Optimal Sensor Placement for Physics-Based Digital Twins

Final Report for NOWRDC Project #154719

Prepared for:

National Offshore Wind Research and Development Consortium

Christine Sloan, Project Manager

Melanie Schultz, Interim Project Manager

Prepared by:

Tufts University Medford, MA

Eric Hines Professor of the Practice

> Babak Moaveni Professor

University of Rhode Island Kingston, RI

Chris Baxter Professor

National Renewable Energy Laboratory Golden, CO

Amy Robertson Principal Engineer

Norwegian Geotechnical Institute Oslo, Norway

James Strout Expert Adviser

University of Nevada, Reno

Reno, NV

Hamed Ebrahimian Assistant Professor

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Abstract

This final report for the NOWRDC Project #154719: *Optimal Sensor Placement for Physics-Based Digital Twins*, includes: a high-level project summary with project benefits and future work; descriptions of project personnel; tasks; schedule; deliverables; and publications.

Project benefits include the successful development of: a BAF framework and accompanying detailed computational models; a roadmap for deployment of a hybrid BAF-AI approach to OWT nacelles; the development of novel, affordable OSP measurement systems for OWTs; successful validation of the BAF and accompanying algorithms with measured OWT data from the BIWF; a detailed assessment of and recommended approach to using the BAF for inverse modeling in the multiphysics domain; and an market assessment, business plan, and approach to scaling the BAF to the commercial level.

Future work includes developing the BAF for the: multiphysics domain; OWT drivetrains; OWT systems; and use with hybrid physics-based-AI methods at the scale of commercial offshore wind farms.

Keywords

Offshore Wind Turbine (OWT), Optimal Sensor Placement (OSP), Bayesian Assimilation Framework (BAF), Structural Health Monitoring (SHM), Finite Element Analysis (FEA), Mutiphysics, OpenSees, OpenFAST, Load Inference (LI), Model Updating (MU), Inverse Modeling, Block Island Wind Farm (BIWF), Jacket-Supported Structure, Monopile-Supported (MS) Structure

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Acronyms and Abbreviations

BAFBayesian assimilation frameworkBIWFBlock Island wind farmCMSCenter of massDAQData acquisitiondegDegreeDLLDynamic linked libraryDOFDegree of freedomEKFExtended Kalman filterFEFinite elementftFeetFAFore-aft direction of the wind turbineIEAInternational Energy AgencyKFKalman filterLILoad inferencem/sMeters per secondMACModal Assurance CriterionMAPMaximum a-posterioriMCMCMarkov chain Monte CarloMHMetropolis-HastingsMSMoopile supportedMSLMean Sea LevelMUMdel uncertaintyMWMegawattsOWTOffshore wind turbinePDFParticle filterRNARotor Nacelle AssemblyROSCOReference Open Source ControllerSCADASupervisory control and data acquisitionsdStandard deviationSHMStructural health monitoringSSSide-to-Side direction of the wind turbineTPTransition PieceTSRTip-speed ratioUKFUnscented Kalman filterWWatts	AKF	Augmented Kalman filter
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	TSR	Tip-speed ratio
W Watts	UKF	Unscented Kalman filter
	W	Watts

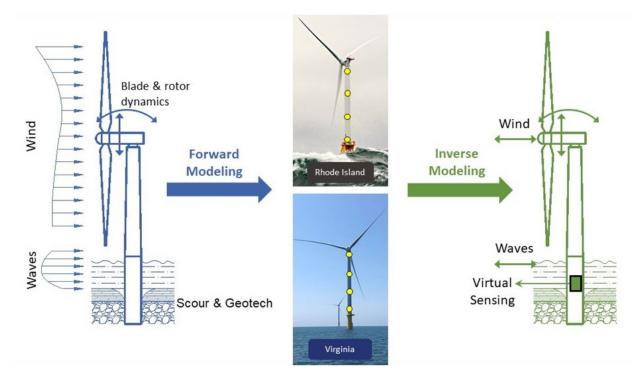
1 Project Overview, Benefits, and Future Work

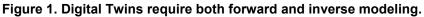
1.1 **Project Overview**

The NOWRDC Project #154719: Optimal Sensor Placement for Physics-Based Digital Twins

(NOWRDC-OSP) has advanced the state of the art in offshore wind turbine (OWT) physics-based digital twin technology. Such technology can be used to track the development of structural fatigue within OWT components, which can lead to longer OWT service life, and to detect and faults within the system, which can lead to reduced operations and maintenance (O&M) costs.

A critical aspect of this project is integrating forward and inverse modeling as shown in **Figure 1**. Forward modeling includes the development of multiphysics models based on OWT data and metocean measurements. Inverse modeling includes the estimation and uncertainty quantification of OWT properties and loads from direct acceleration and strain measurements. Together, forward and inverse models form the basis for affordable and reliable digital twin technology.





With a reliable digital twin, it is possible to use virtual instruments to assess OWT performance while saving substantial resources. This possibility introduces a key engineering question: What are the

minimum number of sensors required to develop an acceptable digital twin? Optimal sensor placement (OSP) is the discipline concerned with identifying this minimum number of sensors.

Figure 2 describes the project partners and overall organization of the multiple funding agencies brought together to accomplish this work. In the upper portion of this figure, NOWRDC-OSP is shown as a bridge between the Block Island Structural Monitoring—Joint Project (BISM-JP), funded by the U.S. Bureau of Safety and Environmental Enforcement (BSEE), and the Innovate UK Project: *Wind Turbine Sensor Placement Optimisation for Digital Twin Development* (Innovate-UK).

Figure 2. The NOWRDC-OSP Project.

This project provided additional analytical capacity to the existing BSEE Block Island Structural Monitoring—Joint Project (BISM-JP) as well as a platform for communication with a concurrent project in the UK.

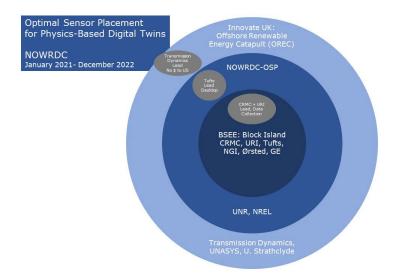


Figure 3 shows project partners for the BISM-JP, the NOWRDC-OSP, and the Innovate-UK projects. The Block Island Wind Farm (BIWF) on the left served as the basis for U.S. measurements, while the Levenmouth Demonstrator Turbine (LDT) served as the basis for UK measurements. As the timeline in **Figure 3** indicates, plans to monitor the BIWF date back to 2012, four years before its construction. Instruments were first installed, however, in 2021, coincident with the early months of the NOWRDC-OSP project.

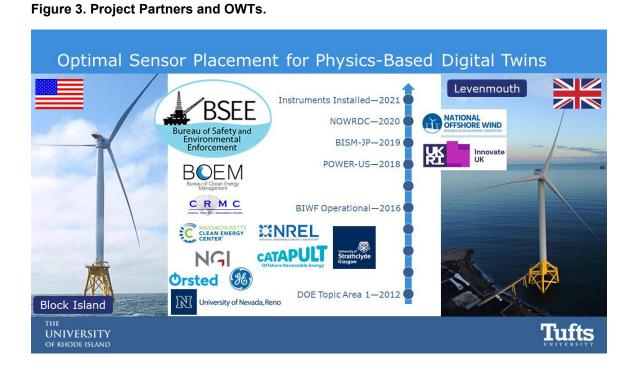


Figure 4 shows the location of the BIWF in Rhode Island state waters. When the BIWF commenced commercial operation in 2016, it became the first U.S. offshore wind farm. Within the BISM-JP, Turbine B-2 was instrumented with a continuous monitoring system. Data from this monitoring system formed the basis of the NOWRDC-OSP BIWF analyses.

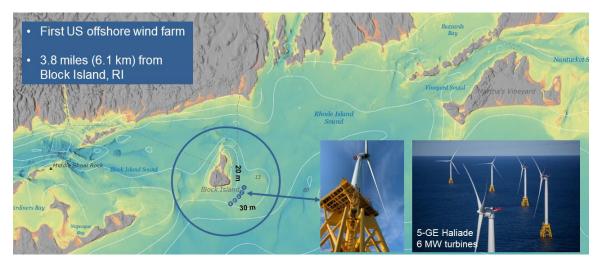


Figure 4. Location and images of the Block Island Wind Farm (BIWF).

1.2 Project Benefits

The NOWRDC-OSP Project benefits can be organized according to the Tasks listed in **Table 2** and the Project Deliverables listed in **Table 4**. The list below highlights the most important project benefits, each of which can be accessed in detail through the relevant project deliverable.

- Task 1: Bayesian Assimilation Framework (BAF)
 - Task 1 developed a framework for inverse modeling complete with detailed computational models, algorithms for model uncertainty and load inference, and special treatment of turbine foundations and nacelles.
 - This framework will allow for detailed estimation of environmental loads as model inputs that can contribute to the improvement of load determination for future OWT designs.
 - The exploratory work for the integration of this framework with artificial intelligence (AI) methods for drivetrains has created a roadmap for further work in this area.
- Task 2: Sensing System and Optimal Sensor Placement
 - This task introduced novel, reliable sensing systems that can be affordably installed on an existing OWT. Combined with the optimal sensor placement (OSP) methods developed in this task, these sensing systems can be designed to gather precisely the relevant data for a given task without having to over-instrument an OWT.

This task was responsive to the primary recommendation of Ørsted, who owns the BIWF turbines and who wrote a letter of support for this project. During the project proposal, Ørsted's recommendation to the project team was to create a method for designing and installing sensors that yielded a clear understanding of the necessity for each sensor as well as the efficient use of data from that sensor.

The benefit of this task is the reduction in cost, and the increase in transparency and reliability of future sensing systems.

• Task 3: Validation

- This task used measured data from the BIWF to validate the algorithms, frameworks, and computational models developed in Tasks 1 and 2. Successful completion of this task has resulted increased confidence in the subject algorithms, BAF framework, and computational models.
- Work within this task produced direct comparisons of finite element (FE) models in OpenSees with similar multiphysics models in OpenFAST. This comparison has paved the way for future work in the development of inverse modeling in OpenFAST, which has previously not been equipped to perform inverse modeling. Future inverse modeling in OpenFAST will allow for the identification and exploration of new system parameters that can be updated within a BAF.
- This task contextualized the BAF and OSP work within this project within several years of model validation work within the OC projects, demonstrating that the deliverables of this research project can be helpful to the future refinement and validation of approaches to multiphysics modeling.
- Task 5: Commercialization
 - This task laid out the business case for a BAF-OSP approach to future instrumentation of OWTs and validated that the hardware and software products developed within this work represent a compelling new approach to OWT condition monitoring.

1.3 Future Work

Considering the project benefits listed above, major opportunities for future work include:

- Develop OSP-BAF inverse modeling capability for the multiphysics platform OpenFAST.
- Expand the parameters that can be estimated and updated beyond structural parameters such as loads and stiffnesses to include a larger multiphysics domain such as metocean, aeroelastic, control, and hydrodynamic parameters.
- Apply the successful framework developed within this project to OWT drivetrains for expanded service life and fault detection.

- Apply the successful framework developed within this project to entire OWTs.
- Integrate the physics-based BAF developed within this project with AI methods to efficiently model entire offshore wind farms with integrated BAF-AI transfer learning methods.
- Work with an offshore wind developer to deploy these sensing systems and methods on a commercial scale offshore wind farm.

2 Project Team and Personnel

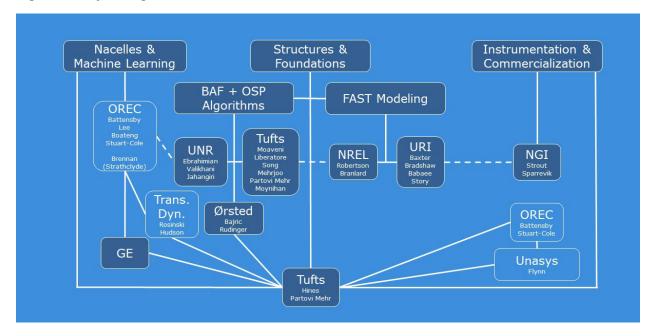
The NOWRDC-OSP Project Team was led by Dr. Eric Hines and Dr. Babak Moaveni of Tufts University, with Dr. Hines acting as project lead and Dr. Moaveni acting as technical lead. Subcontractors included the National Renewable Energy Laboratory (NREL), the University of Rhode Island (URI), the Norwegian Geotechnical Institute (NGI), and the University of Nevada Reno (UNR). **Table 1** lists key institutions and project personnel who collaborated to develop the work and author project reports.

Institution	Last Name	First Name	Title
Tufts	Hines	Eric	Professor of the Practice
	Moaveni	Babak	Professor
	Liberatore	Sauro	Kingsbury Fellow
	Song	Mingming	Research Assistant Professor
	Mehrjoo	Azin	Graduate Research Assistant
	Partovi-Mehr	Nasim	Graduate Research Assistant
	Moynihan	Bridget	Graduate Research Assistant
University of Rhode Island			
(URI)	Baxter	Chris	Professor
	Bradshaw	Aaron	Associate Professor
	Babaee	Amir	Gradaute Research Assistant
	Story	Maeve	Gradaute Research Assistant
National Renewable Energy			
Laboratory (NREL)	Robertson	Amy	Principal Engineer
	Branlard	Emmanuel	Research Engineer
Norwegian Geotechnical			
Institute (NGI)	Strout	James	Expert Adviser
	Sparrevik	Per	Expert Adviser
University of Nevada Reno			
(UNR)	Ebrahimian	Hamed	Assistant Professor
	Jahangiri	Vahid	Postdoctoral Scholar
	Valikhani	Mohammad	Graduate Research Assistant

Table	1.	Pro	iect	Personnel
1 4 5 10	•••		,	

Figure 5 shows the organizational chart for the NOWRDC-OSP project and its relationship with the Innovate-UK project. In this figure, NOWRDC-OSP and BISM-JP entities are shown in dark blue and Innovate-UK entities are shown in light blue. The NOWRDC-OSP and BISM-JP projects were funded through federal and state U.S. resources, as well as in-kind contributions by Ørsted and GE. The Innovate-UK project was funded exclusively through UK resources. The two projects collaborated closely and met throughout the project period but maintained independent control of the NOWRDC-OSP and Innovate-UK projects. The two teams did produce a joint deliverable in October 2022 focused on OWT drivetrain measurements and modeling. This deliverable is listed as Karikari-Boateng et al. (2022) in the Bibliography.

Figure 5. Project Organizational Chart



3 Project Tasks and Schedule

The 24-month project commenced in January 2021 and ran through December 2022. **Table 2** summarizes the project Tasks and Subtasks, which are quoted directly from the SOW (mod. 2, November 30, 2021) for the project-specific Tasks 1-4 in the text following this table. **Table 3** shows the final project schedule, including Milestones and Go / No-Go decision points.

Table 2. Project Tasks

NOWRD	C-154719: Optimal Sensor Placement Project Tasks					
Task 0	Project Management and Progress Reporting					
0.1 Written Progress Reports						
0.2 Project Kick-off Meeting and Report						
0.3 Project Completion Meeting and Report						
0.4	Annual Metrics Report					
Task 1	Develop Bayesian Assimilation Framework (BAF) for OWTs					
Subtask 1.1	Loads					
1.1.1	Develop OpenSEES and OpenFAST models for BIWF and Monopile OWTs					
1.1.2	Develop Model Uncertainty Algorithm					
1.1.3	Develop Load Inference Algorithm Based on a BIWF OWT Structure					
Subtask 1.2	Foundations					
1.2.1	Characterize the Axial Cyclic Behavior of Piles for Jackets					
1.2.2	Characterize the Mechanics of Scour for Monopiles					
1.2.3	Develop Nonlinearity Algorithms Accounting for Foundation Behavior					
Subtask 1.3 Drivetrains						
1.3.1	Estimate Turbine Power Performance from SCADA Data					
1.3.2	Develop Roadmap for Integration of BAF and AI for Drivetrains					
Task 2	Sensing System and Optimal Sensor Placement					
2.1	Design Sensing Hardware Systems Specialized for OWTs					
2.2	Develop Optimal Sensor Placement Algorithm (OSP)					
2.3	Develop Constrained OSP (Practical + Cost) Algorithm					
2.4	Develop Monopile-Specific Constrained OSP Algorithm					
Task 3	Validation					
3.1	Develop Integrated OpenFAST/OpenSEES application					
3.2	Validate BAF and OSP Algorithms with BIWF Data					
3.3	Investigate Frequency and Damping Dependence on Wind and Rotor Speeds					
3.4	Benchmark SCADA Data, AI algorithms and BAF algorithms					
3.5	Benchmark BAF Algorithms against Existing Standards and Best Practices					
Task 4	Commercialization					
4.1	Cost Reduction and Production Scaling of Specialized Sensing Systems					
4.2	Market Analysis					
4.3	Benchmark BAF Algorithms against Existing Commercial and In-House Software					
Task 5	Final Report					
5.1	Draft Version					
5.2	Final Version					

Task 1 – Develop Bayesian Assimilation Framework (BAF) for OWTs

- 1. Subtasks
- 1.1. Develop BAF for OWT Loads

- 1.1.1. Contractor shall develop OpenSEES models of a selected BIWF-OWT, the OREC- 7MW, and a IEA-15MW MS-OWT. Contractor shall direct NREL to develop an OpenFAST model of the same three OWTs.
- 1.1.2. Contractor shall work collaboratively with UNR to develop the Model Uncertainty Algorithm. Contractor shall develop the algorithm for the BIWF-OWT and OREC 7-MW and UNR shall develop the algorithm for the IEA-15MW MS-OWT.
- 1.1.3. Contractor shall work collaboratively with UNR to develop the load inference algorithm based on the BIWF-OWT, OREC-7MW and IEA-15MW MS-OWT Structures, the OpenSEES and OpenFAST models from Task 1.1.1 and the Uncertainty Algorithm from Task 1.1.2.
- 1.2. Develop BAF for OWT Foundations
 - 1.2.1. Contractor shall direct URI to characterize the cyclic behavior of piles for the BIWF-OWT and OREC-7MW modeled in Task 1.1 and deliver these characterizations in a form that can be integrated into the OpenSEES and OpenFAST models developed in Task 1.1.1.
 - 1.2.2. Contractor shall direct URI to work with NGI to characterize the mechanics of scour for an MS-OWT and deliver this characterization in a form that can be integrated into the MS-OWT developed in Task 1.1.1. URI in consultation with NGI shall select appropriate soil springs for the same MS-OWT that account for cyclic and fatigue behavior including degradation and other non-linearities as deemed relevant by URI.
 - 1.2.3. Contractor shall work collaboratively with Tufts to develop the foundation non-linearity algorithm based on the BIWF-OWT, OREC-7MW and IEA-15MW MS-OWT models from Task 1.1 and the foundation characteristics delivered by URI in Tasks 1.2.1 and 1.2.2.
- 1.3. Develop Roadmap for Future BAF of Drivetrains and Optimal use of SCADA Data
 - 1.3.1. Contractor shall direct NREL to estimate the turbine power performance of the BIWF-OWT and the OREC-7MW R&D OWT from SCADA Data and complete a comparative analysis of NREL and OREC Results on the OREC-7MW.
 - 1.3.2. The Contractor, OREC, NREL and UNR shall develop a Roadmap for future integration of BAF and AI for drivetrains based on results from Tasks 1.1, 1.2, and 1.3.1.

Task 2 – Develop Sensing System and Algorithm for Optimal Sensor Placement (OSP)

- 2. Subtasks
 - 2.1. Contractor shall direct NGI to conduct sensor selection and design at least three (3) hardware system scenarios (Jacket in-situ, Monopile in-situ, Monopile pre-install) that can deliver enhanced BAF compatible information in a cost-effective manner.
 - 2.2. Based on the BAF developed in Tasks 1.1 and 1.2, Contractor shall develop an OSP algorithm for the BIWF-OWT. UNR shall develop an OSP algorithm for an IEA-15MW MS-OWT.

- 2.3. Based on the results of Task 2.1 and the OSP algorithm developed in Task 2.2, Contractor shall develop a Constrained OSP algorithm based on the constraints of practicality and cost for the BIWF-OWT with input from and review by NGI and OREC.
- 2.4. Based on the results of Task 2.1 and the OSP algorithm developed in Task 2.2, Contractor shall direct UNR to develop a Constrained OSP algorithm based on the constraints of practicality and cost for and IEA-15MW MS-OWT with input from and review by Contractor.

Task 3 – Validation

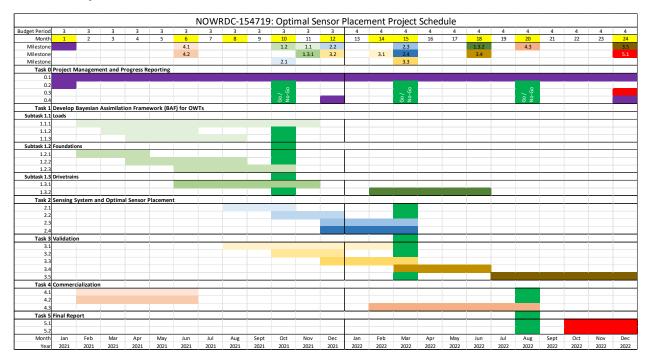
3. Subtasks

- 3.1. Based on the results of Tasks 1.1 and 1.2, the Contractor shall work with NREL to develop a needs assessment for the development of BAF inverse modeling capabilities for OpenFAST. This assessment shall be informed by the inverse modeling capabilities developed within the OpenSEES application for a BIWF-OWT.
- 3.2. Contractor shall work with URI to validate BAF and OSP algorithms from Tasks1.1, 1.2, and 2 for a BIWF-OWT based on the data collected during the BSEEBISM-JP.
- 3.3. Based on data collected from the BIWF-OWT, contractor shall study the dependence of first natural frequency and damping in the fore-aft direction on wind speed and rotor speed. Contractor shall evaluate measurements of frequency and damping according to a multi-variable regression analysis and compare these results to analytical evaluations of the same phenomena.
- 3.4. Contractor shall work with UNR, NREL and OREC to benchmark SCADA Data and AI algorithms from the OREC-7MW against relevant BAF algorithms for the same structure.
- 3.5. Based on the results of Tasks 1.1, 1.2, and 3.1-3.3, the Contractor shall direct NREL to benchmark BAF algorithms against existing standards and best practices with the OC3, 4, 5 & 6 Framework.

Task 4 – Commercialization

- 4. Subtasks
 - 4.1. Contractor shall direct NGI to investigate cost-reduction and scaling of low-noise floor sensing systems relevant to BAF and OSP and summarize this investigation in a technical report.
 - 4.2. Contractor shall direct NGI to investigate the market potential for the sensing systems investigated in Task 4.1 and shall summarize this investigation in a market segment attached to the technical report in Task 4.1.
 - 4.3. Contractor shall work with NGI and OREC to benchmark BAF and OSP algorithms against existing commercial and in-house software in preparation for a utility-scale deployment of OSP systems with BAF digital twinning which would be the site for a follow-on Category C proposal to the Consortium.

Table 3. Project Schedule



4 **Project Deliverables**

Project Deliverables for NOWRDC-OSP include 18-technical reports, totaling 798 pages, and submitted according to the Milestones shown in **Table 3**. In addition to these deliverables, a 69-page joint UK/US report was completed in October 2022. **Table 4** lists the NOWRDC-OSP deliverables, designated as "DTask.Subtask" (where Task and Subtask are identified numerically) as well as each deliverable's lead author, lead institution, date, page length and status as to whether the deliverable is currently confidential. Numerical designations for deliverables in **Table 4** follow project Tasks, Subtasks and Milestones exactly with the exception of D1.1, which includes all three Sub-subtasks under Subtask 1.1 (D1.1.1, D1.1.2, and D1.1.3). Per the request of NOWRDC, Deliverables for Subtasks 1.2 and 1.3 were submitted separately according to Sub-subtask completion.

Table 4. Project Deliverables

Task/Deliverable	Title	Lead Author	Lead Institution	Date	page length	Status
1.0	Develop Bayesian Assimilation Framework (BAF) for OWTs					
1.1	Develop BAF for OWT Loads					
D1.1	Bayesian Assimilation Framework for Offshore Wind Turbines: Loads	Partovi-Mehr	Tufts	08/2021 12/2021 (rev. 1)	213	Confidential
1.2	Develop BAF for OWT Foundations					
D1.2.1	Characterization of the Axial Cyclic Behavior of Piles for Jackets	Bradshaw	URI	10/2021 01/0222 (rev. 1)	23	Confidential
D1.2.2	Characterization of Scour Mechanics and Soil Springs for Monopiles	Baxter	URI	10/2021 01/2022 (rev. 1)	34	Confidential
D1.2.3	Develop Nonlinearity Algorithms Accounting for Foundation Behavior	Song	Tufts	10/2021 01/2022 (rev. 1)	33	Confidential
1.3	Develop Roadmap for Future BAF of Drivetrains and Optimal use of SCADA Data					
D1.3.1	Estimate Turbine Power Performance from SCADA Data	Branlard	NREL	12/2021 02/2022 (rev. 1)	21	Confidential
D1.3.2	Machine Infused Physics-Based Fault Diagnosis for Wind Turbine Drivetrain	Valikhani	UNR	07/2022	29	Confidential
2.0	Develop Sensing System and Algorithm for Optimal Sensor Placement (OSP)					
D2.1	Design of Sensing Hardware Systems Specialised for OWTs	Strout	NGI	10/2021 01/2022 (rev. 1) 02/2022 (rev. 2)	29	Confidential
D2.2	Development of Optimal Sensor Placement (OSP) Algorithm	Mehrjoo	Tufts	12/2021	19	Confidential
D2.3	Develop a Constrained OSP Algorithm based on the Constraints of Practicality and Cost for BIWF-OWT	Mehrjoo	Tufts	03/2022	34	Confidential
D2.4	Develop a Constrained OSP Algorithm based on the Constraints of Practicality and Cost for the IEA-15MW MS-OWT	Mehrjoo	Tufts	03/2023	25	Confidential
3.0	Validation					
D3.1	Future Needs for the Development of Inverse Modeling Capability with OpenFAST	Branlard	NREL	02/2022	36	Confidential
D3.2	Validation of BAF and OSP algorithms within an integrated OpenFAST/OpenSees application for a BIWF-OWT	Song	Tufts	12/2021 02/2022 (rev. 1)	44	Confidential
D3.3	Dependence of first natural fore-aft frequency and damping on wind speed and rotor speed	Partovi-Mehr	Tufts	03/2022 06/2022 (rev. 1)	51	Confidential
D3.4	Benchmark SCADA Data, AI algorithms, and BAF algorithms	Valikhani	UNR	09/2022	63	Confidential
D3.5	The Future of Digital Twin Technologies and their possible Integration in OC Projects	Branlard	NREL	12/2022	21	Confidential
4.0	Commercialization					
D4.1	Cost-Reduction and Scaling of Low-Noise Floor Sensing Systems Relevant to BAF and OSP	Strout	NGI	06/2021	50	Confidential
D4.2	Market Report Investigating the Market Potential for the Low-Noise Floor Sensing Systems	Strout	NGI	06/2021	44	Confidential
D4.3	Benchmark BAF and OSP Algorithms Against Existing Commercial and In-House Software	Strout	NGI	08/2022	29	Confidential

5 **Project Publications**

To date, the project team has developed 3-publications for peer-reviewed archival journals along with 7conference papers and presentations. **Table 5** lists these publications, including each publication's lead author, lead institution, date, and venue. The designation "Venue" refers to the title of the Journal or Conference associated with that publication.

Table 5. Project Publications

Title	Lead Author	Lead Institution	Date	Venue
Archival Journals				
Joint Parameter-input Estimation for Digital Twinning of the Block Island Wind	Song	Tufts	in review 2023	Mechanical Systems &
Turbine using Output-only Measurements	Solig	Turts	III Teview 2025	Signal Processing
Modeling of an Offshore Wind Turbine and Sensitivity Analysis of its Dynamic	Partovi-Mehr	Tufts	in review 2023	Renewable Energy
Properties to Operational and Environmental Conditions	Faitovi-Ivietii	Turts	III TEVIEw 2023	Nellewable Lifelgy
Inverse Modeling of Wind Turbine Drivetrain from Numerial Data	Valikhani	UNR	2023	Renewable & Sustainable
Using Bayesian Inference	Valikilalii	UNK	2023	Energy Reviews
Conferences				
Lessons Learned from One Year of Monitoring	Moaveni	Tufts	2022	IOWTC
of Block Island Offshore Wind Turbines	woaveni	Turts	2022	presentation
Lessons Learned from One Year of Monitoring	Hines	Tufts	2022	NOWRDC Symposium
of Block Island Offshore Wind Turbines	Times	Turts	2022	presentation
Digital Twinning of Block Island Offshore Wind Turbine using One Year of Monitoring	Moaveni	Tufts	2022	GE EDGE Symposium
Data	woaveni	Turts	2022	presentation
Joint Input-Parameter Estimation of Block Island Wind Turbine	Song	Tufts	2022	IMAC-XL
using Output-only Measurements	Jong	Turts	2022	extended abstract
Sensitivity of modal parameters of an offsshore wind turbine to ambient and	Partovi-Mehr	Tufts	2022	IMAC-XL
environmental factors: a numerical study	1 arcovi-ivieni	Turts	2022	extended abstract
Digital Twin Modeling for Offshore Wind Turbine Drivetrain Monitoring:	Jahangiri	UNR	2022	IMAC-XL
A Numerical Study	Janangin	ONIX	2022	extended abstract
Offshore Wind Turbine Modeling and Digital Twinning	Moaveni	Tufts	2021	NOWRDC Symposium
	woodvern	10113	2021	presentation
Optimal Sensor Placement for Physics-Based Digital Twins	Hines	Tufts	2020	NOWRDC Symposium
optimal sensor racement for raysies based Digital Twills	Times	iuits	2020	presentation

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- Bradshaw, Aaron, Maeve Story, Chris Baxter, Nasim Partovi Mehr. 2022. <u>Confidential</u>: Characterization of the Axial Cyclic Behavior of Piles for Jackets. <u>Deliverable D1.2.1</u>. NOWRDC-OSP. October 2021. Revised January 2022. 23 pp.
- Branlard, Emmanuel, Amy Robertson, Eric Hines, Nasim Partovi Mehr, Mingming Song, and Babak Moaveni. 2022. <u>Confidential</u>: Estimate Turbine Power Performance from SCADA Data. <u>Deliverable</u> <u>D1.3.1.</u> NOWRDC-OSP. December 2021. Revised February 2022. 21 pp.
- Branlard, Emmanuel, Amy Robertson, Nasim Partovi Mehr, Eric Hines, and Babak Moaveni. 2022. <u>Confidential</u>: Future Needs for the Development of Inverse Modeling Capability with OpenFAST. <u>Deliverable D3.1</u>. NOWRDC-OSP. February. 36 pp.
- Branlard, Emmanuel, Amy Robertson, Nasim Partovi Mehr, Eric Hines, and Babak Moaveni. 2022. <u>Confidential</u>: The Future of Digital Twin Technologies and their possible Integration in OC Projects. <u>Deliverable D3.5.</u> NOWRDC-OSP. December. 21 pp.
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