data available for the overall wind farm integrity management and for condition monitoring in real time; detect marine wildlife interactions; and develop strategies to avoid or minimize adverse environmental interactions.





Source: Aker Offshore Wind (a Mainstream Renewable Power company)

The project used Cognite's Data Fusion (CDF), an industrial operations data platform, to contextualize the data. CDF makes data available by offering an application programming interface (API), a set of functions and computer procedures allowing the creation of applications that access the features or data of an operating system. This enables real-time decision

making and informs third-party application providers on how to create additional value for wind farm operators using the data foundation.

To achieve the goals of the project, the NextWind project team organized the scope centered around three primary technical tasks:

- Platform architecture of internet of things and integrity data collection for contextualization. The goal of this task was to:
 - Develop a use-case plan that defines the problem and what data is available or could be used to develop a potential digital solution, the features of the solution, and development priority.
 - Identify existing or new technical and operational data from sensors located on operational offshore wind assets to develop an integrated platform architecture for data contextualization.
 - Develop, configure, and validate use-cases that address the potential for reduction in O&M costs by improving production efficiency and maintaining asset integrity.
- Digital solution configuration for offshore wind diagnostics and integrity management. The goal of this task was to:
 - Assess the potential of remote technologies for asset integrity management.
 - Define best practice solutions and available systems for condition monitoring (CM).
 - Assess how condition and performance monitoring (CPM) key components and instruments on offshore wind assets can enable operators to make decisions based on analysis of reliable offshore data.
- Evaluation of systems diagnostics data for environmental monitoring. The goal of this task was to:
 - Define how asset integrity monitoring systems and data for FOSW could be used to understand potential environmental interactions between marine life and FOSW installations and inform actions to minimize those interactions.
 - $\circ\;$ Identify monitoring that can be used to improve understanding of environmental interactions.
 - Define what additional monitoring would improve the industry's understanding of environmental interactions beyond the asset integrity monitoring systems and data.

Benefits

This project will lead to technological advancement of an integrated monitoring solution by liberating data from traditional data silos and, at-scale, translating data into actionable

information for the wind farm operators. It could also create a standard for secure interaction and data sharing.

The use of a digital twin solution could increase production efficiency, reduce operational expenditures by up to 20 percent, and minimize environmental impact by making all relevant data remotely available for humans and machines in a way that drives better decision making and enables new ways of working. Remote monitoring methods also aid in minimizing health, safety, and environmental incidents due to fewer personnel and vessel transfers from onshore to assets.

As such, a digital twin solution benefits the state and the ratepayers alike through lower costs and a strong understanding of surrounding ecosystems.

CHAPTER 2: Project Approach

There are many industrial applications (e.g., transportation, trading, agriculture) where realtime data has been collected, stored in central databases, and made available for use, and there is broad agreement in the industry about the potential of monitoring if it is utilized to its full extent. But due to the limited commercial scale deployment of FOSW projects globally, and since most of the FOSW projects currently deployed are pilot or pre-commercial scale projects, the NextWind project team encountered barriers to accessing real-time or historical operational data from projects. The tasks were therefore formulated around the available data sets, which are described below. Three main tasks were identified for this project and are described here in detail:

Task 2: Platform Architecture of Internet of Things, and Integrity Data Collection for Contextualization

The goals of this task were to: design and develop an integrated platform architecture; integrate existing technical and operational data (information and operational technology) infrastructures to liberate a wide variety of industrial data; upload the developed platform with the information and operational technology as a secure, comprehensive set in the cloud that is without space limitations; and structure the sensor data in relation to other relevant data (e.g., process diagrams, three-dimensional models, event data). This contextualization process effectively creates an operational digital twin of an asset or system, making data available in a user-friendly platform.

Integrated Architecture Platform

The NextWind digital twin solution is developed on the CDF integrated architecture platform. For more details on CDF and the process for developing the architecture, refer to Appendix A.

Use-Case Plan

The NextWind project team followed the outlined project approach and initiated the development process of a digital twin by developing a Use-Case Plan that captured the information of problem definition, key features of the solution, what the solution was intended to resolve, what external or internal solutions already existed that could solve the problem, and what relevant data sources were currently available and/or required to develop the solution.

The Use-Case Plan addressed methods for configuring a use-case for production optimization, CM, maintenance, and the environment. The use-cases were identified through a series of workshops, with the NextWind project team members assessing the primary challenges for stakeholders and evaluating historical applications for remote monitoring for offshore wind and other industrial project applications and applying them to FOSW applications.

Each use-case was exercised by clearly defining the problem, the value hypothesis, the key digital solution features with the end users, data sources, and success criteria. Table 1 summarizes the list of use-cases that the NextWind project team identified. The use-cases are listed in no order but are rather given a number to provide a reference between the use-case, solution development metrics, and the commercial impact assessment.

Additionally, during the Critical Progress Review meeting, the Technical Advisory Committee and the California Energy Commission identified additional use-cases that could further enhance the digital twin offering, addressing issues such as seismic monitoring for natural disasters and continued environmental monitoring nearshore for research purposes. Although these use-cases weren't developed in this project, there is likely great value in having these capabilities, which can be explored in future development phases.

Category	Use-Case						
-	1. Turbine Power Production Performance Monitoring						
Optimization	2. Imbalance Cost Mitigation/1-Day Power Production Forecasting						
opennización	3. Wind Farm Availability						
	4. Monitoring Critical Components w/Alerting						
	5. Turbine Surface Integrity Management						
Condition	6. Mooring System Monitoring						
riomoning	7. Power Cables Advanced Monitoring						
	8. The Hull Monitoring (incl. meteorological monitoring)						
	9. Integrated Inspection of Failure Data						
	10. Critical Data Alerts						
	11. Digital Maintenance Planner						
Maintenance	12. In-field Access to Live Data and Documents						
	13. Using Drone for Simple Maintenance Jobs						
	14. Drones, Remotely Operated Vehicle, Unmanned Aerial Vehicle, Autonomous Underwater Vehicle Collecting Data Sets						
	15. Airside Interactions						
	16. Upper-Water Column Interactions						
	17. Midwater Column Interactions						
Environmental	18. Benthic Interactions						
Environmental	19. Seabird Collision and Avoidance						
	20. Marine Animal Collision and Secondary Entanglement						
	21. Underwater Marine Mammal Monitoring						
	22. Artificial Structure as Habitat						

Table 1: Summary of Identified Use-Cases

Category	Use-Case
	23. Electromagnetic Fields (EMF)
	24. Seabed Scour from Anchors and Mooring Systems

Source:

Ranking Methodology

The NextWind project team developed a ranking methodology to define the importance of each use-case and further assessment in prioritization.

- Criteria (1): High importance High likelihood to be required by permitting agencies
- Criteria (2): Moderate importance Ranking in terms of operational expenditure to the project — for example, if interactions would require interruption of power generation due to WTG shutdowns
- Criteria (3): Additional considerations applied Ranking in terms of potential impact to the physical integrity of the asset

Scoping, Planning, and Prioritization

A viability and value metric was defined for each use-case to facilitate prioritization based on the biggest impact on the LCOE and environment.

Figure 2 represents the list of use-cases and their individual ranking based on the assigned viability and value metric and the use-cases that were prioritized for further development.

The NextWind project team assessed all use-cases individually based on their viability and value to operators and regulatory agencies. Use-cases 1, 2, 3, 16, 19, and 21 were of particular interest, were highly viable for solution development, and provided a high value.

Other use-cases that were categorized as low or medium on the viability and value metric represented the current state of those use-cases. Their viability and value metric could change as technological advancements are made and should be monitored for further development.

Figure 2: Use-Case Ranking



Source: Aker Offshore Wind (a Mainstream Renewable Power company)

Architecture Contextualization for Offshore Wind

The NextWind project team developed a data architecture to contextualize the data sources and develop the prioritized applications. All relevant weather, maintenance, WTG operational data, and wildlife data were uploaded to a dedicated CEC project area within CDF.

A varying number of datasets were used in the solution development. Aker Offshore Wind (a Mainstream Renewable Power company) provided procured datasets from the Offshore Renewable Energy Catapult technology and innovation center based in the UK. This dataset was provided as a time-series on a 1-second granularity and provided three years of operational data from approximately 572 turbine sensors. Open-source data from an Engie wind turbine in La Borne Haute, France provided one year's duration of operational data.

The project team retrieved live weather data from a subscription-based platform (stormglass.io) for high-resolution marine weather data, ingested it into CDF, and then used WindSim software models to predict weather.

Cognite ingested meteorological mast, signals, logs, and turbine failure data received as part of an EDP Wind Turbine Failure Detection Challenge.

Data from the ThermalTracker-3D, a technology developed by Pacific Northwest National Laboratory, was ingested into CDF. The ThermalTracker-3D provided data on bird and bat flight height and speed from the U.S. Department of Energy's floating LiDAR (FLiDAR) buoy that was deployed in the Humboldt Wind Energy Area off the Northern California coast. For additional details on data sources, refer to the Offshore Wind Data Platform Architecture Report submitted as part of this agreement, which can be requested from the California Energy Commission. In Figure 3 the WTG datasets are represented as time series that monitor the sensors on the WTG. Maintenance data is represented as events showing work orders and other notifications around failure of the equipment.



Figure 3: Hierarchy of a Representative Asset, Components, and Data Sources

Source: Cognite

Weather data was represented as time series and was used to track weather patterns and conditions. The wildlife data came from structured data, video files, and acoustic files. All data from these sources were represented as events and time series; for example, the events helped track individual records, such as an instance of one bird in a video that has multiple birds, while the time series reflected aggregated data such as how many birds were seen in that exact second in the video.

Task 3: Digital Solution Configuration for Offshore Wind Diagnostics and Integrity Management

Ranking – Technical Use-Cases

The technical use-cases were categorized in terms of production optimization, CM, and maintenance. The NextWind project team prioritized the following three technical use-cases:

• WTG power production performance monitoring – identifying underperformance and taking action to remediate identified issues

- Imbalance cost mitigation / 1-day power production forecasting minimizing imbalance costs that resulted from producing a different energy volume than what had been committed
- Wind farm availability a key performance indicator for operations, assessing an asset's uptime and availability in relation to commercial contracts

The three listed use-cases were assessed and developed based on the ranking methodology and assigned value and viability metrics for development.

Product Optimization

Production optimization was accomplished by identifying underperformance and taking actions to remediate identified issues. Underperformance was identified by comparing actual production with expected production given the weather variables, or by comparing current production to historical production with given weather conditions.

Precise wind power predictions are a must for wind power to be reliably integrated into power grids. Improved generation profile predictions can help optimize production by minimizing the lag between changing wind angle and yaw angle. Machine learning (ML) can be used to provide good results in the short term, compared to physics-based models, when the input variables are properly selected. This is especially true when there are abundant data. This happens because ML can cover the shortages that physics-based models have in terms of assumptions and lack of statistical capabilities.

Condition Monitoring

CM is the surveillance and continuous assessment of the condition of equipment. CM aims to detect irregular behavioral symptoms during operation and is therefore an important enabler for predictive maintenance.

Sensor data, generated alarms, and visual data can all provide information related to temperature, pressure, and vibration. The best practice applications include the use of CM of WTG, rotor blades, tower, and nacelle, while the condition of the substructure and WTG exterior are typically monitored through visual inspections. While mainly done manually, visual data can be collected and assessed automatically. Another application for rotating equipment includes time-frequency analyses of vibration data, data mining, and statistical models and applying ML techniques for detailed monitoring and understanding of operations.

WTG components are designed for extreme and fatigue loads. Understanding the current state of the WTG components and forecasting their degradation is a valuable contribution to keeping WTG availability and reliability high. Therefore, the FOSW industry placed an emphasis on improving the reliability of WTG. It has been demonstrated that approximately 26 percent of the failures occur in gearboxes, 17 percent in generators, and 13 percent in drive lines, making them the most important components for CM of FOSW.

Maintenance

Offshore WTG maintenance operations are expensive primarily because they are located far from shore and require valuable vessel time. Reductions in time spent and improved accuracy for offshore maintenance may therefore have a significant financial impact.

Offshore Wind Operational Diagnostics

The Offshore Wind Operational Diagnostics philosophy is a critical input for many users, including operations O&M teams and original equipment manufacturers (OEM). Insight into offshore wind operational diagnostics through a continuous condition and performance monitoring (CPM) approach may have multiple key features built in but, in this context, the essential function was gathering housekeeping and diagnostics data from the core system components and instrumentation of the offshore wind installation. CPM was a key input to CDF, which provided algorithms, data processing, and data visualization capabilities.

A successful CPM solution relies on being able to draw data from all relevant data sources, thereby providing high-definition and reliable data. To achieve this, it is necessary to establish a "data highway" from the FOSW installation to the onshore operations team. An essential element is edge gateway software with the capability of collecting all relevant processes and housekeeping data from data sources offshore and transferring them onshore in real time.

Implementing an advanced CPM philosophy into the operational diagnostics recommended practices enables optimal decisions to be made based on analysis of reliable data, and it is an important step on the digital roadmap for FOSW installations. Some of the shared benefits of CPM are:

- Increased and optimized power production due to continuous data-driven system optimization and avoidance of downtime.
- Ability to perform more active risk management and mitigation through enhanced control of an overall system's health.
- Reduced operational expenditure by using an accurate, real-time view of the system status to improve planning of intervention operations and the ability to predict failure.
- Quicker resolution of issues offshore by having O&M experts continuously connected and able to access critical system performance and housekeeping data.

Advanced Monitoring Key Principles

By allowing open access to the power of cloud computing services, ML models, and the ability to combine data from different sources such as maintenance logs and system data, advanced monitoring is archived by connecting data to the cloud and making the real-time data readily available to subject matter experts.

An advanced FOSW monitoring system must be based on recognition that a failure is typically the result of a chain of events that occur on different sub-systems where data has historically been disparate, in varying formats, and with different levels of fidelity. Applying ML models and advanced analytics provides value-adding services to operators. The more data that is received and analyzed, the more advanced the ML models and the data analytics algorithms become.

Such a solution should be available to the O&M teams and working in the background providing notifications to the operations team. The O&M team monitors and interfaces directly with the system to ensure any notification reaching the operation room adds value and does not distract from busy schedules. If a notification is raised, the digital twin solution can be used as a collaborative tool to investigate and resolve issues, enabling the expanded team to define the most appropriate maintenance plan.

A digital twin solution for advanced CM must be actively used to provide diagnostic and prognostic services to an FOSW installation and should support the following functionality:

- Data ingestion from any source;
- The main systems and components CPM in real time;
- Diagnostics failure statistics and root cause failure analysis;
- Prognostics for example, indicating the remaining useful life of the equipment;
- Data validation assessing the validity of the sensor data;
- Fault management enabling the user to read and acknowledge alarms and events;
- Baseline comparison enabling the user to compare monitoring parameters to a baseline; and
- Reporting enabling the user to read and generate monitoring reports.

Task 4: Evaluation of Systems Diagnostics Data for Environmental Monitoring

Uncertainty about Environmental Interactions between Marine Life and FOSW Installations

Although there is information on marine species distributions and migration timing, there is a lack of high-resolution, site-specific information for the wind energy areas (WEAs) off California, which increases uncertainties about potential interactions with FOSW installations in these areas.

All proposed installations will be required to conduct pre- and post-construction monitoring for environmental impacts and, because many of these interactions may be rare, short-term, or occur during inclement conditions, monitoring may need to be continuous for the first FOSW installations in the water.

Monitoring will often need to occur under challenging conditions — in remote offshore areas with high winds, large waves, fog, and strong winter storms — and novel technologies will be required to facilitate requisite monitoring needs for these locations.

Early FOSW installations will likely experience greater regulatory scrutiny until information gaps can be addressed. Overcoming the challenges associated with monitoring in remote offshore environments will also likely require early installations to bear the excessive costs of research and development to produce effective monitoring instrumentation and protocols.

Types of Environmental Monitoring and Nexus with Asset Integrity Monitoring

A primary goal of developing environmental use-cases was to support the NextWind project team by providing information on monitoring needs, types of monitoring instrumentation and protocols available, and relative costs of monitoring. The project team also wanted to explore potential data sources available to support development of a digital twin, the ability to turn these data into actionable insights, and implications for potential adaptive management, mitigation, and minimization.

The NextWind project team identified 10 environmental use-cases intended to address the information gaps regarding potential interactions between FOSW installations and marine organisms; most of the use-cases focused on specific stressor-receptor interactions that will likely need to be evaluated for permitting installations and assessing project-specific adaptive management and mitigation needs. Two categories of environmental use-cases were identified:

- General environmental monitoring that may be achieved by instrumentation and sensors installed to support monitoring of WTG power production, performance, and integrity management (four use-cases).
- Environmental stressor-receptor interactions that will likely need to be evaluated for permitting installations (six use-cases).

Overview of Specific Environmental Monitoring Use-Cases

The general environmental monitoring use-cases were based on the four distinct environments that will interact with the WTG in an offshore environment:

- 1. Airside interactions for example, above-water monitoring by instruments attached to the platform, nacelle, WTG, or mobile instruments such as drones or other remotely operated vehicles.
- 2. Upper-water column interactions for example, photic zone monitoring by instrumentation attached to the underside of the floating platform or moorings, or mobile instruments such as autonomous underwater vehicles.
- 3. Mid-water column interactions for example, mostly autonomous or robotic devices.
- 4. Benthic interactions for example, near-bottom monitoring by moored instrumentation or autonomous devices.

In addition to the broader general environmental monitoring use-cases, the project team generated six additional stressor-receptor use-cases that are likely to be required as a condition of project permitting due to:

- Uncertainties about the magnitude of interactions between offshore WTG and sensitive marine organisms;
- The potential to result in a negative interaction with species of concern;

- The need to have information to forecast and permit take for example, harm, harass, injure, or kill listed species;
- The need to understand population-level effects; and
- The need to develop appropriate minimization and mitigation, as necessary.

These cases are:

- 1. Seabird Collision and Avoidance;
- 2. Marine Mammal Collision and Secondary Entanglement;
- 3. Artificial Structure as Habitat;
- 4. Underwater Marine Mammal Monitoring;
- 5. EMF Impacts; and
- 6. Seabed Scour from Anchors and Mooring Systems.

Prioritizing Environmental Monitoring Use-Cases for the Digital Twin

All 10 environmental use-cases were ranked to identify the top 3 that should be further developed for incorporation into the digital twin. The NextWind project team prioritized use-cases based on the following criteria:

- Criteria 1: Monitoring likely to be required by permitting agencies.
- Criteria 2: Potential for interactions to increase the operational expenditure to the project (for example, if interactions would require interruption of power generation due to curtailment-related WTG shutdowns).
- Criteria 3: Potential for interactions to impact the physical integrity of the asset itself.

Ranking the environmental use-cases within the context of the likelihood of being required by permitting agencies prior to installation/operation (Criteria 1), resulted in the following case-by-case ranking for the top six use-cases:

- 1. Seabird Collision and Avoidance due to certain likelihood of occurrence of interactions with threatened and endangered species;
- 2. Marine Mammal Collision and Secondary Entanglement due to unknown likelihood of potential interactions with threatened and endangered species (but data is limited);
- 3. Underwater Marine Mammal Monitoring for broader understanding of if/how marine mammal use of the broader area is impacted post-installation;
- 4. Airside Interactions to assess use and potential attraction to WTG platforms and airside structures by threatened and endangered species;
- Seabed Scour from Anchors and Mooring Systems anchors and bottom sections of moorings will result in changes to the seafloor that include scour, disturbance, and potential to act as an artificial reef, attracting some benthic fish and invertebrates; it is important to quantify those changes and the resultant effects to benthic fauna; and

6. Electromagnetic Field (EMF) Impacts – ranked lowest due to the impacts being spatially limited and potentially not problematic to threatened and endangered species, but with awareness of concern in the community regarding the impact from EMFs.

The seabird collision and avoidance use-case ranked highest within the context of the likelihood of interactions to increase the operational expenditure to the project (Criteria 2), because collisions between seabirds and the blades could cause agencies to require WTG curtailment strategies.

Within the context of Criteria 3, two use-cases were ranked relatively high: artificial structure as habitat due to the uncertainty of the biofouling impact on mooring line integrity, and marine mammal collision and secondary entanglement due to the uncertainty of lost fishing gear and/or secondary entanglement issues impacting installed infrastructure integrity.

Given collective consideration of all prioritization criteria, the two use-cases with the highest priority were Seabird Collision and Avoidance and Marine Mammal Collision and Entanglement. While data were available from the Humboldt WEA to incorporate the Seabird Collision and Avoidance use-case into a digital twin framework and support a better understanding of potential interactions, there were no known available data to inform the Marine Mammal Collision and Entanglement use-case, so any further exploration of this use-case would have been theoretical. Solutions to understand this interaction and incorporate it into a digital twin framework still need to be developed.

CHAPTER 3: Results

Results of Task 2: Platform Architecture of Internet of Things, and Integrity Data Collection for Contextualization

Use-Case 1 and 2: Turbine Power Production Performance Monitoring / Imbalance Cost Mitigation / 1-Day Power Production Forecasting

Challenge

The process of production monitoring varies greatly from operator to operator and offshore wind farm to offshore wind farm, due both to limited data access and a lack of appropriate tools. OEM monitoring tools are typically designed to work only with data from a particular system, and they rarely use more than sensor data, that is, not maintenance data, weather data, or other data types. This limits the operators' understanding of WTG performance, as planned maintenance events may cause downtime that should not actually impact the perceived performance of a WTG.

Operators also struggle with accurately estimating future energy production. Grid operators typically require production forecasts and penalize producers that fail to deliver committed energy volumes, depending on project agreements. Operators refer to this as imbalance costs, which are typically 5–10 percent of annual revenue but can be as much as 15 percent, depending on forecasting efficiency and local market regulations. Given the inherent uncertainty associated with weather, imbalance costs will remain a cost for operators but can be mitigated with improved power forecast accuracy.

Solution

The turbine production performance monitoring and production forecasting use-case was a work product of Task 2 activities for developing and configuring use-cases that address the potential reduction of O&M costs through improved production efficiency.

The NextWind project team used available and low-cost dashboard tools such as Grafana and Power BI to create monitoring dashboards. The dashboards featured parameters such as current power production, wind speed and direction, and they synthesized metrics such as historical power generation and a 24-hour forecast of power production, based on the current production level using an application programming interface from stormglass.io to access live weather data in the Humboldt Bay area.

Visualizations such as graphs, gauges, wind roses, key performance indicators, and bar charts allow a user to interpret data and understand the current state of production. By using contextualized data in CDF, the dashboard can be scaled from one WTG to another, and from one park to another. Figure 4 is a dashboard showing predicted power production for a set of WTGs.

Using highly granular forecasts from WindSim, an ML model based on historical production and wind speeds was developed to assess relationships between wind speed and power production, producing a trend and forecasted production volume. The trend is relevant, as the efficacy of the WTG changes over time. On a technical level, data was shared from WindSim using Cognite's data ingestion application programming interface, where only the values that were updated in the forecast were written to the digital twin on an hourly basis. The model was continuously trained on the day-by-day expanding data sets for each WTG, picking up the relevant values from the WindSim forecasts and using them to produce an hourly production forecast based on WTG historical production at given wind speeds.

Both the wind forecasts from WindSim and the power production forecasts were stored in the digital twin, contextualized to each WTG so that the model and the dashboard were inherently scalable.

Key Findings

A better understanding of WTG performance may result in quicker action when a WTG is underperforming. The Electric Power Research Institute (Fitchett and Pulikollu, 2018) estimates that a mere 1 percent boost in productivity at a typical wind farm with 100 two-MW WTGs results in revenue increases of \$250,000–\$500,000.

The solution may add significant value to wind power producers that do not have established methods for estimating power production, while also being expected to outperform the known existing tools for such an estimation. It is difficult to estimate the operational expenditure reduction for these use-cases as it primarily impacts the operator's ability to optimize wind energy production and, through monitoring weather forecasts, predict energy production. With respect to the NREL reference case, this use-case primarily impacted the LCOE for projects and, combined, was estimated to reduce the LCOE by as much as 5.39 percent.



Figure 4: Visualization of Predicted Power Production (Created in Grafana)



Source: Cognite

Use-Case 3: Wind Farm Availability

Challenge

Wind farm availability is a key performance indicator for operations and is measured for warranty, energy estimates, revenue projections, WTG design performance evaluation, and performance bonuses or penalties. There are various ways to determine availability, which require some degree of manual work, and all availability definitions are not always readily available in the commissioned supervisory control and data acquisition system but require some post-processing.

The contractual availability involves manual effort to agree on the responsibility of "STOP" events and allocating the stops in the pre-agreed contractual formula (90 percent automated from alarm list, 10 percent manual). Responsibility allocation is 90 percent automated, based on a pre-agreed alarm classification, and 10 percent manual work. Regular alignment is required, and the operator signs off on excusable events to exclude them from the availability calculation, resulting in significant manual and administrative effort and is prone to errors.

Solution

If not specified in the project requirements, availability figures are not always calculated by the supervisory control and data acquisition system and delivered by the OEM. Depending on the contractual availability guarantee (time, energy, revenue), the OEM provides a parallel interface to agree on the excusable events/values, but these tools require manual efforts to extract and process data.

The various WTG availability figures, in conjunction with production performance, provide a starting point to assess WTG performance. Using a standard approach of calculating and

representing availability will improve experience sharing support in securing better contracts and drive maintenance solutions adapted to unique projects.

The NextWind project team started the solution development by defining alarm classifications (DNV GL 2017) for each "STOP" event in the event history data and correlating alarm/event history data with operational data to determine moments with no power production that were classified as a stoppage event. A stoppage event that resulted in no power production correlated to an OEM's responsibility allows for clarity on contractual availability. This use-case was identified late in the project and the NextWind project team proceeded with developing a temporary solution by assessing the large volume of event history data outside of CDF, as indicated in Figure 5. Cognite used a software development kit to present the results in terms of percentage of time spent per alarm classification for a specific event.

Key Findings

The wind farm availability use-case was a work product of Task 2 activity for assessing how CPM of key components of offshore wind assets can enable operators to make decisions based on reliable offshore data.

Through the analysis of wind farm availability, a system defined by the operator can:

- Support in challenging OEMs on contractual availability and O&M strategy;
- Automate work/reduce administrative work and support performance monitoring;
- Support in calculating various "availability types" (for the named purposes);
- Support in discovering trends in the root cause of unavailability;
- Recognize trends to help root cause analysis; and
- Improve performance overview.

With respect to the NREL reference case, the NextWind Project team estimated that, by estimating availability of wind farms and the responsible party for unavailability, operators could minimize the LCOE by as much as 0.40 percent.

Figure 5: Visualization of STOP Events for Contractual Availability

min t stamp f	max t stamp f	percent																								
or_0_power	or_0_power	_event																								
97/2018 9:43	9/8/2018 0:43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.23	4.24	0.00	4.21	4.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9/8/2018 5:13	9/18/2018 6:33	0.00	0.00	0.00	0.00	0.48	0.00	0.00	0.00	1.43	0.71	59.52	36.90	0.00	0.71	0.00	0.00	0.00	0.00	0.00	0.24	0.00	0.00	0.00	0.00	0.00
9/18/2018 7:23	9/25/2018 4:13	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	1.33	5.00	72.00	10.33	0.00	3.00	0.00	0.00	6.33	0.67	0.00	0.33	0.00	0.00	0.00	0.00	0.00
9/25/2018 4:33	9/26/2018 19:13	0.00	0.00	0.00	0.00	0.61	0.00	0.00	0.00	0.61	0.00	89.02	3.66	0.00	5.49	0.00	0.00	0.00	0.00	0.00	0.61	0.00	0.00	0.00	0.00	0.00
9/26/2018 19:33	9/27/2018 7:23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	10.00	0.00	40.00	20.00	0.00	30.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9/27/2018 7:43	9/30/2018 1:43	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	6.00	71.00	7.00	0.00	13.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00
9/30/2018 3:43	10/8/2018 3:43	0.00	0.00	0.00	0.00	1.69	0.00	0.00	0.00	1.27	1.69	86.02	4.24	0.00	3.39	0.00	0.00	0.00	0.42	0.85	0.00	0.42	0.00	0.00	0.00	0.00
10/12/2018 0:23	10/12/2018 0:03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.45	2.48	65.20	27.27	0.00	4.13	0.00	0.00	0.00	0.00	0.90	0.00	0.00	0.00	0.83	0.00	0.00
10/14/2018 14:03	10/15/2018 8:33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	66.67	0.00	16.67	0.00	0.00	0.00	0.00	0.00	0.00	0.00	16.67	0.00	0.00	0.00	0.00	0.00
10/15/2018 8:53	10/15/2018 15:03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10/15/2018 15:33	10/15/2018 18:43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10/15/2018 19:03	10/20/2018 21:23	0.00	0.00	0.00	0.00	0.86	0.00	1.72	0.00	1.72	1.72	29.31	56.03	0.00	7.76	0.00	0.86	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10/20/2018 21:43	10/28/2018 7:53	0.00	0.00	0.00	0.00	6.67	0.00	0.00	0.00	5.56	2.22	55.56	23.33	0.00	0.00	5.56	1.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
10/28/2018 8:23	10/31/2018 6:53	0.00	0.00	0.00	0.00	6.67	0.00	0.00	0.00	23.33	43.33	3.33	20.00	0.00	0.00	0.00	0.00	0.00	0.00	3.33	0.00	0.00	0.00	0.00	0.00	0.00
10/31/2018 7:33	11/4/2018 21:23	0.00	0.00	0.00	0.00	2.65	0.00	0.00	0.00	0.00	6.99	83.80	7.04	0.00	4.93	0.70	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.60	0.00
11/11/2018 1-03	11/11/2018 7:03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11/11/2018 8:13	11/12/2018 13:53	0.00	0.00	0.00	0.00	6.25	0.00	0.00	0.00	0.00	12.50	6.25	37.50	0.00	37.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11/12/2018 14:13	11/13/2018 8:13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	42.86	0.00	0.00	57.14	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11/13/2018 8:33	11/14/2018 10:43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	33.33	11.11	0.00	55.56	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11/14/2018 11:03	11/16/2018 8:13	0.00	0.00	0.00	0.00	0.94	0.00	0.00	0.00	2.83	4.72	80.19	5.66	0.00	4.72	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.94	0.00
11/16/2018 8:33	11/28/2018 8:53	0.00	0.00	0.00	0.00	0.63	0.00	0.00	0.00	0.00	1.59	92.70	1.27	0.00	2.22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.59	0.00
11/28/2018 9:13	11/29/2018 11:33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.42	90.70	3.49	0.00	4.65	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.16	0.00
12/2/2018 11:55	12/2/2018 8:33	0.00	0.00	0.00	0.00	0.46	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12/2/2018 16:33	12/2/2018 17:33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12/2/2018 19:43	12/4/2018 23:03	0.00	0.00	0.00	0.00	22.22	0.00	22.22	0.00	0.00	22.22	0.00	0.00	0.00	33.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12/4/2018 23:23	12/5/2018 1:13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12/5/2018 5:53	12/5/2018 22:43	0.00	0.00	0.00	0.00	0.00	0.00	66.67	0.00	33.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12/6/2018 1:13	12/11/2018 11:33	0.00	0.00	0.00	0.00	2.88	0.00	0.00	0.00	0.00	6.73	74.04	12.50	0.00	2.88	0.00	0.00	0.00	0.96	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12/17/2018 12:33	12/17/2018 13:53	0.00	0.00	0.00	0.00	2.09	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12/17/2018 18:13	12/21/2018 9:03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.39	75.00	2.78	0.00	19.44	0.00	0.00	0.00	0.00	1.39	0.00	0.00	0.00	0.00	0.00	0.00
12/21/2018 9:23	1/2/2019 8:43	0.00	0.00	0.00	0.00	3.02	0.00	0.00	0.00	2.51	4.52	62.81	8.54	0.00	17.59	1.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1/2/2019 9:13	1/2/2019 10:53	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1/2/2019 11:13	1/3/2019 7:03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	33.33	33.33	0.00	33.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1/3/2019 8:03	1/3/2019 9:03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1/3/2019 14-53	1/8/2019 19:43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	20.83	0.00	37.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	41.67
1/6/2019 20:23	1/9/2019 9:03	0.00	0.00	0.00	0.00	1.18	0.00	0.00	0.00	1.18	2.37	28.40	60.95	0.00	2.96	0.59	0.00	0.00	0.59	0.59	0.00	0.00	0.00	0.00	0.00	1.18
1/9/2019 10:03	1/14/2019 4:03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.10	0.70	83.22	6.29	0.00	5.59	0.70	0.00	0.00	0.70	0.70	0.00	0.00	0.00	0.00	0.00	0.00
1/14/2019 5:13	1/14/2019 9:13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	33.33	0.00	66.67	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1/14/2019 9:33	1/16/2019 9:03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	85.27	1.55	0.00	13.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1/16/2019 9:23	1/18/2019 10:23	0.00	0.00	0.00	0.00	1.75	0.00	0.00	0.00	1.75	7.02	68.42	14.04	0.00	1.75	3.51	0.00	0.00	0.00	1.75	0.00	0.00	0.00	0.00	0.00	0.00
1/22/2019 9-13	1/23/2019 0:03	0.00	0.00	0.00	0.00	33.33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	33.33	0.00	0.00	0.00	0.00	33.33	0.00	0.00	0.00	0.00	0.00
1/23/2019 11:13	1/23/2019 23:53	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1/24/2019 0:13	1/24/2019 1:23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1/24/2019 1:43	1/31/2019 5:03	0.00	0.00	0.00	0.00	0.54	0.00	1.09	0.00	4.89	2.72	77.17	11.41	0.00	0.00	1.09	0.00	0.00	0.54	0.00	0.54	0.00	0.00	0.00	0.00	0.00
1/31/2019 8:03	2/1/2019 19:53	0.00	0.00	0.00	0.00	20.00	0.00	0.00	0.00	20.00	20.00	0.00	20.00	0.00	0.00	20.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2/1/2019 20:13	2/4/2019 5:33	0.00	0.00	0.00	0.00	7.14	0.00	0.00	0.00	7.14	14.00	73.68	5.26	0.00	0.00	10.53	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2/5/2019 7:13	2/6/2019 22:33	0.00	0.00	0.00	0.00	7.14	0.00	0.00	0.00	3.57	21.43	53.57	10.71	0.00	0.00	3.57	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2/6/2019 22:53	2/7/2019 8:23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	33.33	66.67	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2/7/2019 8:43	2/10/2019 7:43	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	82.47	4.12	0.00	0.00	1.03	0.00	10.31	2.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2/10/2019 8:23	2/11/2019 8:03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2/11/2019 8:23	2/19/2019 5:13	0.00	0.00	0.00	0.00	1.14	0.00	0.00	0.00	0.46	2.06	89.70	5.26	0.00	0.23	0.69	0.00	0.00	0.46	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2/19/2019 5:43	2/19/2019 7:33	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	75.00	25.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2/19/2019 8:03	2/24/2019 5/23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.16	4.65	68.60	10.47	0.00	12.79	0.00	0.00	0.00	0.00	0.00	2.33	0.00	0.00	0.00	0.00	0.00
2/24/2019 7:03	2/24/2019 9:53	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	50.00	0.00	50.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2/24/2019 10:13	2/26/2019 14:23	0.00	0.00	0.00	0.00	5.88	0.00	0.00	0.00	20.59	41.18	0.00	26.47	0.00	0.00	5.88	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2/26/2019 21:03	2/28/2019 17:53	0.00	0.00	0.00	0.00	12.50	0.00	0.00	0.00	12.50	25.00	0.00	12.50	0.00	12.50	12.50	0.00	0.00	0.00	12.50	0.00	0.00	0.00	0.00	0.00	0.00
2/28/2019 23:03	3/1/2019 7:03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	20.00	60.00	0.00	20.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Source: Cognite

Results of Task 3: Digital Solution Configuration for Offshore Wind Diagnostics and Integrity Management

Use-Case 4: Monitoring Critical Components & Use-Case 11: Digital Maintenance Planner Challenge

Several factors affect offshore maintenance operations, including weather data, equipment master data, maintenance logs, active incidents, risk, vessel schedules, personnel availability, and, potentially, equipment performance and CM data. Data from a range of sources is needed to plan campaigns but can be difficult to obtain, process, and assess. Maintenance planners have a challenging task of collecting and evaluating data to produce optimal maintenance schedules, and legacy maintenance systems lack useful system overviews and visualizations that address customers' optimization needs.

Solution

The NextWind project team ingested and contextualized data, maintenance information, 3D models, and event data such as risks, incidents, and work order history made available through the Cognite Maintain application (Figure 6), which provides a data-driven approach for optimizing O&M operations. Key functionalities of the application include letting the operator scope, schedule, and report on maintenance campaigns and visualizing relevant data in a single location, to enable optimal scope creation supported by a suggestion algorithm. This solution lets the operator adjust the sequence of events, considering capacity and balance of plant limits. Relevant reports are created providing useful insight into status to stakeholders and other colleagues in the field.

Key Findings

The CM and maintenance planning use-case was a work product of Task 3 activity for assessing how the CPM of key components of offshore wind assets can enable operators to make decisions based on reliable offshore data. It was estimated to potentially reduce as much as 10 percent of time spent on maintenance planning. This was based on historical results from applying the solution to offshore oil and gas rigs. For example, an oil and gas operator indicated up to a 30 percent annual reduction in planned shutdowns and 5 percent efficiency gains on overall maintenance execution. The NextWind project team estimated that CM of critical components of offshore wind assets and developing an optimized maintenance plan could yield an operational expenditure reduction of up to 1.37 percent and an LCOE reduction of up to 0.39 percent.



Figure 6: Example Visualization in Cognite Maintain

Source: Cognite

Results of Task 4: Evaluation of systems diagnostics data for environmental monitoring

Use-Case 19: Seabird Collision and Avoidance

Challenge

Operators are required to conduct thorough environmental monitoring and use patterns in areas planned for offshore developments. For an operator in Europe, this was resolved by having 10 full-time equivalent employees (FTEs) monitoring and tracking bird and bat activity for one year at the site.

Once in operation, authorities might require post-construction monitoring, bird activity tracking, and collision mortality and might potentially curtail production at times of high-risk migration. A Northern European offshore wind operator maintains a two-person ornithology team on rotation on the support vessel, which is based offshore, pointing to employment of at least three times as many FTEs.

Solution

Optical video feeds are not considered suitable for offshore monitoring due to offshore environmental conditions and the long distance between bird detections and the resulting low resolution of data captured. . As a result, the NextWind project team used post-processed data from the ThermalTracker-3D, which captured data during 24-hour operations that optical feeds would not have been able to capture during the night. The LiDAR buoy was commissioned by the BOEM and deployed by Pacific Northwest National Laboratories at the Humboldt WEA (Office of Energy Efficiency & Renewable Energy, 2021). The NextWind project team developed functional algorithms that were able to detect birds among more than 2,000 different objects, track them through video, and differentiate among more than 150 species. The algorithms assess video on a frequency of up to 10 frames per second to monitor birds in flight. A positive detection gets a calculated confidence score indicating the algorithm's confidence that the detected object is a bird.

A dashboard was developed for the operator to use the bird tracking data and define thresholds for alerting notified users of varying times of high bird activity detection in CDF.

Key Findings

The seabird collision and avoidance use-case was a work product of Task 4 activity for assessing what additional monitoring solutions would improve the industry's understanding of environmental interactions beyond the asset integrity monitoring systems.

Tasks such as counting birds and bats through camera feeds can be automated to conduct efficient site assessment campaigns while increasing frequency and resolution of captured data.

Video streams can be assessed by algorithms running on devices offshore or streamed for onshore processing, resulting in reduced FTEs during site assessment and operational phases and insight on adverse interactions.

Evaluation of the PNNL Thermal Tracker 3D data, able to identify occurrences of bird flight paths in the height of the rotor swept zone, allows operators to detect high bird activity and make data-driven decisions that may include the potential to curtail production.

With respect to the NREL reference case, the NextWind project team estimated that implementing this type of monitoring solution would result in an increase of as much as 0.14 percent operational expenditures and impact the LCOE by as much as 0.09 percent. It was assumed that sensors could be mounted to the floaters and the actual number of monitoring units needed during pre- and post-construction would be determined based on a statistically robust survey design that will need to be developed in collaboration with the industry, regulatory agencies, and the scientific community. This estimate was primarily assessing the deployment of thermal tracking systems and excluded operational costs such as data analysis and reporting.

Wind turbines were not present in the Humboldt Wind Energy Area when this dashboard (Figure 7) was generated but, to simulate a dashboard relevant to future collision monitoring efforts, the following hypothetical elements were incorporated into this dashboard: camera video streams of monitored turbines and an indication of the days that have elapsed since the last known collision for the assets being monitored.

Figure 7: Bird Monitoring Dashboard Using Seabird Movement Data, May through August 2021



Source: Cognite & H. T. Harvey & Associates

Use-Case 16: Upper-Water Column Interactions Challenge

Monitoring environmental interactions undersea, from the surface to approximately 150 meters in depth, requires instrumentation mounted to the floater or mooring structures or on standalone platforms with a field of view of the system. These data streams may be used to address specific upper-water column stressor-receptor use-cases for artificial structures as habitat, as there is little data to assess how marine life will interact with FOSW platforms.

Solution

Monitoring metrics could include number of targets over time and target size (sounders/ sonars), species identification (camera imagery), and use of the project area by vocalizing marine mammals (hydrophones to detect presence when vocalizing).

Hydrophones can also provide information on project-generated acoustic levels, which may be required by permitting agencies. What monitoring protocols will be required by regulatory agencies is not known, but it is unlikely that real-time continuous monitoring will be necessary to provide data on the general condition of the upper-water column environment.

Remotely operated vehicles, autonomous underwater vehicles, or other autonomous systems with camera feeds could be used to survey asset integrity and provide information on interactions, but research and development on instrument packages will be needed to further understand this potential effect.

The NextWind project team could not access remotely operated vehicle, autonomous underwater vehicle, and other autonomous system camera feeds and did not have the expertise inhouse for processing audio files of marine mammal vocalizations from sonar, echo sounders, or hydrophones sources, resulting in the inability to develop this use-case. Although this did not result in an application, the NextWind project team identified a development pathway based on passive acoustic hydrophone data available for ML algorithms (Monterey Bay Aquarium Research Institute) and processed audio data as spectrograms that provided a visual representation of the frequency of a signal over time.

Key Findings

The upper-water column monitoring use-case was a work product of Task 4 activity for assessing what additional monitoring solutions would improve the industry's understanding of environmental interactions beyond the asset integrity monitoring systems.

This type of monitoring would enhance understanding of species attraction to the belowsurface platform structures and moorings — for example, fish, which could attract predators; marine mammal, sea turtle, and diving bird use of the photic waters around project platforms; and lost gear entanglement with moorings. The optimal mounting location and orientation of instruments is required to address the challenges.

Upper-water column monitoring could provide information on use of the project area, just below the surface of the water in the photic zone of the ocean, by diving birds, marine mammals, sea turtles, and fish. Instrumentation for upper-water column monitoring could include optical cameras, imaging sonars, echo sounders, and hydrophones. Upper trophic level communities may change in response to FOSW projects due to effects on wind fields and localized circulation patterns on upwelling and nutrient dynamics (Raghukumar et al., 2022), as well as behavioral interactions such as fish attraction to structure (Kramer et al., 2015).

Environmental DNA is quickly becoming a useful tool for understanding biodiversity of organisms in the marine environment and shows promise for monitoring ecosystem interactions at offshore sites.

The NextWind project team estimated that implementing this use-case would result in a net increase of operational expenditure by as much as 0.01 percent and would increase the LCOE by as much as 0.35 percent.

Use-Case 20: Marine Animal Collision and Secondary Entanglement

Challenge

FOSW deployment at commercial scale is novel to United States territorial waters, and marine mammals that transit through project areas might encounter adverse interactions termed as "secondary entanglement," where a marine mammal gets entangled in lost fishing gear or other debris that is caught in mooring line anchors.

Solution

There is no data available to inform of marine mammal collision and entanglement use-case. If data exists, it is likely to be from the oil and gas industry and is more than likely considered proprietary.

Since the NextWind project team did not have the required data for this use-case and this was one of the prioritized use-cases, the project team decided to describe the solution theoretically.

The next phase of this project will be to digitize relevant available data streams and extract information needed to support an understanding of marine mammal use and upper-water column/artificial structure as habitat resulting from FOSW structures.

Further work will be required to understand this interaction and address this use-case in the future.

Key Findings

The upper column monitoring use-case was a work product of Task 4 activity for assessing what additional monitoring solutions would improve the industry's understanding of environmental interactions beyond the asset integrity monitoring systems.

Measures to address this interaction potentially include passive acoustic monitoring systems that detect marine mammal vocalization over extended distances and provide either a directional bearing or location of the mammals.

Passive acoustic monitoring can also provide information about noise generated by wind farm components, and changes over time can potentially be used to monitor asset integrity.

Detecting and localizing marine mammals in the project areas will inform studies of the presence and use patterns of different species. Pre- and post-installation studies can inform of changes in species behavior or avoidance.

The NextWind Project team estimates that implementing this use-case would result in a net increase of operational expenditure by up to 0.09 percent and would increase the LCOE by up to 0.07 percent.

Interoperability Principles of the Monitoring Equipment

A primary goal of developing environmental use-cases was to support the NextWind project team, providing information to support the development of regulatory governance for monitoring, types of monitoring instrumentation and protocols available, relative costs of monitoring, potential data sources for development of a digital twin, the ability to turn these data into actionable insights, and implications for potential adaptive management and mitigation.

The environmental use-cases were prioritized differently from asset performance and CM usecases as the former prioritized according to the need to address information gaps for permitting, whereas the latter were prioritized according to their ability to reduce the lifetime operational expenditures of the FOSW project.

The burden of gathering this data will be greatest for the first FOSW projects and may require financial investments to help develop the required monitoring technologies, protocols, and artificial intelligence/machine learning (AI/ML) algorithms to gather and process continuous data streams in real time. Monitoring impacts in the remote offshore environment of the Pacific Ocean will likely require the research and development of sensors capable of capturing relevant information autonomously for extended periods of time while withstanding extreme conditions such as wind, rain, wave action, and submersion.

For some use-cases, the interactions could be relatively rare, and quantifying occurrence rates and detecting changes resulting from FOSW installations may require intensive round-the-clock monitoring coupled with rapid data processing.

The tremendous amount of data gathered during environmental monitoring will require development of AI/ML algorithms to facilitate data transfer to onshore receiving stations, minimize data storage requirements, and extract meaningful information in real time (Stanchev et al., 2020). AI/ML would be particularly useful for rapid identification of seabirds and marine mammals from relevant data streams — for example, imagery from optical and thermal cameras, acoustics from hydrophones. There is also potential that vibrational and optical sensors focused on the blades could be trained to provide real-time detections of collision events.

One benefit highlighted by this report is that optical, thermal, and acoustic sensors designed to provide insights about asset performance and condition may be leveraged to provide insights about environmental interactions (and vice versa). This process of integrating sensor and data streams across use-cases will be facilitated through the development of a digital twin for FOSW projects with this goal in mind.

Rasheed et al. (2020) defined a digital twin as "a virtual representation of a physical asset enabled through data and simulators for real-time prediction, optimization, monitoring, controlling, and improved decision making," which can play a transformative role throughout the life cycle of various cyber-physical assets. For an FOSW project, a digital twin can facilitate multidisciplinary collaboration during the conceptualization and prototyping phase to identify overlaps in sensor types and placement used for CM and environmental interaction monitoring as a way of minimizing duplicitous data streams while maximizing information gained from each sensor.

LCOE Calculations

Methodology

The impact of each use-case was quantified by comparing the use-case's LCOE with a reference case. LCOE is a metric used to assess the cost of electricity generation and serves as a good measure for comparing use-cases. To benchmark the LCOE impacts from the implementation of a digital twin, the NextWind project team used the *2020 Cost of Wind Energy Review* (Stehly and Duffy, 2022) to formulate a reference case.

Both the methodology and all inputs used in the LCOE calculations were identical to the assumptions from the *2020 Cost of Wind Energy Review*, where the impact of each use-case was quantified as a percent change in capital expenditures (CapEx), operational expenditures (OpEx), and energy production estimates.

NREL used the following formula for LCOE calculations:

$$LCOE = \frac{(CAPEX * FCR) + OPEX}{AEP_{net}/1000}$$

Where:

- LCOE = levelized cost of energy (\$/MWh)
- FCR = fixed charge rate (%)
- CapEx= capital expenditures (\$/kW)
- AEP_{net} = net average annual energy production (MWh/MW/yr.)
- OpEx = operational expenditures (\$/kW/yr.)

The CapEx, OpEx, and AEP_{net} enable the LCOE methodology to capture the effect of design changes. The last input, fixed charge rate, represents, according to NREL, "the amount of revenue required to pay the annual carrying charges as applied to the CapEx on that investment during the expected project economic life." To assess the costs, NREL used project data from installed projects in Europe and Asia. The AEP and the cost of the balance-of-system (BOS) was based on North Atlantic site conditions.

Reference Case

Table 2 summarizes the reference system parameters and cost inputs used from the 2020 *Cost of Wind Energy Review* in support of LCOE comparison and represents the estimated LCOE for the NREL reference project. Additional information on the reference case can be found in the NREL report.

Parameter	Estimate
Project Nameplate Capacity (MW)	600
Rated WTG Capacity (MW)	8

Table 2: Reference Case Parameters

Parameter	Estimate
# of Units Installed	75
Water Depth (m)	740
Avg. Wind Speed (m/s)	8.2
Net Capacity Factor (%)	38
Operating Period (yrs.)	25
Floating Platform Technology	Steel semi-submersible
СарЕх	93.5 \$/MWh
OpEx	35.4 \$/MWh
AEP (net)	3332 MWh/MW/yr.
Fixed Charge Rate real (%)	5.8 %
LCOE	129 \$/MWh

Source: Aker Offshore Wind (a Mainstream Renewable Power company)

LCOE Impact

The NextWind project team used the value and viability metrics assessment completed for preparing the Use-Case Plan as the basis for determining the impact of the CapEx, OpEx, and AEP_{net} for each use-case. As part of the commercial assessment, the NextWind project team developed a low- and high-range estimate for each use-case, estimating the percent reduction or increase from the reference case to the operational expenditures and the LCOE.

Table 3 summarizes the percent reduction and increase for each use-case. Although many of the use-cases were fully defined in the Use-Case Plan, only the prioritized use-cases were assessed for impact to LCOE due to the viability of the solutions and likelihood for a specific type of environmental monitoring to be included in the regulatory requirements.

Table 3: Est	timated Impact	to OpEx and	LCOE (%)
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	Opera Expen	ational ditures	LC	OE	
	Low	High	Low	High	
1. Turbine Power Production Performance Monitoring	0.00%	0.00%	-0.50%	-1.47%	
2. Imbalance Cost Mitigation/1-Day Power Production Forecasting	0.00%	0.00%	-1.55%	-3.92%	
3. Wind Farm Availability	-0.01%	-0.02%	-0.21%	-0.40%	
4. Monitoring Critical Components w/Alerting	-1.09%	-1.30%	-0.31%	-0.37%	
5. Turbine Surface Integrity Management	-1.27%	-1.53%	-0.36%	-0.43%	
6. Mooring System Monitoring	-5.22%	-7.46%	-0.60%	-0.79%	

	Opera Exper	ational ditures	LCOE			
	Low	High	Low	High		
7. Power Cables Advanced Monitoring	0.00%	0.00%	-0.87%	-1.09%		
8. The Hull Monitoring (Including Meteorological Monitoring)	-0.07%	-0.11%	-0.02%	-0.03%		
9. Integrated Inspection of Failure Data	-0.02%	-0.05%	-0.01%	-0.01%		
10. Critical Data Alerts	0.00%	0.00%	0.00%	0.00%		
11. Digital Maintenance Planner	-0.05%	-0.07%	-0.01%	-0.02%		
12. In-field Access to Live Data and Documents	-0.05%	-0.07%	-0.01%	-0.02%		
13. Using Drone for Simple Maintenance Jobs	-1.27%	-1.65%	-0.31%	-0.41%		
14. Drones, Remotely Operated Vehicle, Unmanned Aerial Vehicle, Autonomous Underwater Vehicle Collecting Data Sets	0.00%	0.00%	0.00%	0.00%		
15. Airside Interactions	0.03%	0.25%	0.01%	0.18%		
16. Upper-water Column Interactions	0.00%	0.01%	0.27%	0.35%		
17. Midwater Column Interactions	0.04%	0.06%	0.03%	0.03%		
18. Benthic Interactions						
19. Seabird Collision and Avoidance	0.14%	0.10%	0.09%	0.09%		
20. Marine Mammal Collision and Entanglement	0.08%	0.09%	0.05%	0.07%		
21. Underwater Marine Mammal Monitoring	0.04%	0.05%	0.02%	0.03%		
22. Artificial Structure as Habitat						
23. Electromagnetic Fields (EMF)						
24. Seabed Scour from Anchors and Mooring Systems						
Net Reductions	-9.06%	-12.26%	-4.76%	-8.96%		
Net Increases	0.34%	0.56%	0.46%	0.75%		
Net Total	-8.72%	-11.70%	-4.29%	-8.21%		

Source: Aker Offshore Wind (a Mainstream Renewable Power company)

The percent reduction was in relation to the technical category use-cases, where production optimization, CM of equipment, and optimized maintenance reduced the OpEx for the project and ultimately improved the project economics.

The percent increase was in relation to the environmental category use-cases, where implementation of varying environmental monitoring solutions increased the CapEx and OpEx for the project and thus weakened the project economics.

Please note that the aggregate reduction was presented with the implementation of all technical and environmental use-cases and the results can be individually applied for impact to the OpEx and LCOE for the use-case that an operator seeks to implement.

Table 4 provides the estimated impact to the LCOE in \$/MWh in comparison to the reference case based on a 25-year operating period and is subject to change depending on varying parameters for project comparisons — for example, regulatory monitoring requirements for sites, economic factors such as inflation, changes in project nameplate capacity, water depths, associated export system technical concept, project execution plans for WTG integration location, floater fabrication and assembly location, tow to shore distance, and distance from the O&M site.

LCOE	Low	High
Reductions (\$/MWh)	-6.0	-11.3
Increases (\$/MWh)	0.6	0.9
Net (\$/MWh)	-5.4	-10.4

Table 4: Estimated Impact to LCOE (\$/MWh)

Source: Aker Offshore Wind (a Mainstream Renewable Power company)

Benefits

The planning of global commercial-scale renewable energy deployments offers several gridrelated, socio-economic, macro-economic, and environmental benefits. This project is intended to lead to technological advancement of an integrated monitoring solution by liberating data from traditional data silos and, at-scale, translating data into actionable information.

The NextWind project team used open-source and reference site operational data to develop a digital twin that is estimated to reduce operational expenditures in the range of 9.1 percent to 12.3 percent and the LCOE in the range of 4.7 percent to 8.9 percent over a 25-year operating period. With the implementation of environmental monitoring solutions in addition to the operational expenditure reduction, the net operational expenditure reduction is estimated to be in the range of 8.7 percent to 11.7 percent and the estimated LCOE reduction in the range of 4.3 percent to 8.2 percent over a 25-year operating period.

As such, a digital twin solution would benefit the ratepayers, research community, state and federal entities, and the offshore wind industry through an improved understanding of how FOSW installations: interact with ecosystems; lower energy procurement contract prices, resulting in lower electricity prices for consumers; and provide increased availability/uptime for projects, resulting in a stable supply of energy and increased productivity for operators.

Knowledge Transfer

The NextWind project team developed a Knowledge Transfer Plan outlining the information dissemination and communication strategy used throughout the duration of the project activities and beyond.

The NextWind project team has been engaged and publicly sharing information about the NextWind project and the solutions being developed at many events, including CeraWeek 2022, which had more than 5,000 attendees, and American Clean Power 2022, with a recorded presentation about Data-driven Sustainability in Floating Offshore Wind, and with other relevant stakeholders like regulatory authorities, entities focused on sustainable renewable energy development, and educational institutions. Other notable documented means for knowledge sharing include publications in the National Ocean Industries Associated annual Environmental Social & Governance report and BOEM OCS 2021-030, *Floating Offshore Wind Turbine Development Assessment, Final Report and Technical Summary*. For a complete list of information dissemination activities, please refer to the Knowledge Transfer Report, which can be requested from the California Energy Commission.

CHAPTER 4: Conclusion

Summary

The NextWind project was funded through the EPIC program, which is intended to facilitate the development of next-generation wind energy technologies, resulting in increased compete-tiveness, performance, and reliability while lowering the levelized cost of energy (LCOE) and the environmental impacts of floating offshore wind (FOSW) installations.

The NextWind project team explored methods and tools to establish a digital twin of an FOSW installation using real-time and representative data from offshore assets and the surrounding environment; the goal was to tackle two of the major challenges facing a burgeoning offshore wind industry in the United States: high cost and a lack of understanding about environmental interactions.

The project resulted in the identification of tools that enable regulatory governance to address likely monitoring needs for FOSW installations and to address information gaps and how asset integrity condition monitoring (CM) data can potentially aid in understanding environmental interactions between marine life and FOSW installations and inform action to address those interactions. Through identification and development of prioritized use-cases, the project benefitted from implementing digital solutions to optimize production and minimize operational expenditure over an FOSW project's lifecycle.

The primary driver behind operational expenditure reduction was estimated to come from a change in the operations and maintenance philosophy. Monitoring of mooring systems is an example where traditional methods for scheduled inspection of mooring lines can be adapted to implement monitoring of single or a sub-set of mooring lines within the entire FOSW array and implementing a risk-based inspection method.

LCOE reduction was primarily driven by turbine performance monitoring and production forecasting where turbine performance, coupled with wind farm availability, can warn of potential turbine unavailability due to an original equipment manufacturer error or a component failure during the initial warranty period and operators can minimize negative exposure from improper production forecasting to balancing authorities.

In comparison to the NREL reference case, through optimizing production, implementing CM of sys-tems, and optimizing maintenance regimen, analysis estimated the operational expenditure reduction to be in the range of 9.1 percent to 12.3 percent and the LCOE reduction in the range of 4.7 percent to 8.9 percent over a 25-year operating period. With the implementation of environmental monitoring solutions in addition to the above, the net operational expenditure reduction was estimated to be in the range of 8.7 percent to 11.7 percent and the LCOE reduction to be in the range of 4.3 percent to 8.2 percent over a 25-year operating period.

The NextWind Project team had targeted as much as a 20 percent operational expenditure reduction through the implementation of digital solutions for production optimization and

condition and performance monitoring of systems. Although the NextWind Project team addressed the operational expenditure reduction of up to 12.3 percent, this can be expanded through some of the recommendations that follow. The remote environmental monitoring solutions assessed are novel and are not commercially available, but that is expected to change with the global trend toward adoption of renewable energy technologies in support of the transition to renewable energy sources.

Monitoring impacts in the remote offshore environment of the Pacific Ocean will likely require research and development of sensors capable of capturing relevant information autonomously for extended periods of time while withstanding extreme conditions (for example, wind, rain, wave action, and submersion). For some use-cases presented here, the interactions could be relatively rare, and quantifying occurrence rates and detecting changes resulting from FOSW installations may require intensive round-the-clock monitoring coupled with rapid data processing. The tremendous amount of data gathered during environmental monitoring will require development of artificial intelligence/machine learning (AI/ML) algorithms to facilitate data transfer to onshore receiving stations, minimize data storage requirements, and extract meaningful information in real time (Stanchev et al., 2020). AI/ML would be particularly useful for rapid identification of seabirds and marine mammals from relevant data streams (for example, imagery from optical and thermal cameras, acoustics from hydrophones). There is also potential that vibrational and optical sensors focused on the blades could be trained to provide real-time detections of collision events.

One benefit highlighted by this report is that optical, thermal, and acoustic sensors designed to provide insights about asset performance and condition may be leveraged to provide insights about environmental interactions (and vice versa). This process of integrating sensor and data streams across use-cases will be facilitated through the development of a digital twin for FOSW projects with this goal in mind. For FOSW, a digital twin can facilitate multidisciplinary collaboration during the conceptualization and prototyping phase to identify overlaps in sensor types and placement used for asset condition monitoring and environmental interaction gained from each sensor.

The NextWind project team achieved the goals of the project and demonstrated the ability to allow for continuous streaming of all relevant data sources to the integrated data platform, contextualized various data sources, drove reduction of operational expenditures by improving production efficiencies, reduced maintenance costs, and implemented environmental monitoring solutions into the integrated data platform. As the United States national energy policy matures, the uncertainties about energy procurement mechanisms, energy market development, and transmission development will play an integral role in developing offshore wind projects and will impact a project's commercial viability. A digital twin demonstrates that it can aid developers in their ability to make projects commercially viable through reduced LCOE and can ultimately benefit consumers.

The next phase of this project will be to digitize relevant available data streams and extract the information needed to support an understanding of seabird collision and avoidance, marine mammal use, and upper-water column/artificial structure as habitat resulting from FOSW

structures. The digital twin is intended to be an additional level of monitoring that operators can implement to supplement and validate solutions offered by original equipment manufacturers; moreover, as proven in the holistic solution that the NextWind project team developed, it is not a closed system and can be expanded to include aftermarket solutions for expanded monitoring needs that address critical operational and environmental issues.

Future Development Considerations

The NextWind project team encountered many challenges and received suggestions for consideration in future development of the NextWind solution.

Data Availability, Accessibility, and Viability Awareness

The framework developed by the NextWind project team forms the foundation for a remote monitoring system of FOSW installations and, with access to proper datasets, the framework can be expanded in the future to address a larger number of use-cases. As the FOSW industry and projects mature, the level of data available from projects will increase the industry's understanding of interactions between FOSW installations and the environment and methods to verify and validate solutions that reduce operational expenditures.

Aftermarket Solutions

The foundation of existing instrumentation used for this project can be expanded to include aftermarket instrumentation that brings additional insight to other parts of the system, to address a varying range of monitoring applications for stress/strain, fatigue, vibration, and many other factors that could extend the lifetime of FOSW installations and lead to design improvements.

Environmental Monitoring

The anticipated deployment of FOSW installations at commercial scale off California's coast provides an opportunity to further enhance the solutions developed, by assessing environmental monitoring solutions from a macro view of bird flight patterns, marine mammal transits, and critical factors both above the ocean and underwater.

Scientific Research

As site-specific data is gathered, it can be used to continuously improve machine-based learning models that improve the accuracy of algorithms and inform of environmental interactions.

Operating Period

Extending the operating period of an FOSW installation from 25 to 35 years has the potential to reduce the LCOE, even as operating expenses may include increased frequency of main-tenance. Working with original equipment manufacturers, implementing CM solutions for operational insight, and optimizing maintenance routines can potentially extend operating periods.

Seismic Monitoring

FOSW installations off the Northern California coast, one of the most seismically active areas in North America, offer the opportunity to expand upon existing seismic monitoring systems.

GLOSSARY AND LIST OF ACRONYMS

Term	Definition
AEP	annual energy production
AI	artificial intelligence
API	application programming interface
BI	business intelligence
BOEM	Bureau of Ocean Energy Management
BOS	balance-of-system
CapEx	capital expenditures
CDF	Cognite Data Fusion
CEC	California Energy Commission
СМ	condition monitoring
СРМ	condition and performance monitoring
EMF	electromagnetic field
EPIC	Electric Program Investment Charge
FOSW	floating offshore wind
FTE	full-time equivalent
GW	gigawatt
LCOE	levelized cost of energy
ML	machine learning
MW	megawatt
NREL	National Renewable Energy Laboratory
O&M	operations and maintenance
OEM	original equipment manufacturer
OpEx	operational expenditures
RPS	Renewables Portfolio Standard
SB	Senate Bill
WEA	wind energy area
WTG	wind turbine generator

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Project Deliverables

The following list includes deliverables that were produced by the various NextWind Project team members over the duration of the project. These are available upon request by submitting an email to <u>ERDDpubs@energy.ca.qov</u>.

- Use-Case Plan
- Benefits Questionnaire
- Production Optimization Evaluation
- Condition Monitoring Evaluation
- Data Sharing Evaluation
- Offshore Wind Data Platform Architecture Report
- Offshore Wind Operational Diagnostics Report
- Environmental Interactions Metrics Report
- Final Project Fact Sheet
- Technology/Knowledge Transfer Plan
- Technology/Knowledge Transfer Report
- Production Readiness Plan

The Final Report will be accessible on the California Energy Commission publications site: <u>https://www.energy.ca.gov/resources/publications/energy-commission-publications</u>





ENERGY RESEARCH AND DEVELOPMENT DIVISION

Appendix A: Cognite Data Fusion (CDF) – Data Platform

[Month Year] | CEC-500-XXXX-XXX



APPENDIX A: Cognite Data Fusion (CDF) – Data Platform

Cognite Data Fusion (CDF)

CDF is an industrial DataOps software, which uses a combination of pre-trained ML-based models, custom ML-based models, rules engine, and manual/expert-sourced mappings with built-in continuous learning for horizontal contextualization. Automatic models are applied to handle changing data.



Figure A-1: Typical Data Pipeline for Analytics

AI-driven active metadata creation permeates industrial data management, shifting the emphasis from data storage and cataloging to a true human data discovery experience. For application developers and data scientists, understanding — and handling — industrial data is not as straightforward as dealing with most tabular data. What is even more difficult (for all who are not subject matter experts with years of intimate experience with the asset) is understanding the context of, as well as further contextually related, industrial data.

Through AI and ML augmentation, multiple diverse structures and insights emerge from the data, creating active metadata, rather than a single structure manually imposed on the data as in traditional master data management. Active, dynamically inferred, and trusted metadata is a common thread and key enabler in making data understandable and useful.

For different data sets to be successfully matched and appended into the reference and application data models, matching signals need to be present. Even in the case of weaker matching

Source: Cognite

signals, there remains robust benefit from a data contextualization engine to structure and govern more subject matter expert intensive data contextualization work. Industrial DataOps is about breaking down data silos and optimizing the broad availability and usability of industrial data generated in asset-heavy industries.

Data Architecture

At the center of the methodology is a set of prioritized business questions that need to be answered. The business questions serve as competency questions and as a success metric.

In the initial knowledge capture phase, the first business question is analyzed, understood, and modeled into a minimal viable ontology. The question/use-case could be captured in the Use- Case Report. In the following knowledge implementation phase, the ontology and mappings are implemented. The resulting data can be accessed from CDF, validated, and imported into one or more business intelligence (BI) tools. In the final self-service analytics phase, the BI dashboards are used to answer the initial business questions.

Once this initial iteration has occurred, the next business question is analyzed until it can be answered with the current ontology and mappings. Otherwise, the ontology is extended incrementally with its corresponding mappings. With this approach, the ontology and mappings are developed simultaneously in an agile and iterative manner. The ontology scope is limited to concepts, properties, relationships, and parent/child concepts. This flexibility is sufficient to address the BI needs of customers. We refer to Concepts, Attributes and Relationships as CARs.

The methodology is organized into three phases, with different expectations from each actor throughout the process:

Phase 1 - Knowledge Capture

The Solution Architect works with the Business User to understand the business questions, define a "whiteboard" version of the ontology, and work with the IT Developer to determine which data is needed.

- Analyze processes
- Collect documentation
- Develop knowledge capture

A Solution Architect creates the overall technical vision for a specific solution to a business problem. They design, describe, and manage the solution. A Business User represents the end user and analyzes the page design from a user point of view.

Phase 2 - Knowledge Implementation

The goal of the knowledge implementation phase is to formalize the content of the knowledge capture into an ontology, mappings, and queries and to subsequently validate the data. Table 2 is an example of data integrity mapping and is recommended when capturing data relationships across an asset.

Table A-1: Knowledge Capture Attributes

Attribute Name	The Agreed Name for the Attribute	
Attribute Definition	The agreed definition for the Attribute	
Attribute ID	The ID that will uniquely identify the Attribute and forms a URI	
Applied to Concept	The Concept to which the Attribute is associated with	
Unique ID of a		
Concept instance	The column from the table name/SQL query that uniquely identifies each instance of the Concept	
Table Name or SQL query	The table name or SQL query logic that represents the Concept	
Datatype	The expected datatype of the Attribute	
Format	The expected format, for example, a date	
Range	The expected limits, for example, 0 to 180 for an angle	
Is NULL possible?	Can there be NULL values (inexistant) in the column? Yes or No	
If NULL	If the column can have NULL, what is the replacement value? (None, N/A, ?)	
Relationship Name	The agreed name for the Relationship	
Relationship Definition	The agreed definition for the Relationship	
Relationship ID	The ID that will uniquely identify the Relationship and forms a URI	
From Concept	The Concept this relationship comes from (relationship domain)	
Unique ID of		
From Concept	The column name from the table/SQL query that uniquely identifies the From Concept	
Table Name or SQL query	The Table Name or SQL query logic that returns the data for the Relationship. This query usually returns a pair of attributes that includes the IDs of the From and To Concept	
To Concept	The Concept this relationship connects to (relationship range)	
Unique ID of To Concept	The column name from the table/SQL query that uniquely identifies the To Concept	

Phase 3 - Self-Service Analytics

The Business User is now exposed to the data in a simplified and easy-to-understand view that enables straightforward data access with common BI tools. They can now create reports and dashboards to provide answers to new and existing business questions without having to further interface with IT.

Architecture Contextualization

Confronted with an exponential rise in data volume, velocity, variety, and value creation expectations, large and small enterprises are rushing to upskill their workforces to become better data customers, or to be more data literate. Gartner, the technology research firm, formally defines data literacy as "the ability to read, write and communicate data in context," more informally expressed as "Do you speak data?" Data literacy includes an understanding of data sources and constructs, analytical methods and techniques applied to data, and the ability to describe the use-case applications and resulting value.

Data contextualization involves connecting all available data for a clear understanding of an asset or facility. Data context is the sum of meaningful use-case supportive relationships within and across different data types and data artifacts. It's the result of data relationship mining, and curation is a so-called contextualization pipeline. The key to creating value from data lies in data context and interpretability by data consumers in business operations, not on the collection of more data. Figure B-2 visualizes the data architecture flow where operational data (OT) and industrial data (IT) form the basis for solution development through a structured workflow.



Figure A-2: Example of Data Architecture Workflow

Source: Cognite