Final Technical Report

INTEGRATE – Inverse Network Transformations for Efficient Generation of Robust Airfoil and Turbine Enhancements

University of Maryland (with NREL effort)

In Response to ARPA-E FOA3 DE-FOA-0002107:
Design Intelligence Fostering Formidable Energy Reduction and Enabling Novel Totally Impactful Advanced Technology Enhancements (DIFFERENTIATE)

DE-AR0001206

Award:	DE-AR0001206
Sponsoring Agency	USDOE, Advanced Research Project Agency – Energy (ARPA-E)
Lead Recipient:	University of Maryland
Project Team Members	University of Maryland
Project Title:	**INTEGRATE – Inverse Network Transformations for Efficient Generation of Robust Airfoil and Turbine Enhancements**
Program Director:	Dr. David E. Tew
Principal Investigator:	Dr. James Baeder
Contract Administrator:	ARPA-E
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PUBLIC EXECUTIVE SUMMARY

The INTEGRATE (Inverse Network Transformations for Efficient Generation of Robust Airfoil and Turbine Enhancements) project developed a new inverse-design capability for the aerodynamic design of wind turbine rotors using invertible neural networks. Training data was obtained from improved turbulence and transition models for RANS and hybrid RANS/LES solvers with machine-learned physics-based data-augmented corrections and then using the resulting neural-network(s) augmented RANS model to run thousands of 2-D and 3-D CFD simulations.

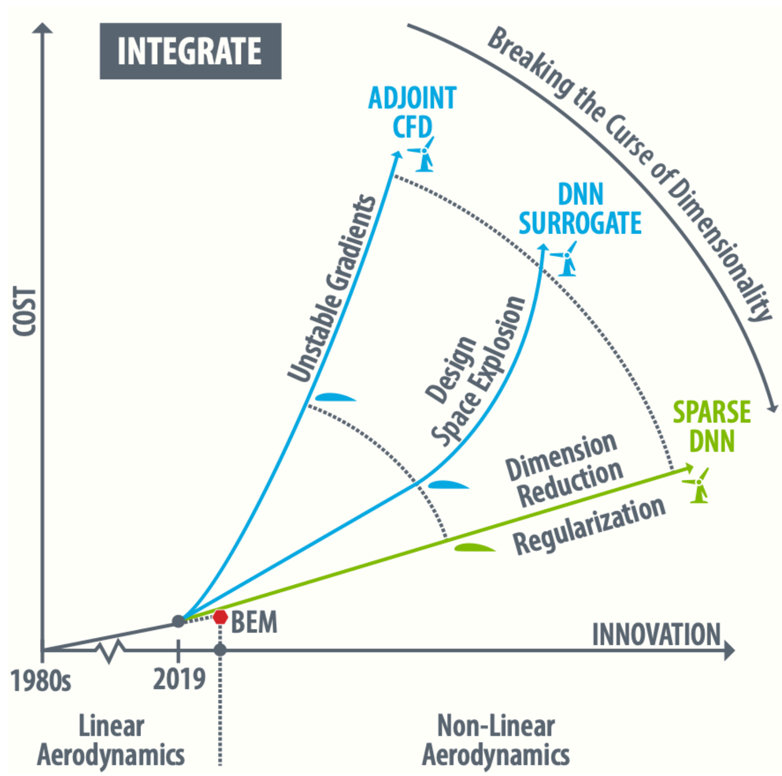
This AI-based design technology can capture complex non-linear aerodynamic effects while being several orders of magnitude times faster than design approaches based on purely computational fluid dynamics. The results from this project enable innovation in wind turbine design by accelerating time to market through higher-accuracy early design iterations to reduce the levelized cost of energy.

Specifically, this work enabled: (1) Getting new designs with desired performance on a laptop in under one second; (2) Accelerating time to market by improving early design iterations with more certainty; (3) Increasing design space exploration for improved performance and robustness; (4) Capturing complex nonlinear aerodynamics in design several orders of magnitude times faster than comparable approaches; and (5) Increasing annual energy production by up to 2% compared to traditional design approaches.

ACCOMPLISHMENTS AND OBJECTIVES

Next-Generation Aerodynamic Tools
This award allowed The National Renewable Energy Laboratory (NREL), in partnership with the University of Maryland, to develop the next generation of aerodynamic tools for 2D airfoil and 3D wind turbine blade design.
Researchers leveraged a specialized invertible neural network (INN) architecture that learns complex relationships between airfoil or blade shapes and their associated aerodynamic and structural properties.
This INN architecture accelerates designs by providing a cost-effective alternative to current industrial aerodynamic design processes, including:

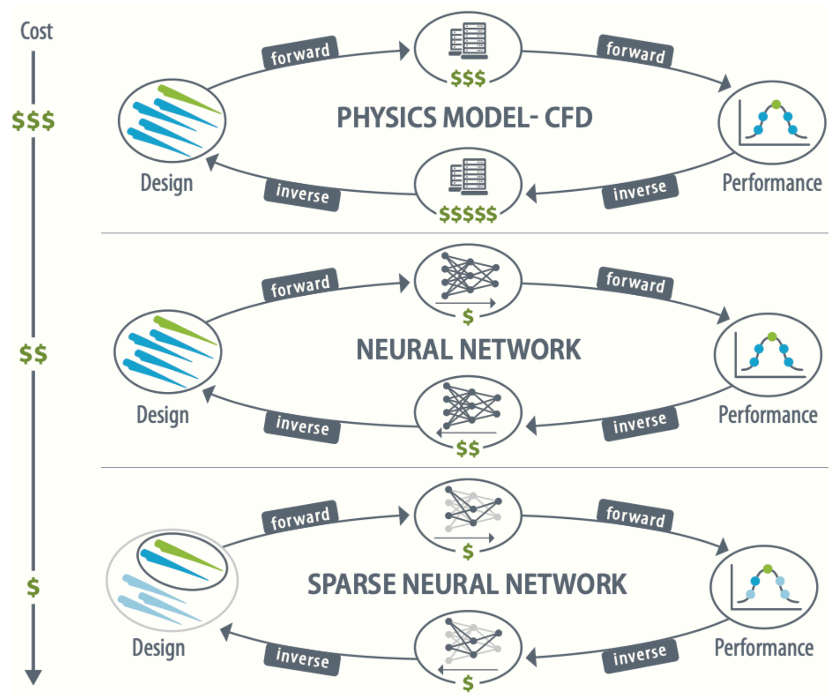
- **Blade element momentum (BEM) theory models:** limited effectiveness for design of offshore rotors with large, flexible blades where non-linear aerodynamic effects dominate
- **Direct design using computational fluid dynamics (CFD):** cost-prohibitive
- **Inverse-design models based on deep neural networks (DNNs):** attractive alternative to CFD for 2D design problems, but it is quickly overwhelmed with increased number of design variables in 3D problems.



Innovation potential versus cost for competing technology pathways. Illustration by Brittany Conrad, NREL

The Approach

INTEGRATE's specialized INN architecture—along with the novel dimension-reduction methods and airfoil/blade shape representations developed by collaborators at the National Institute of Standards and Technology (NIST)—learned complex relationships between airfoil or blade shapes and their associated aerodynamic and structural properties. The INN was trained on data obtained using the University of Maryland's Mercury Framework, which has with robust automated mesh generation capabilities and advanced turbulence and transition models validated for wind energy applications.

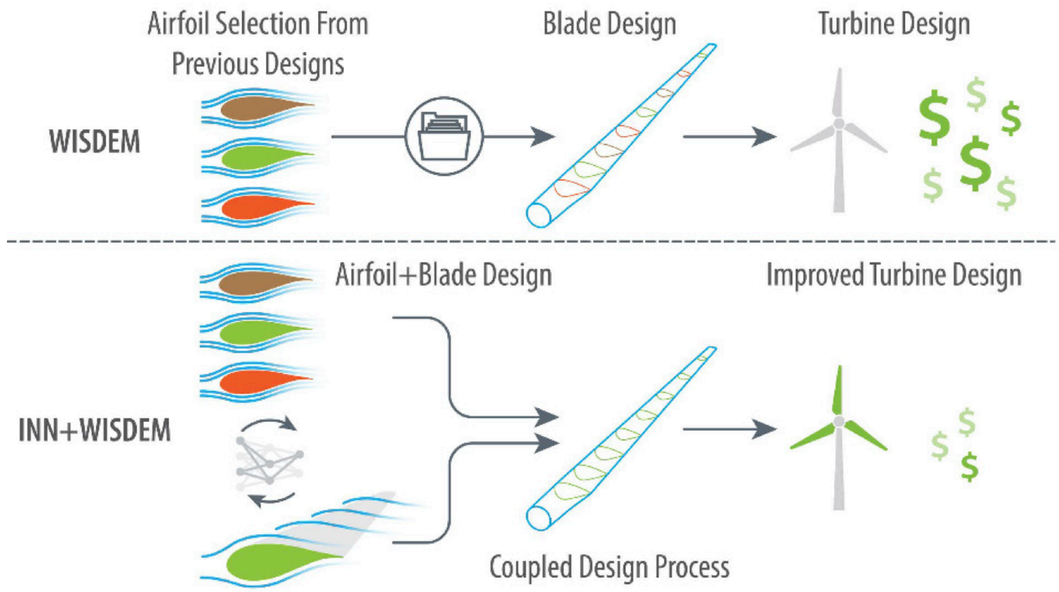


Aerodynamic design of wind turbine rotors using inversion of deep neural networks. Illustration by Julia Laser, NREL

Technology Transfer Demonstration: INN-Airfoil + WISDEM

As part of a technology transfer demonstration, researchers integrated the inverse-design tool for 2D airfoils (INN-Airfoil) into the Wind-Plant Integrated System Design and Engineering Model (WISDEM), a multidisciplinary design and optimization framework for assessing the cost of energy. The traditional approach to wind turbine design involves creating a 3D blade from a preselected set of 2D airfoils. However, the multidisciplinary nature of design means that the most aerodynamically efficient airfoils may not be the best choice for all types of design constraints for wind turbines.

The integration of INN-Airfoil into WISDEM allowed for the design of airfoils and blades that meet the dynamic design constraints of cost of energy, annual energy production, and capital costs. Through preliminary studies, researchers have shown that the coupled INN-Airfoil + WISDEM approach reduces the cost of energy by around 1% compared to the conventional design approach.



Coupled INN-Airfoil + WISDEM approach. Illustration by Besiki Kazaishvili

Impacts

- Get new designs with desired performance on your laptop in under one second
- Accelerate time to market by improving early design iterations with more certainty
- Increase design space exploration for improved performance and robustness
- Capture complex nonlinear aerodynamics in design several orders of magnitude times faster than comparable approaches
- Increase annual energy production by up to 2% compared to traditional design approaches

A number of tasks and milestones were laid out in the Technical Milestones and Deliverables, at the beginning of the project. The actual performance against the stated milestones is summarized here:

Tasks	Milestones and Deliverables
M1.1: **Validation of Field Inversion Machine Learning (FIML) augmented turbulence model**	Validate the ML-augmented turbulence model used in CFD data generation against available experimental data for 2D airfoils. **Actual Performance:** (04/07/21) Performer validated CFD data against experimental data. Demonstrate that the ML-augmented model shows 50% improvement in predicting the stall angle and the max. Cl compared to traditional turbulence models. **Actual Performance:** (04/07/21) Performer achieved desired improvement.
M2.1: **Implement current state-of-the-art DNN inversion**	Implement an invertible neural network that conforms to the functional requirements established in M3.1. **Actual Performance:** (10/07/20) NREL implemented. Establish baseline complexity of brute-force inversion as a benchmark toassess sparsification strategies insubsequent milestones. **Actual Performance:** (10/07/20) NREL established baseline.
M2.2: **Implement sparsification technique**	Demonstrate network sparsification capability that reduces the number of parameters by an order of magnitude. **Actual Performance:** (07/07/21) Performer demonstrated sparsification. Compare performance of the sparsified network against the performance baselines established in M2.1 and M3.1 with goal of less than 5% error on lift and drag. **Actual Performance:** (07/07/21) NREL achieved goal.
M2.3: **Reduction of training data requirements**	Explore transfer learning to extend 2D data to the 3D problem and reduce training time. Apply shape manifold dimension reduction techniques to reduce training data requirements. **Actual Performance:** (01/07/22) Performer with NREL explored and applied. Achieve a 50% reduction in training requirements while maintaining 95% of predictive accuracy. **Actual Performance:** (01/07/22) NREL achieved goal.

M3.1: **Functional requirements for inverse design of 2D airfoil**	Establish the requirements specification of the inverse design model (i.e., inputs and outputs) such as geometry representation (Class Function/Shape Function Transition, CST), Reynolds number, lift and drag coefficient, stall margin, etc. **Actual Performance:** (07/07/20) Performer established the requirements.
M3.2: **Generate initial training data for 2D ML model training**	Run CFD simulations (~4000 cases) for at least 3 different airfoil families currently used in wind turbine designs, over the range of Re from 1 million to 8 million. Create database of data generated (including surface pressure distributions) in a form ingestible by machine learning models. We will need at least O(k log(N)) simulations for a rank k active subspace dimension reduction from original N dimensional space. **Actual Performance:** (07/07/20) Performer ran cases over the range of Re from 3 million to 12 million.
M3.3: **Go/No-go: Inverse design of 2D airfoil**	Go/No-go milestone: Complete training of the inverse DNN model and test it for two different existing airfoils (representative of root and tip of the blade). The trained model must be able to generate known airfoil designs given their aerodynamic performance characteristics (established in M1.1) such that the difference of the L2 norm of error of generated CST parameters from actual geometry is <5%. **Actual Performance:** (01/07/21) Performer with NREL met Go/No-go milestone.
M4.1: **Functional requirements for inverse design of 3D blades**	Establish the requirements specification for the inverse design model capable of designing the full wind turbine blade. **Actual Performance:** (11/30/22) Performer established requirements.
M4.2: **Complete training data generation for 3D wing sections**	Run CFD simulations (~6000 cases) to create database of spanwise performance metrics that can be used to train different aspects of the ML model. The simulations will use baseline CST parameters from turbine geometries available to NREL (e.g., NREL-5MW, DTU 10MW, NM80) and apply random perturbations to explore the design space. The simulations will generate data for Re over the range of 1-8 million. Will need at least O(k log(N)) simulations for a rank k active subspace dimension reduction from original N dimensional space. **Actual Performance:** (07/07/21) Performer ran cases over the range of Re from 3 million to 12 million.

M4.3: **Inverse design of a 3D section**	Complete training of the sparsified inverse DNN model and generate a 3D blade section design given spanwise aerodynamic performance and structural constraints (spar thickness) targeting an overall integrated thrust and power coefficient for this blade span. Perform CFD analysis of the resulting design to establish that the aerodynamic performance of the wing section is within 5% of the integrated performance design parameters provided to the ML model. **Actual Performance:** (10/07/21) Performer with NREL did this using WISDOM with BEM and 2-D airfoil inverse DNN.
M5.1: **3D blade design demonstration**	Demonstration of the complete inverse design model, that follows the functional requirements in M4.1, showing that the model can generate aerodynamic shapes that conform to the structural design constraints. Verify using CFD analysis that aerodynamic performance of the resulting geometry is within a 5% margin of the design inputs. **Actual Performance:** (11/30/22) Performer with NREL did this using WISDOM with BEM and 2-D airfoil inverse DNN.
M6.1: **Initial Draft of U.S. Commercialization Plan**	Initial Commercialization Plan developed and communicated to ARPA-E that includes: (a) an explicit identification of the software and/or data that is expected to be a primary outcome of the project and subject to the U.S. Commercialization Plan and requirements set forth in Attachment 4, (b) targeted markets and customer segments; (c) customer value proposition, (d) competing alternatives, (e) potential strategic partnerships required for deploying the solutions (f) preliminary business model hypothesis, (g) IP strategy, (h) anticipated benefits to the US economy, and (i) a plan to report to ARPA-E the utilization of the software and data specified in the Commercialization Plan for a period of 10 years following its reporting. (This report is to include a description of any modifications made to the software or data and the manner in which such modifications are being commercialized.) Additional requirements that must be included in the Plan can be found in the clause in Attachment 2 entitled Intangible property (University awardee) or Rights in Data (for profit awardee). Any draft of the Commercialization Plan that has been approved by ARPA-E, supersedes any prior approved draft and is automatically incorporated by reference as part of this Agreement by the provisions of Attachment 2. **Actual Performance:** (07/07/20) Done by NREL.

M6.2: **Second Draft of U.S. Commercialization Plan and Updates to Data Acquisition/Storage and Software Development Plans**	Commercialization plan updated to include: (a) preliminary cost/benefit analysis; (b) definition of potential launch markets, including critical performance and design features needed facilitate customer acceptance; (c) potential follow-on funding arrangements and (d) a detailed business model based on selected markets/competitive landscape. Additional requirements that must be included in the Plan can be found in the clause in Attachment 2 entitled Intangible property (University awardee) or Rights in Data (for profit awardee). Any draft of the Commercialization Plan that has been approved by ARPA-E, supersedes any prior approved draft and is automatically incorporated by reference as part of this Agreement by the provisions of Attachment 2. Data acquisition/storage and software development plans updated if necessary. **Actual Performance:** (10/07/21) Done by NREL.
M6.3: **Final iteration of U.S. Commercialization and Formal Reporting of the Software Developed**	Commercialization plan updated to include results of technical investigation, cost/benefit analysis, and market analysis to assess impact, value, and plans for further technological development. Specific updates include: (a) refined cost/benefit analysis; (b) results of market outreach, including formalization of partnerships with other entities to support next-stage development; (c) target performance characteristics of final prototype necessary to spur adoption; (d) revision/update of business model(s); (e) revision and/or expansion of IP plan; (f) propose organizational development requirements necessary to succeed in next-stage development activities. Report the completion of the software and data specified in the Commercialization Plan to ARPA-E per the procedures specified in Attachment 4 of the Award. Additional requirements that must be included in the Plan can be found in the clause in Attachment 2 entitled Intangible property (University awardee) or Rights in Data (for profit awardee). Any draft of the Commercialization Plan that has been approved by ARPA-E, supersedes any prior approved draft and is automatically incorporated by reference as part of this Agreement by the provisions of Attachment 2. **Actual Performance:** (11/30/22) Done by NREL.

Description of the computer model, key assumptions, how the model was validated, are given in the peer-reviewed publications, conference papers and datasets as listed in the project outputs.

PROJECT ACTIVITIES

The INTEGRATE (Inverse Network Transformations for Efficient Generation of Robust Airfoil and Turbine Enhancements) project developed a new inverse-design capability for the aerodynamic design of wind turbine rotors using invertible neural networks. This AI-based design technology can capture complex non-linear aerodynamic effects while being several orders of magnitude times faster than design approaches based on purely computational fluid dynamics. This project enabled innovation in wind turbine design by accelerating time to market through higher-accuracy early design iterations to reduce the levelized cost of energy.

PROJECT OUTPUTS

A. *Journal Articles*

Jung, Y. S., Vijayakumar, G., Ananthan, S., and Baeder, J., "Local Correlation-Based Transition Models for High-Reynolds-Number Wind-Turbine Airfoils," Wind Energy Science, Vol. 7, No. 2, 2022, pp. 603–622.

Marepally, Koushik, et al. "Uncertainty quantification of wind turbine airfoil aerodynamics with geometric uncertainty." *Journal of Physics: Conference Series*. Vol. 2265. No. 4. IOP Publishing, 2022.

B. *Papers*

Glaws, Andrew, Vijayakumar, Ganesh, King, Ryan, Doronina, Olga, Baeder, James, Lee, Bumseok, Marepally, Koushik, & Grey, Zachary (2022). Invertible Neural Networks for Aerodynamic Design of Wind Turbine Blades.

Vijayakumar, G., Jung, Y. S., Baeder, J. D., and Ananthan, S.: Design-space exploration for inverse-design of wind turbine blades using data-driven methods, in: SciTECH 2022, 3–7 January 2022, San Diego, CA, and online, AIAA 2022-1293, https://doi.org/10.2514/6.2022-1293, 2021.

C. *Other Products (e.g. Databases, Physical Collections, Audio/Video, Software, Models, Educational Aids or Curricula, Equipment or Instruments)*

Vijayakumar, G., King, R., Glaws, A., Baeder, J., Doronina, O., Lee, B., Marepally, K., Jasa, J., & Grey, Z. (2021). INTEGRATE - Inverse Network Transformations for Efficient Generation of Robust Airfoil and Turbine Enhancements. [Data set]. Open Energy Data Initiative (OEDI). National Renewable Energy Laboratory (NREL). https://doi.org/10.25984/1868906

Ramos, Dakota, Andrew Glaws, Ryan King, Bumseok Lee, Olga Doronina, James Baeder, Ganesh Vijayakumar, and Zachary Grey. *Airfoil Computational Fluid Dynamics-2k shapes, 25 AoA's, 3 Re numbers*. No. 5970. DOE Open Energy Data Initiative (OEDI); National Renewable Energy Laboratory (NREL), 2023.