Forecasting & Operations for the Rising U.S. Offshore Wind Energy Sector

Ahmed Aziz Ezzat, Ph.D.

Renewables & Industrial Analytics Research Lab

Rutgers, The State University of NJ

aziz.ezzat@rutgers.edu
https://sites.rutgers.edu/azizezzat/
@AAzizEzzat
Ahmed Aziz Ezzat

National Plan:
- 30 GW by 2030
- 85 GW by 2050

State Plan:
- 11 GW by 2040
  For NJ (Currently, none)

OSW Potential:
- >2000 GW
  (5 major geographical regions)
**Motivation:** The Rise of the U.S. Offshore Wind Energy Sector – Great Promise Ahead

The U.S. Mid/North Atlantic
The largest and first contributor to the U.S OSW goal

$4.21 B
Total Lease Auction

OCS-A 0544
MID- ATLANTIC
Joint venture of Shell, EDF Renewables

$285M

OCS-A 0541
ATLANTIC SHORES
offshore wind
Shell New Energies & EDF Renewables

$780M

OCS-A 0542
Joint venture of EDPR, Engie

$765M

OCS-A 0537
Total Energies

$795M

OCS-A 0538
Attentive Energy (subsidiary of Total Energies)

$645M

OCS-A 0539
Bight Holding LLC (Joint venture of EWE & NE)

$1.1 B

Source: Bureau of Ocean Energy Management – February 2022
**Goal:** Tailored **Analytics (i.e., DS/OR)** to minimize the uncertainties in operating ultra-scale offshore wind farms.

**Case #1:** Analytics for Offshore Wind Energy Forecasting

**Case #2:** Analytics for Offshore Wind Operations & Maintenance
Rutgers’ tailored version of WRF for the U.S. Mid- & North Atlantic

10-min observations from two NYSERDA buoys in the NY/NJ Bight

Existing Technology: RU-WRF
- Developed by RU COOL at Rutgers University
- Independently validated by NREL (2020)
- Best “Tailored” model in the region.

Goal: To develop AIRU-WRF:
- AI-powered
- Site-specific
- Short-term
- High-resolution
- Accurate 😊
AIRU-WRF: The AI-Powered Rutgers University Weather Research & Forecasting Model

\[ F(s_i, t) = \mu(s_i, t; \theta^{\mu}) + \eta(s_i, t; \theta^{\eta}) \]

Forecast Variable (with transformations)

- **Meso-scale**
  - Low-frequency, coarser-scale variations
- **Sub-meso-scale**
  - High-frequency, finer-scale variation

Numerical Weather Predictions are most useful here...

Machine Learning is most useful here...

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Machine Learning is most useful here...

AIRU-WRF: The AI-Powered Rutgers University Weather Research & Forecasting Model

\[ F(s_i, t) = \mu(s_i, t; \theta^{\mu}) + \eta(s_i, t; \theta^{\eta}) \]

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Machine Learning is most useful here...
Multi-type biases found:

- **Shift Biases** (over- & under- prediction)
- **Temporal Biases** (early/late)
- **Spatial Biases** (where)
- **Nonlinear Biases** (complex meteorological drivers)

1 More about NWP biases in forecasting: Sweeney et al. (2020)
**Modeling** $\mu(s, t; \theta^\mu)$

$\mu(s, t; \theta^\mu)$ is essentially a calibration of the NWP…

**Key difference:** Existing literature mostly focuses on “shift biases,” and does not fully link the biases to their driving meteorological conditions.\(^1,2,3\)

\(^{1,2,3}\) Y. Gel et al. (2004), Chen, Niya, et al. (2013), Du, Pengwei (2018), Kosovic, Branko, et al. (2020)

\[
\mu(s, t) = a^T \tilde{Y}^\ell(s, t) + b^T \tilde{G}(s, t) + (c^T \tilde{G}(s, t)) \tilde{Y}(s, t)
\]

**Additive Bias**

**Multiplicative Bias**

Goal is to select $\tilde{Y}^\ell(s, t)$ and $\tilde{G}(s, t)$ so that they comprise features that are both meteorologically relevant & statistically significant.

We postulate the use of three sets of features, $g = \{g^e, g^\ell, g^c\}$

- $g^e$ : Exogeneous features (pressure, surface temperature, relative humidity, wind gust)
- $g^\ell$ : Future & lagged values of NWPs $\rightarrow$ temporal bias correction
- $g^c$ : Physically Motivated Features
Examples of New Constructed features $g^C$

1. Geostrophic wind

More about estimating geostrophic winds:

2. Thermal & Pressure Gradients
With three sets of features, a question of interest is:

**Are all features relevant at all times?**

- From a **physics** standpoint: Meteorological drivers of NWP bias change over space-time → distinct bias types/magnitudes.

- From an **ML** perspective: The law of parsimony…

**Dynamic Feature Selection**

*Only select features when they matter!*

\[
\tilde{G}(s, t) = \{GW_{9}, GST_{2}, U_{12}, V_{13}, STPD_{-1}\}
\]

\[
\tilde{G}(s, t) = \{GST_{-2}, U_{6}, P_{4}\}
\]

\[
\tilde{G}(s, t) = \{GST_{1}\}
\]

\[
\tilde{G}(s, t) = \{GW_{-18}, GST_{-1}, U_{0}, STPD_{-2}\}
\]

\[
G(s, t) = \{GST_{-2}, U_{6}, P_{4}\}
\]
Back to **AIRU-WRF:**

\[ F(s_i, t) = \mu(s_i, t; \Theta^\mu) + \eta(s_i, t; \Theta^\eta) \]

- **Forecast Variable (with transformations)**
- **Meso-scale**
  - Low-frequency, coarser-scale variations
- **Sub-meso-scale**
  - High-frequency, finer-scale variation
• Assume data has been de-trended, i.e., we have:

\[ Z(s, t) = Y(s, t) - \mu(s, t) \]

• We model \( z(s, t) \) as a spatio-temporal **Gaussian Process** (GP):

\[ Z(s, t) \sim \mathcal{GP}\left( m(s, t), C(u, w) \right) \]

- **GP mean function**
- **GP covariance function (Kernel)**

• **Covariance functions** (Kernels):

\[ C(u, w) = \text{cov}\{Z(s_i, t_j), Z(s_{i'}, t_{j'})\} \]

- **Spatial Lag**
  \[ w = |t_j - t_{j'}| \]
- **Temporal Lag**
  \[ u = ||s_i - s_{i'}|| \]

**But, how to select** \( C(u, w) \)
Prevalent approach to modeling spatio-temporal correlations:

\[ C(u, \omega) = C^s(u) \times C^t(\omega) \]

Spatial kernel

Temporal kernel

Wind Advection and Its impact on Spatio-Temporal Correlations:

\[
\text{cov}\left\{ Z(s_i, t_j), Z(s_{i'}, t_j + \Delta t) \right\} \Rightarrow \text{cov}\left\{ Z(s_i, t_j + \Delta t), Z(s_{i'}, t_j) \right\}
\]

Statistical test based on space-time variograms rejects the hypothesis of symmetry in the local wind field, especially in the \(~1\text{-}3\text{-hour range}\)
Physically Justifiable Modeling of Spatio-Temporal Correlations:

The Lagrangian reference framework\(^1,^2\)

\[ C'(u, w) = \mathbb{E}_\theta \tilde{C}'(u - \theta w), \quad \theta \in \mathbb{R}^d \]

- Spatial lag
- Advection vector
- Temporal lag

\(^1\)More: Cox, Isham (1988), Salvana & Genton (2022)

\(^2\)Closed-form expressions can be derived (Schlater, 2010)
Back to AIRU-WRF:

\[ Y(s, t) = \mu(s, t; \theta^\mu) + \eta(s, t; \theta^\eta) + \epsilon(s, t; \theta^\epsilon) \]

Wind Speed

The Meso-scale
Low-frequency, coarse-scale variations

The Turbine-scale
High-frequency, fine-scale variations

Unexplained Variability
White Noise
Back to our case study…

---

**Experimental Setup**

<table>
<thead>
<tr>
<th>Data Coverage</th>
<th>6 months (4-month in winter, 2-month in Summer)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast horizon</td>
<td>6 hours x 10-min resolution</td>
</tr>
<tr>
<td></td>
<td>= 36 forecasting instances/hour</td>
</tr>
<tr>
<td># of locations</td>
<td>3 locations (E05, E06, ASOW)</td>
</tr>
</tbody>
</table>

**Benchmarks:**

- (B₁) RU-WRF: Physics-based model tailored to the region of interest.
- (B₂) GOP: Hybrid (statistical-physical) approach
- (B₃) LSTM: Time Series Deep Learning model – Purely data-driven
- (B₄) PER: Persistence forecast – widely used as a benchmark
- (B₅) ARIMA-X: Autoregressive time series model – statistical approach

**Evaluations:**

- (C₁) Point forecasts: MAE & RMSE
- (C₂) Probabilistic forecasts: CRPS
Result #1: Filling the ML-Physics Chasm

Average hourly MAE at E05

- AIRU-WRF
- ARIMAX
- NWP

Average hourly MAE at E06

- Data leads
- Physics lead
- AIRU-WRF leads all the way
Result #2: Filling the ML-Physics Chasm

Percentage Improvement (%)

Physics
Hybrid
Data-Driven

Forecast horizon (hours)

Percentage Improvement (%)

Physics
Hybrid
Data-Driven

Forecast horizon (hours)

NWP
GOP
PER
LSTM
Result #3: Filling the ML-Physics Chasm

Bias = 0.769

Bias = 0.025
Wind Field Forecast Maps via AIRU-WRF

Result #4: Filling the ML-Physics Chasm

Joint venture of Shell & EDF Renewables
Shell New Energies & EDF Renewables
InventivEnergy, LLC

Joint venture of EDPR & Engie
Attentive Energy (sub. of Total Energies)

Bight Holding LLC (Joint venture of EWE & NE)

Currently showing forecasts at ★ E06
Result #5: From Wind Speed to Wind Power

- Statistical power curves from an operational wind farm (Ding, 2022)
- Evaluation using Power Curve Error Loss (Hering and Genton, 2010).
Result #6: Scenarios/Trajectories for Decision-Making Under Uncertainty

Correlations ignored (Marginal Densities)

Correlations considered (Trajectories)
Operations & Maintenance for Offshore Wind Farms

(ℂ₁) High maintenance requirements
Transportation costs account for 30-70% of offshore wind maintenance expenditures.

(ℂ₂) Limited accessibility
56% of inaccessibility, with up to 6 days of consecutive in-access.

(ℂ₃) Significant opportunity losses
Cost of failing 15 MW turbine >> cost of a failing 3 MW turbine

Potential Solution: Opportunistic Maintenance
i.e., Grouping maintenance actions at time of “opportunity”
(1) Transportation-Based Opportunities
Grouping maintenance to maximize the utilization of transportation/crew resources

Total vessel rentals: 2

Time

T
Planned maintenance

T + 5
Planned maintenance
(1) **Transportation-Based Opportunities**

Grouping maintenance to maximize the utilization of transportation/crew resources

Total vessel rentals: 1

![Diagram showing time T and time T+5 for planned maintenance](image-url)
(2) Revenue-Based Opportunities
Grouping maintenance at times of minimal revenue losses
(2) Revenue-Based Opportunities
Grouping maintenance at times of minimal revenue losses

Revenue Losses

Total revenue loss

T+4
Planned maintenance

T+7
Planned maintenance
(3) Access-Based Opportunities

Grouping Maintenance at times of “open” access

Accessibility = $f(\text{on}, \text{on})$

Vessel rentals: 3
Risk of failure: high

Time

Accessibility

T+3
Planned maintenance

T+5
Planned maintenance
(3) Access-Based Opportunities
Grouping Maintenance at times of “open” access

Accessibility = \( f(\frac{\text{T+3}}{\text{T+5}}, \frac{\text{Planned maintenance}}{\text{Planned maintenance}}) \)

- Vessel rentals: 1
- Risk of failure: low

\[
\max \left\{ s + \sum_{d \in \mathcal{D}} l_d \right\}
\]

\[
s = \sum_{i \in \mathcal{I}, t \in \mathcal{T}} \left[ \Pi_t \cdot p_{t,i} - K \cdot m_{t,i} - \Phi \cdot n_{t,i} - \Psi \cdot x_{t,i} \right] - \Omega \cdot v - Q \cdot q
\]

\[
l_d = \sum_{i \in \mathcal{I}} \left[ \Pi_d \cdot p_{d,i}^L - K \cdot m_{d,i}^L - \Phi \cdot n_{d,i}^L - \Psi \cdot \tau_i \left( m_{d,i}^L + n_{d,i}^L \right) \right] - \Omega \cdot v_d^L \quad \forall d \in \mathcal{D}
\]

<table>
<thead>
<tr>
<th>Method</th>
<th># vessel rentals</th>
<th>vessel utilization (%)</th>
<th>total downtime (h)</th>
<th>production loss (MWh)</th>
<th># PM actions</th>
<th># CM actions</th>
<th>total cost ($K)</th>
<th>total cost reduction (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HOST</td>
<td>6.8</td>
<td>83.7</td>
<td>131.8</td>
<td>312.6</td>
<td>9.9</td>
<td>1.2</td>
<td>118.9</td>
<td>-</td>
</tr>
<tr>
<td>BESN</td>
<td>8.0</td>
<td>74.2</td>
<td>136.7</td>
<td>348.9</td>
<td>9.8</td>
<td>1.3</td>
<td>126.4</td>
<td>5.9%</td>
</tr>
<tr>
<td>PBOS</td>
<td>9.4</td>
<td>79.9</td>
<td>137.3</td>
<td>331.1</td>
<td>9.7</td>
<td>1.3</td>
<td>128.9</td>
<td>7.8%</td>
</tr>
<tr>
<td>TBS</td>
<td>13.3</td>
<td>63.7</td>
<td>156.3</td>
<td>504.0</td>
<td>7.2</td>
<td>3.9</td>
<td>182.4</td>
<td>34.8%</td>
</tr>
<tr>
<td>CMS</td>
<td>12.9</td>
<td>81.0</td>
<td>518.8</td>
<td>2624.3</td>
<td>0.0</td>
<td>11.0</td>
<td>412.5</td>
<td>71.2%</td>
</tr>
</tbody>
</table>
What happens when you introduce uncertainties?

Opportunistic Maintenance is a double-edged sword! *Small* forecast errors can incur *large* cost implications

- Vessel rentals: 2
- False opportunities: 1
- Missed opportunities: 2
- Risk of failure: **high**

Accessibility

<table>
<thead>
<tr>
<th>forecast</th>
<th>true</th>
</tr>
</thead>
<tbody>
<tr>
<td>Missed!</td>
<td>Missed!</td>
</tr>
</tbody>
</table>

T+3

**Planned maintenance**

T+5

**Planned maintenance**

\[
\begin{align*}
\max_{m_t,i,m^L_{d,i,s},r^L_{d,s}} & \left\{ \text{short-term profit} \right. \\
& \left. \begin{aligned}
l^{\text{STH}} & + \sum_{d \in D} l^{\text{LTH}} \\
\end{aligned} \right\} \\
& \text{long-term profit} \\
& \text{prolonged interruptions} \\
& \text{spot resource contracting} \\
& \text{stochastic penalty term}
\end{align*}
\]

<table>
<thead>
<tr>
<th>Metric</th>
<th>PK-HOST</th>
<th>STOCHOS</th>
<th>PF-HOST</th>
<th>TBS</th>
<th>CMS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vessel rentals</td>
<td>2.36</td>
<td>2.18</td>
<td>2.26</td>
<td>4.92</td>
<td>6.72</td>
</tr>
<tr>
<td>Production loss (MWh)</td>
<td>101.21</td>
<td>141.05</td>
<td>154.59</td>
<td>597.68</td>
<td>1037.24</td>
</tr>
<tr>
<td>Revenue loss ($K)</td>
<td>5.10</td>
<td>7.10</td>
<td>7.83</td>
<td>29.85</td>
<td>51.64</td>
</tr>
<tr>
<td>Total PM tasks</td>
<td>5.00</td>
<td>4.53</td>
<td>4.48</td>
<td>2.35</td>
<td>0.00</td>
</tr>
<tr>
<td>Total CM tasks</td>
<td>0.00</td>
<td>0.47</td>
<td>0.52</td>
<td>2.65</td>
<td>5.00</td>
</tr>
<tr>
<td>Maintenance interruptions</td>
<td>0.66</td>
<td>0.43</td>
<td>0.64</td>
<td>1.23</td>
<td>1.83</td>
</tr>
<tr>
<td>Avg. total cost ($K)</td>
<td>38.92</td>
<td>43.43</td>
<td>45.00</td>
<td>86.90</td>
<td>127.91</td>
</tr>
<tr>
<td>Cost increase from opt ($K)</td>
<td>0.10</td>
<td>4.60</td>
<td>6.14</td>
<td>48.07</td>
<td>89.08</td>
</tr>
<tr>
<td>Median total cost ($K)</td>
<td>35.86</td>
<td>39.69</td>
<td>42.36</td>
<td>84.11</td>
<td>127.16</td>
</tr>
</tbody>
</table>
What if we could influence the degradation process of OSW turbines by controlling certain turbine settings?

Revenue loss = f(_weather, _data)

Accessibility = f( _cost, _location )

Early maintenance!

Better maintenance opportunity

Time

T+4
Remaining useful life
WT1

T+7 T+8
Remaining useful life
WT2

Remaining useful life
WT1 & 2
Trade-off: alleviate loading and increase the RUL, at the cost of reduced power production, and vice versa.

- Effect on degradation:
  - Potential to alleviate certain load variations up to 70%
\[ j = 1 \] \[ j = 2 \] \[ j = 3 \] \[ j = 4 \] \[ j = 5 \]

**2**

**Yaw-Adjusted Wind Power Curves**

**3**

**Yaw-Dependent Degradation Modeling**

\[ \lambda_{i,s} = \lambda_{i,s}^0 + \zeta_{i,s}^0 \sum_{t \in T} \left( \frac{1}{24} - \sum_{j \in J} \gamma_{t,i,j} \cdot F_{t,i,j,s} \right) + \sum_{d \in D} \zeta_{d,i,s}^L \left( 1 - \sum_{j \in J} \gamma_{d,i,j,s}^L \cdot F_{d,i,j,s}^L \right) \]

**Discretizing yaw decisions**

**1**

**Yaw-Adjusted Wind Power Curves**

**Discretizing yaw decisions**

**Yaw-Dependent Degradation Modeling**

**Day-ahead equivalent RUL gain/loss**

**LTH equivalent RUL gain/loss**

\[
\max_{m_{t,i}, \gamma_{t,i,j}} \left\{ \begin{array}{l}
\text{short-term profit} \quad l^{\text{STH}} \\
\text{long-term profit} \quad \sum_{d \in D} l^{\text{LTH}} - \frac{1}{N_s} \sum_{s \in S} \sum_{i \in I} \left[ \overbrace{U_s \cdot w_{i,s} + Y_s \cdot b_{i,s}}^{\text{prolonged interruptions}} \right] \\
\text{RUL gain} \quad \left( \lambda_{i,s}^0 - \sum_{t \in T} m_{t,i} - \sum_{d \in D} (\lambda_{i,s}^0 - d) \cdot m_{d,i,s}^L \right) \\
\text{cycle days lost due to early maintenance} \quad C^{\lambda} \cdot \left( \lambda_{i,s} - \lambda_{i,s}^0 \right) \\
\text{end of horizon cost} \quad \end{array} \right\}
\]

<table>
<thead>
<tr>
<th>Metric</th>
<th>POSYDON</th>
<th>STOCHOS</th>
<th>DET</th>
<th>TBS</th>
<th>CMS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost (K$)</td>
<td>159.3</td>
<td>273.8</td>
<td>398.4</td>
<td>715.0</td>
<td>1215.4</td>
</tr>
<tr>
<td>Revenue loss (K$)</td>
<td>74.4</td>
<td>121.6</td>
<td>283.5</td>
<td>475.8</td>
<td>999.2</td>
</tr>
<tr>
<td>Production loss (GWh)</td>
<td>1.5</td>
<td>2.5</td>
<td>5.8</td>
<td>9.7</td>
<td>20.8</td>
</tr>
<tr>
<td>Downtime (days)</td>
<td>11.0</td>
<td>21.3</td>
<td>32.5</td>
<td>52.0</td>
<td>102.5</td>
</tr>
<tr>
<td>Cycle days unused/task</td>
<td>11.2</td>
<td>8.9</td>
<td>2.9</td>
<td>17.5</td>
<td>0.0</td>
</tr>
<tr>
<td>Preventive tasks</td>
<td>12</td>
<td>15</td>
<td>7</td>
<td>12</td>
<td>0</td>
</tr>
<tr>
<td>Corrective tasks</td>
<td>0</td>
<td>3</td>
<td>4</td>
<td>8</td>
<td>14</td>
</tr>
<tr>
<td>Vessel rentals</td>
<td>7</td>
<td>14</td>
<td>11</td>
<td>28</td>
<td>20</td>
</tr>
<tr>
<td>Attempts per rental</td>
<td>2.0</td>
<td>1.3</td>
<td>1.2</td>
<td>1.1</td>
<td>1.1</td>
</tr>
<tr>
<td>Successes per rental</td>
<td>1.7</td>
<td>1.3</td>
<td>1.0</td>
<td>0.7</td>
<td>0.7</td>
</tr>
</tbody>
</table>
How Maintenance Actions are Grouped:
The Renewables & Industrial Analytics (RIA) Research Group at Rutgers University

Vision: “Addressing fundamental technical challenges of #RenewableEnergy through an #Analytics lens”
Forecasting & Operations for the Rising U.S. Offshore Wind Energy Sector

Ahmed Aziz Ezzat, Ph.D.
Renewables & Industrial Analytics Research Lab
Rutgers, The State University of NJ

aziz.ezzat@rutgers.edu
https://sites.rutgers.edu/azizezzat/
@AAzizEzzat
Ahmed Aziz Ezzat