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

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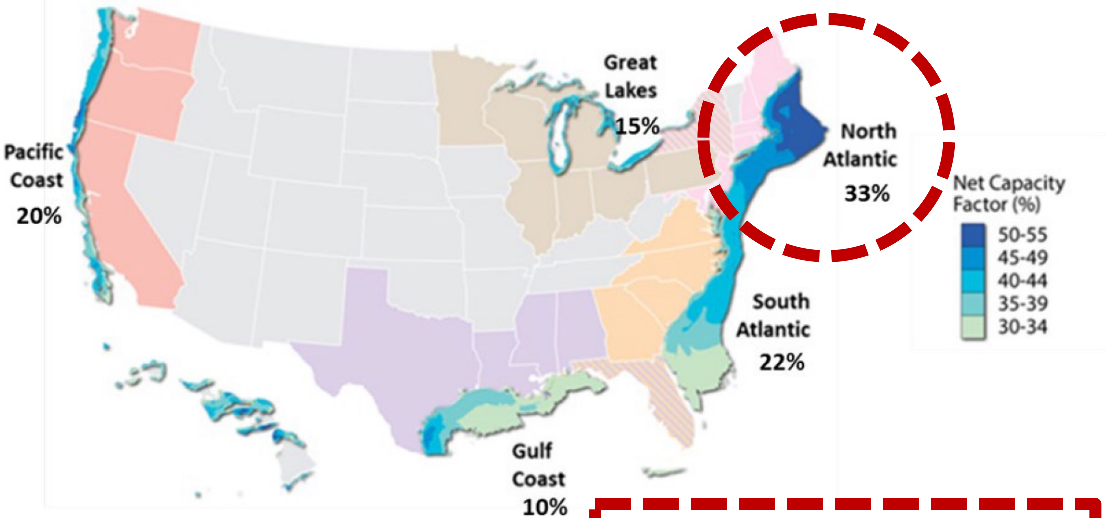
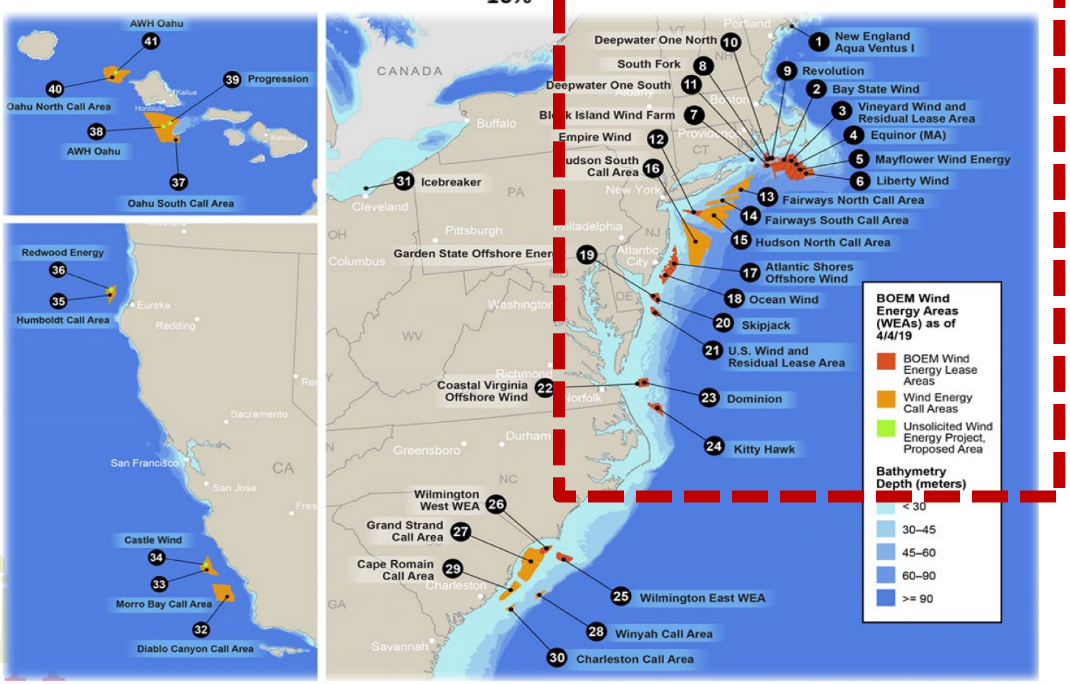
Motivation: The Rise of the U.S. Offshore Wind Energy Sector – Great Promise Ahead





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)

Source: National Offshore Wind Research & Development Consortium: Research and Development Roadmap Version 2.0, 2019

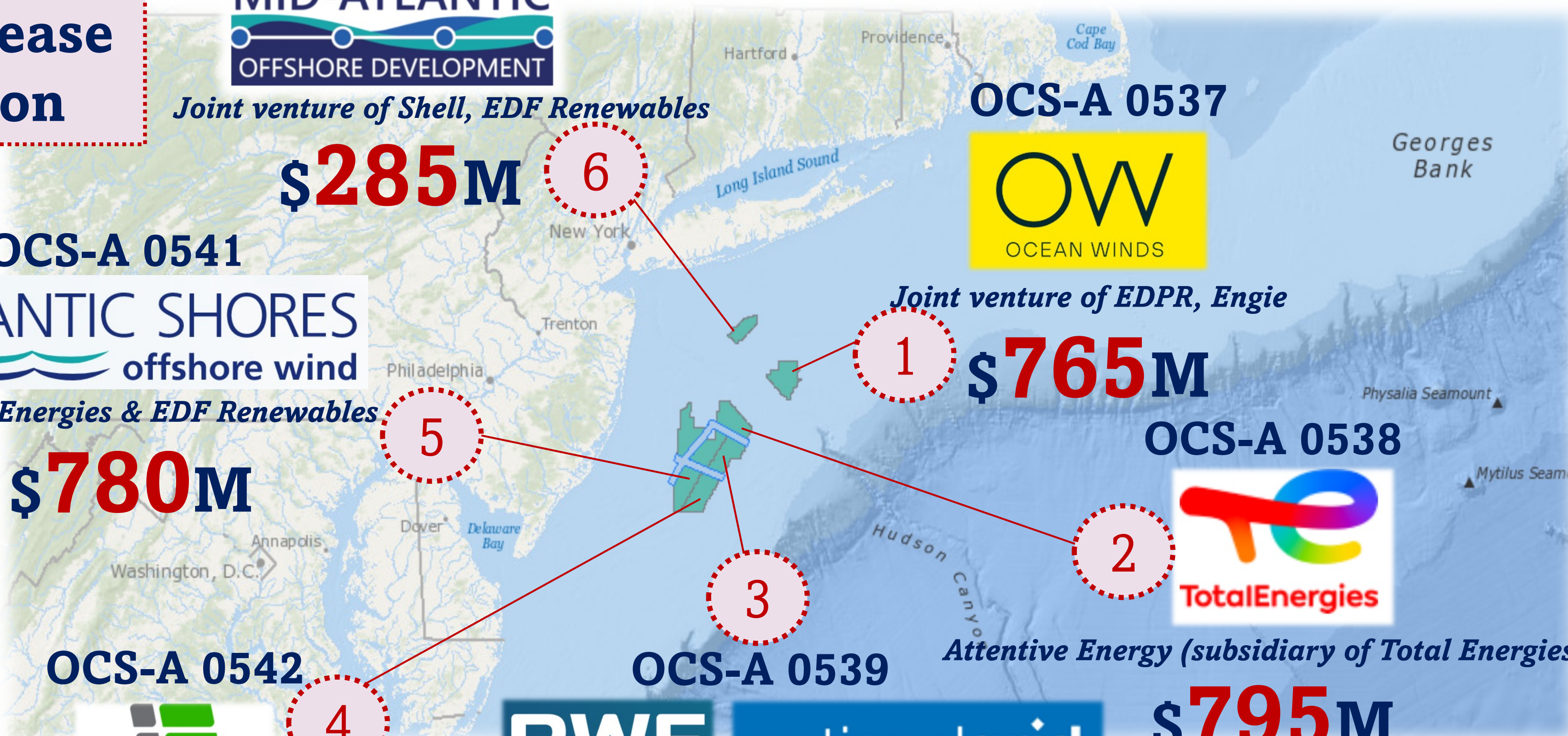
Motivation: The Rise of the U.S. Offshore Wind Energy Sector – Great Promise Ahead

The U.S. Mid/North Atlantic

The largest and first contributor to the U.S OSW goal

Source: Bureau of Ocean Energy Management – February 2022

$4.21B
Total Lease Auction



OCS-A 0544
MID-ATLANTIC OFFSHORE DEVELOPMENT
Joint venture of Shell, EDF Renewables
$285M

OCS-A 0537
OW OCEAN WINDS
Joint venture of EDPR, Engie
$765M

OCS-A 0541
ATLANTIC SHORES offshore wind
Shell New Energies & EDF Renewables
$780M

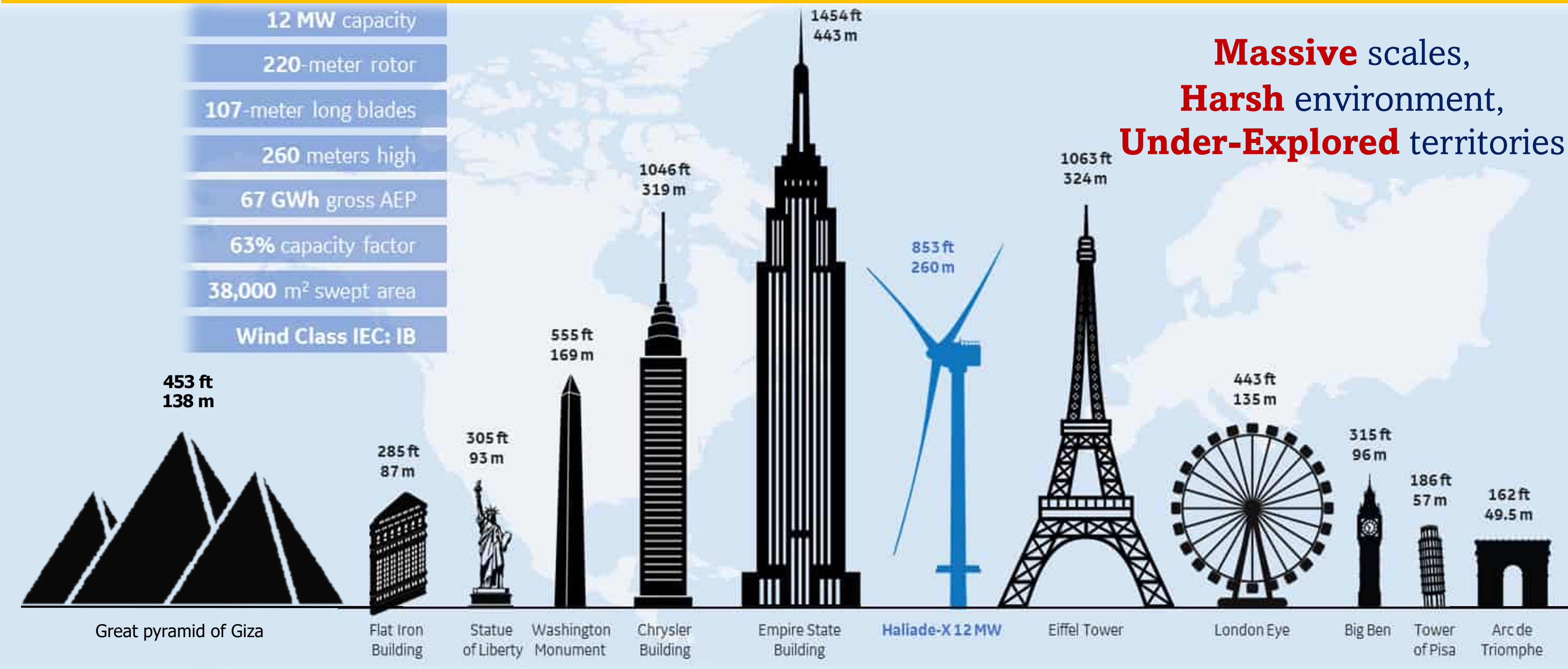
OCS-A 0538
TotalEnergies
Attentive Energy (subsidiary of Total Energies)
$795M

OCS-A 0542
InventivEnergy
$645M

OCS-A 0539
RWE nationalgrid
Bight Holding LLC (Joint venture of EWE & NE)
$1.1B

RIA Renewables & Industrial Analytics

Motivation: The Rise of the U.S. Offshore Wind Energy Sector – Great Promise Ahead



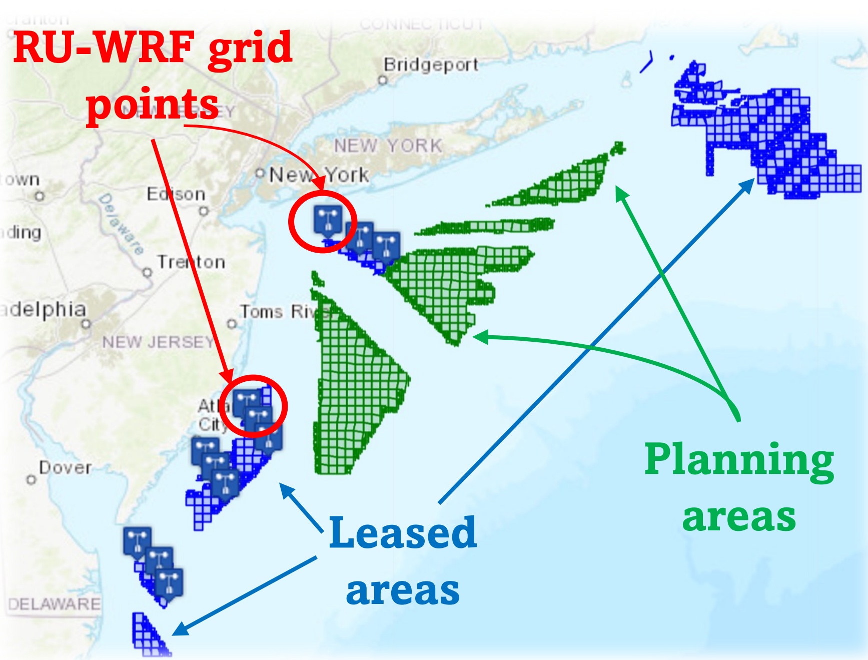
Massive scales,
Harsh environment,
Under-Explored territories

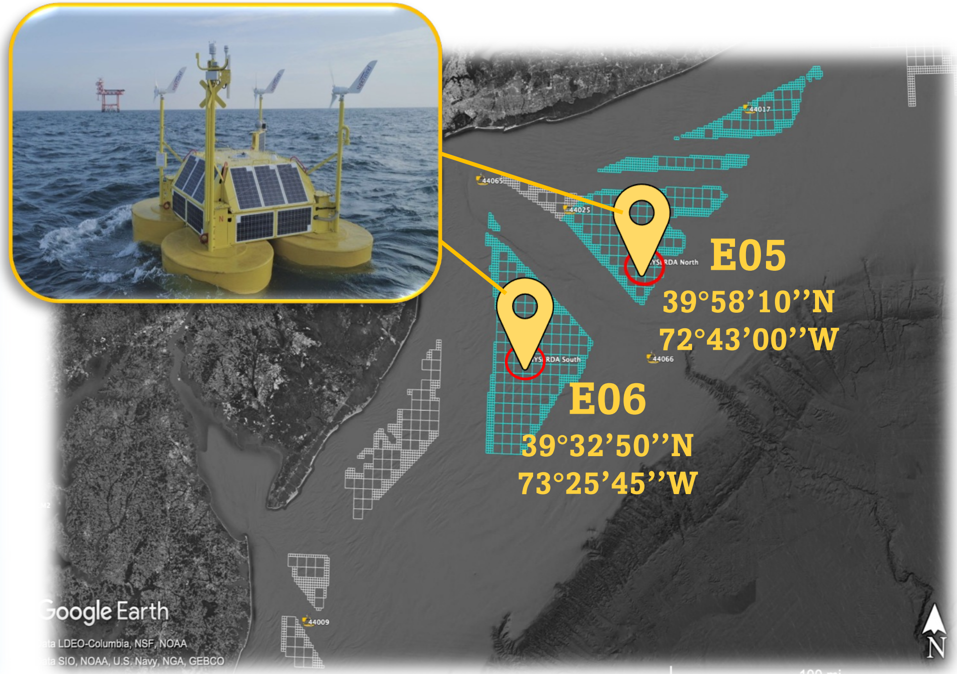
Goal: Tailored **Analytics (i.e., DS/OR)** to minimize the uncertainties in operating ultra-scale offshore wind farms.

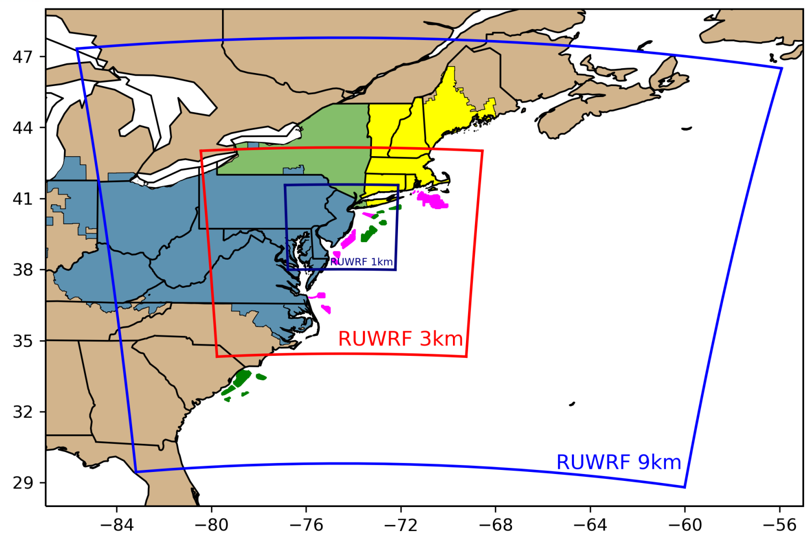
Case #1: Analytics for Offshore Wind Energy Forecasting
Case #2: Analytics for Offshore Wind Operations & Maintenance

Rutgers' tailored version of WRF for the U.S. Mid- & North Atlantic 1

10-min observations from two NYSERDA buoys in the NY/NJ Bight 2







Existing Technology: RU-WRF

- Developed by RUCOOL 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

$$F(\mathbf{s}_i, t) = \boxed{\mu(\underbrace{\mathbf{s}_i, t; \boldsymbol{\theta}^{\mu}}_{\text{Meso-scale}})} + \eta(\underbrace{\mathbf{s}_i, t; \boldsymbol{\theta}^{\eta}}_{\text{Sub-meso-scale}})$$

Forecast Variable
(with transformations)

Meso-scale
Low-frequency, coarser-scale variations

Sub-meso-scale
High-frequency, finer-scale variation

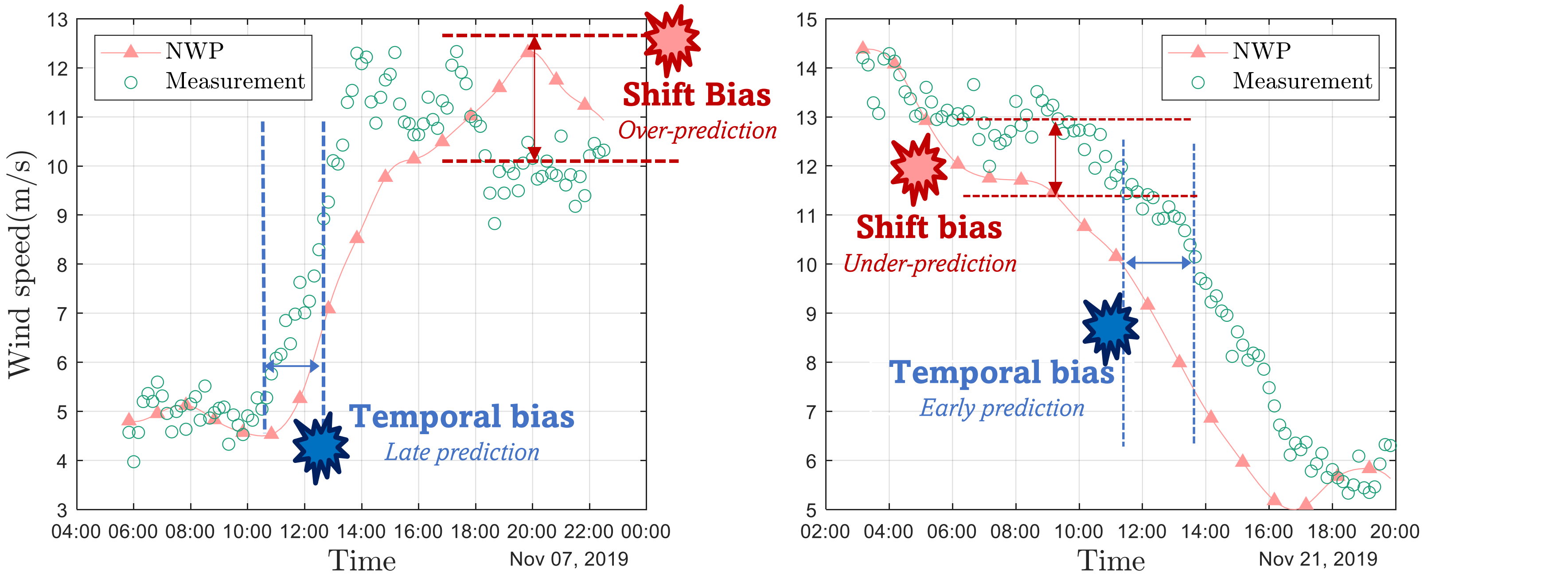
Numerical Weather Predictions are most useful here…

Machine Learning is most useful here…

[1]More about NWP biases in forecasting: Sweeney et al. (2020)

Modeling $\mu(\mathrm{s}, t; \boldsymbol{\theta}^{\boldsymbol{\mu}})$

NWP biases when downscaling to higher resolutions[1]



Multi-type biases found:

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

$\mu(\mathbf{s}, t; \boldsymbol{\theta}^{\boldsymbol{\mu}})$ 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)

$$\mu(\mathbf{s}, t) = \overbrace{\mathbf{a}^T \tilde{\mathbf{Y}}^{\ell}(\mathbf{s}, t) + \mathbf{b}^T \tilde{\mathbf{G}}(\mathbf{s}, t)}^{\text{Additive Bias}} + \overbrace{\left(\mathbf{c}^T \tilde{\mathbf{G}}(\mathbf{s}, t)\right)}^{\text{Multiplicative Bias}} \tilde{Y}(\mathbf{s}, t)$$

Bias-related Features

Numerical Weather Predictions

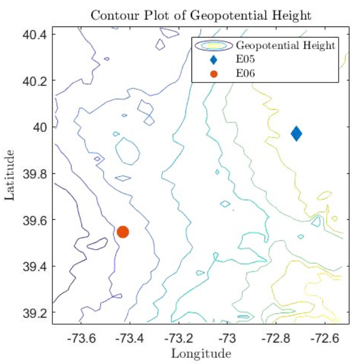
Goal is to select $\tilde{\mathbf{Y}}^{\ell}(\mathbf{s}, t)$ and $\tilde{\mathbf{G}}(\mathbf{s}, t)$ so that they comprise features that are both meteorologically relevant & statistically significant.

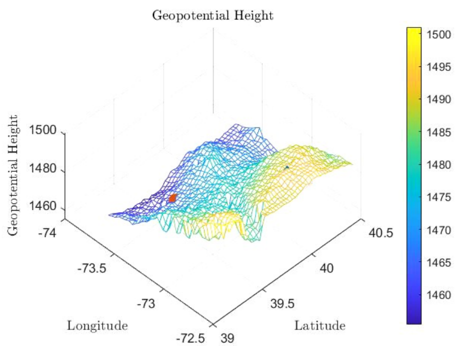
We postulate the use of three sets of features, $\mathbf{g} = \{\mathbf{g}^e, \mathbf{g}^{\ell}, \mathbf{g}^c\}$

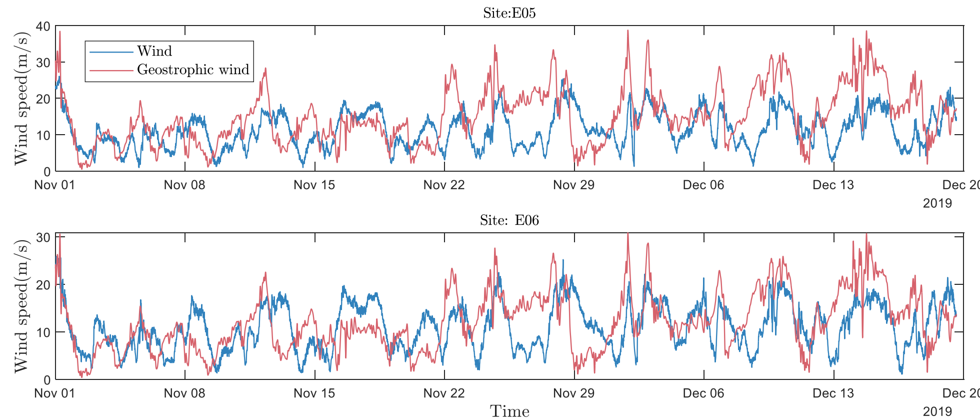
- $\mathbf{g}^e$: Exogeneous features (pressure, surface temperature, relative humidity, wind gust)
- $\mathbf{g}^{\ell}$: Future & lagged values of NWPs → temporal bias correction
- $\mathbf{g}^c$: Physically Motivated Features

Examples of New Constructed features g^c

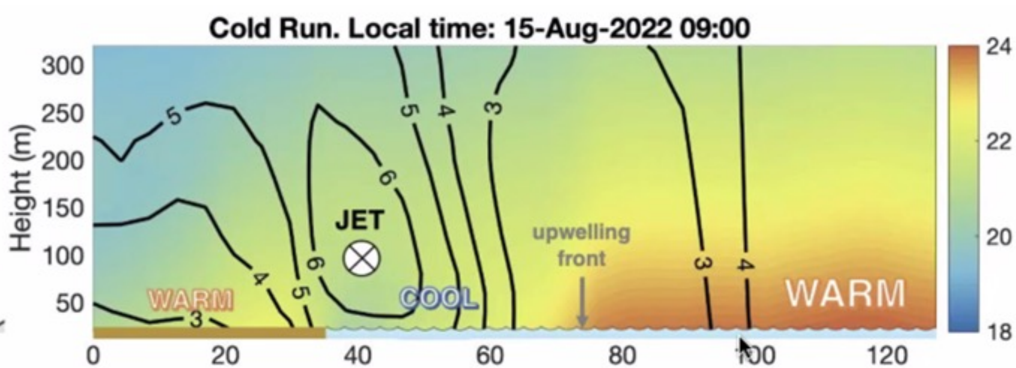
1. Geostrophic wind[1]

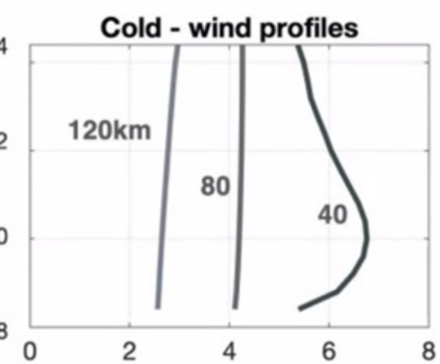






2. Thermal & Pressure Gradients





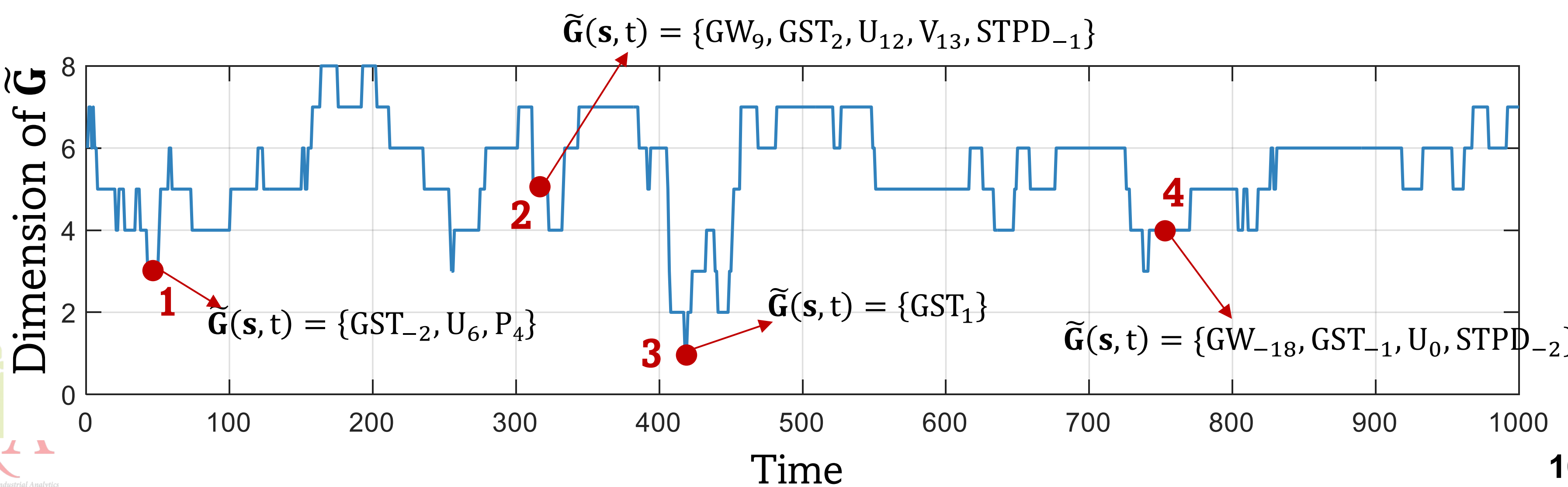
Modeling of $\mu(\mathbf{s}_i, t; \boldsymbol{\theta}^{\boldsymbol{\mu}})$

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!



Back to AIRU-WRF:

$$F(\mathbf{s}_i, t) = \underbrace{\mu(\mathbf{s}_i, t; \boldsymbol{\theta}^{\boldsymbol{\mu}})}_{\text{Meso-scale}} + \boxed{\underbrace{\eta(\mathbf{s}_i, t; \boldsymbol{\theta}^{\boldsymbol{\eta}})}_{\text{Sub-meso-scale}}}$$

Forecast Variable
(with transformations)

Meso-scale
Low-frequency, coarser-scale variations

Sub-meso-scale
High-frequency, finer-scale variation

Modeling of $\eta(\mathbf{s}_i, t; \boldsymbol{\theta}^{\eta})$

- Assume data has been de-trended, i.e., we have:

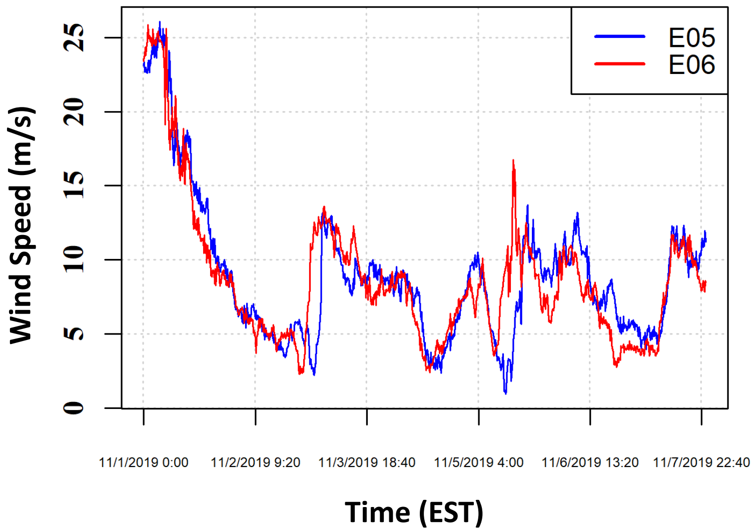
$$Z(\mathbf{s}, t) = Y(\mathbf{s}, t) - \mu(\mathbf{s}, t)$$

- We model $z(\mathbf{s}, t)$ as a spatio-temporal **Gaussian Process** (GP):

$$Z(\mathbf{s}, t) \sim \mathcal{GP}\Big(m(\mathbf{s}, t), C(\mathbf{u}, w)\Big)$$

GP mean function

GP covariance function (Kernel)



- **Covariance functions** (Kernels):

$$C(\mathbf{u}, w) = cov\{Z(\mathbf{s}_i, t_j), Z(\mathbf{s}_{i'}, t_{j'})\}$$

Spatial Lag

$\mathbf{u} = ||\mathbf{s}_i - \mathbf{s}_{i'}||$

Temporal Lag

$w = |t_j - t_{j'}|$

$\boxed{\text{But, how to select } C(\mathbf{u}, w)}$

Modeling of $\eta(\mathbf{s}_i, t; \boldsymbol{\theta}^{\eta})$

[1]More about spatio-temporal asymmetry
M. Stein, JASA (2005)

Prevalent approach to modeling spatio-temporal correlations:

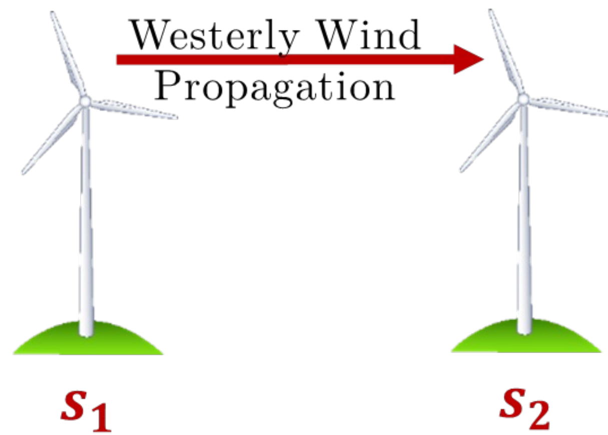
$$C(\mathbf{u}, w) = C^s(\mathbf{u}) \times C^t(w)$$

Spatial kernel — $C^s(\mathbf{u})$

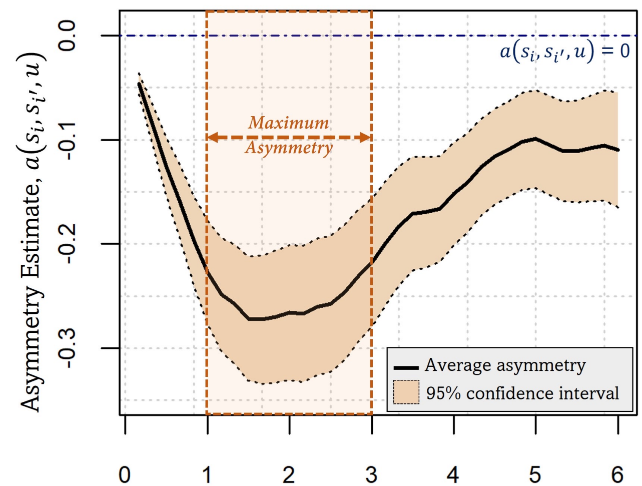
Temporal kernel — $C^t(w)$

Wind Advection and Its impact on Spatio-Temporal Correlations[1]:

$$cov\{Z(\mathbf{s}_i, t_j), Z(\mathbf{s}_{i'}, t_j + \Delta t)\}$$
$$\gg$$
$$cov\{Z(\mathbf{s}_i, t_j + \Delta t), Z(\mathbf{s}_{i'}, t_j)\}$$



Statistical test based on space-time variograms rejects the hypothesis of symmetry in the local wind field, especially in the ~1-3-hour range



Physically Justifiable Modeling of Spatio-Temporal Correlations:

The Lagrangian reference framework[1,2]

$$C(\mathbf{u}, w) = \mathbb{E}_{\boldsymbol{\theta}} \tilde{C}(\mathbf{u} - \boldsymbol{\theta} w), \quad \boldsymbol{\theta} \in \mathbb{R}^d$$

Spatial lag ($\mathbf{u}$) **Advection vector** ($\boldsymbol{\theta}$) **Temporal lag** (w)

Back to AIRU-WRF:

$$\underbrace{Y}_{\text{Wind Speed}}(\mathbf{s},t) = \underbrace{\mu(\mathbf{s},t;\boldsymbol{\theta}^{\boldsymbol{\mu}})}_{\text{The Meso-scale}} + \underbrace{\eta(\mathbf{s},t;\boldsymbol{\theta}^{\boldsymbol{\eta}})}_{\text{The Turbine-scale}} + \underbrace{\epsilon(\mathbf{s},t;\boldsymbol{\theta}^{\boldsymbol{\epsilon}})}_{\text{Unexplained Variability}}$$

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

Data Coverage	**6** months (4-month in winter, 2-month in Summer)
Forecast horizon	**6** hours x **10**-min resolution **= 36** forecasting instances/hour
# of locations	**3** locations (E05, E06, ASOW)

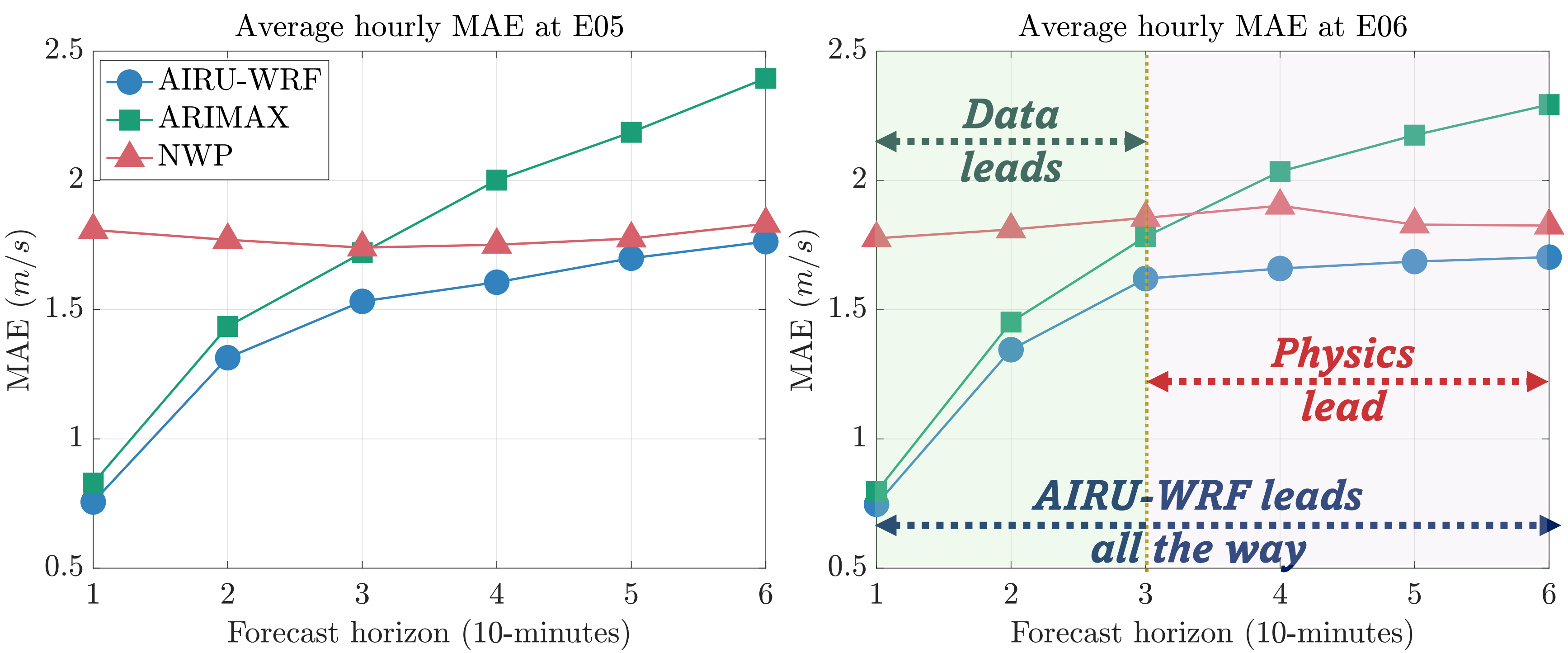
Benchmarks:

- **($\mathfrak{B}_1$) RU-WRF** : Physics-based model tailored to the region of interest.
- **($\mathfrak{B}_2$) GOP** : Hybrid (statistical-physical) approach
- **($\mathfrak{B}_3$) LSTM** : Time Series Deep Learning model - Purely data-driven
- **($\mathfrak{B}_4$) PER** : Persistence forecast – widely used as a benchmark
- **($\mathfrak{B}_5$) ARIMA-X** : Autoregressive time series model – statistical approach

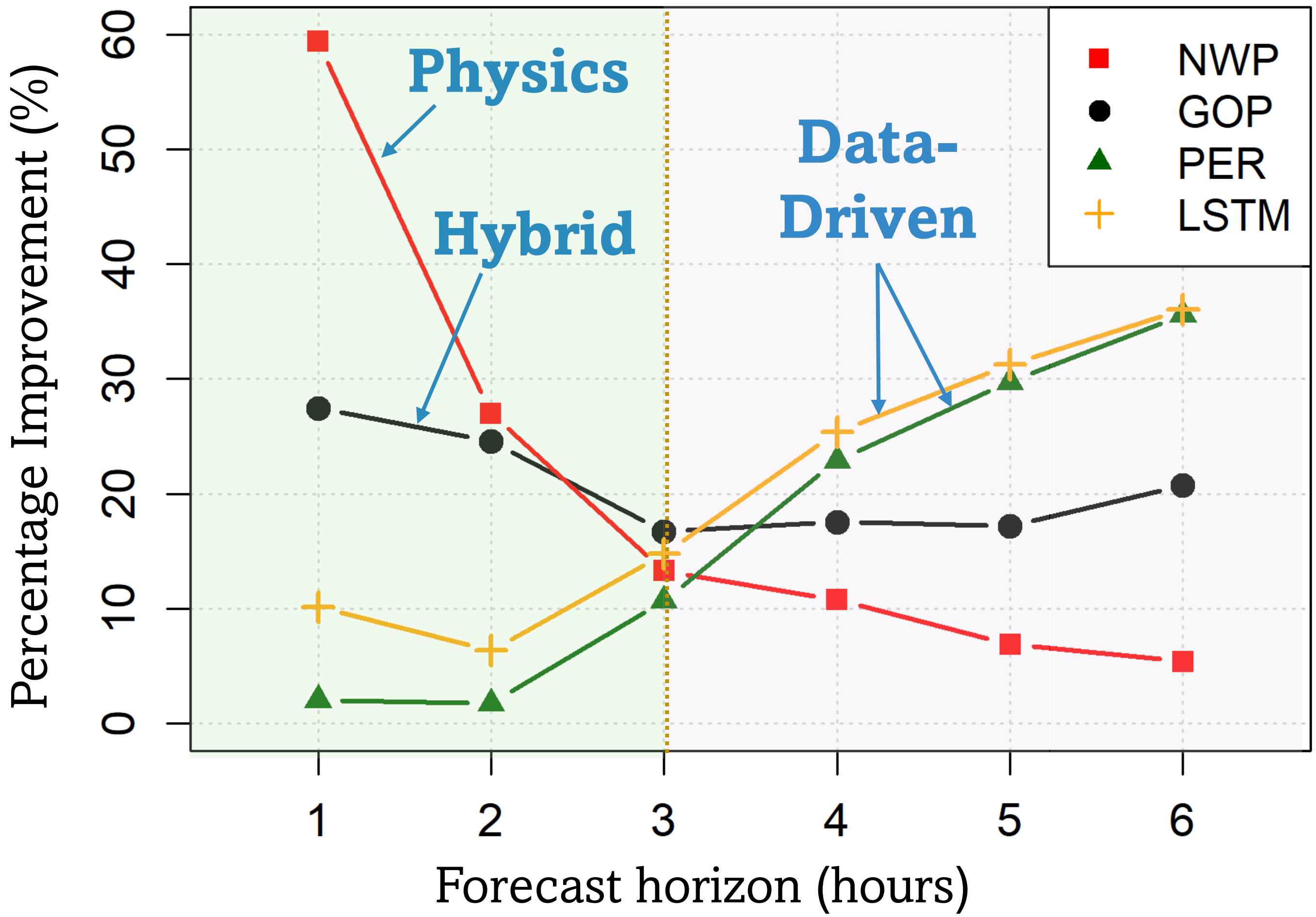
Evaluations:

- **($\mathfrak{E}_1$) Point forecasts** : MAE & RMSE
- **($\mathfrak{E}_2$) Probabilistic forecasts** : CRPS

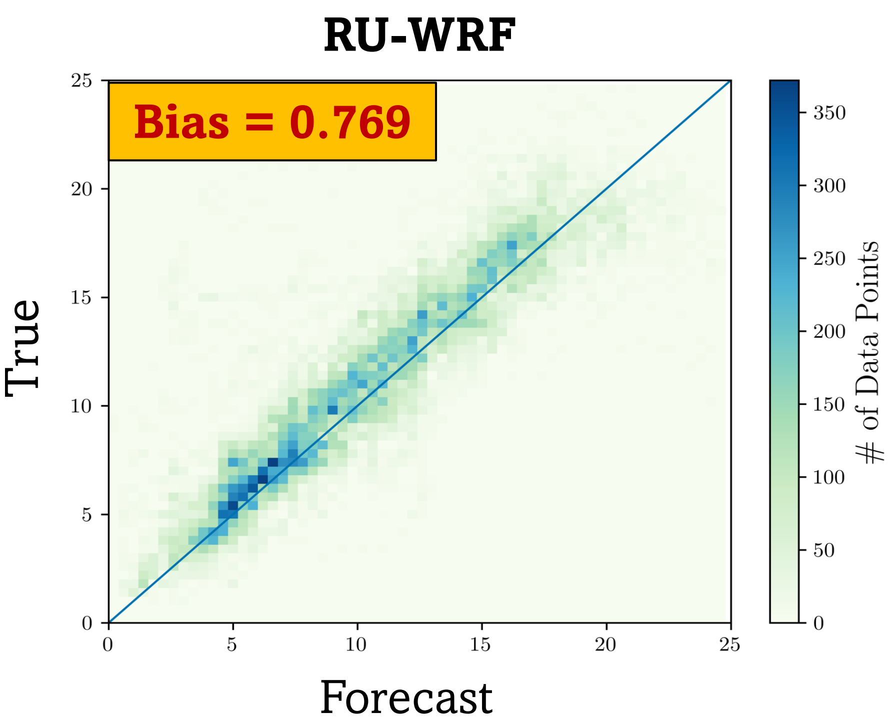
Result #1: Filling the ML-Physics Chasm

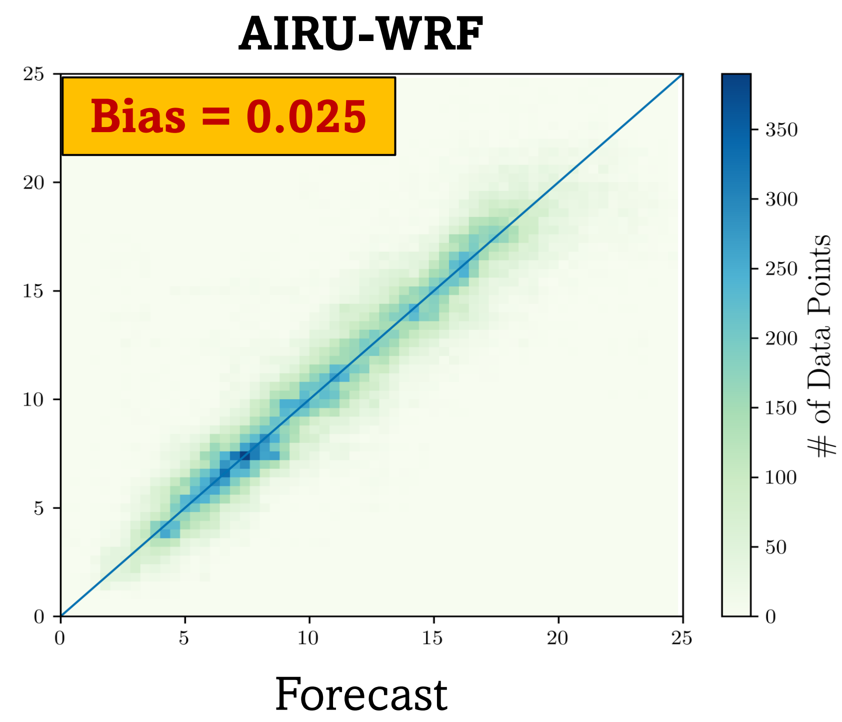


Result #2: Filling the ML-Physics Chasm



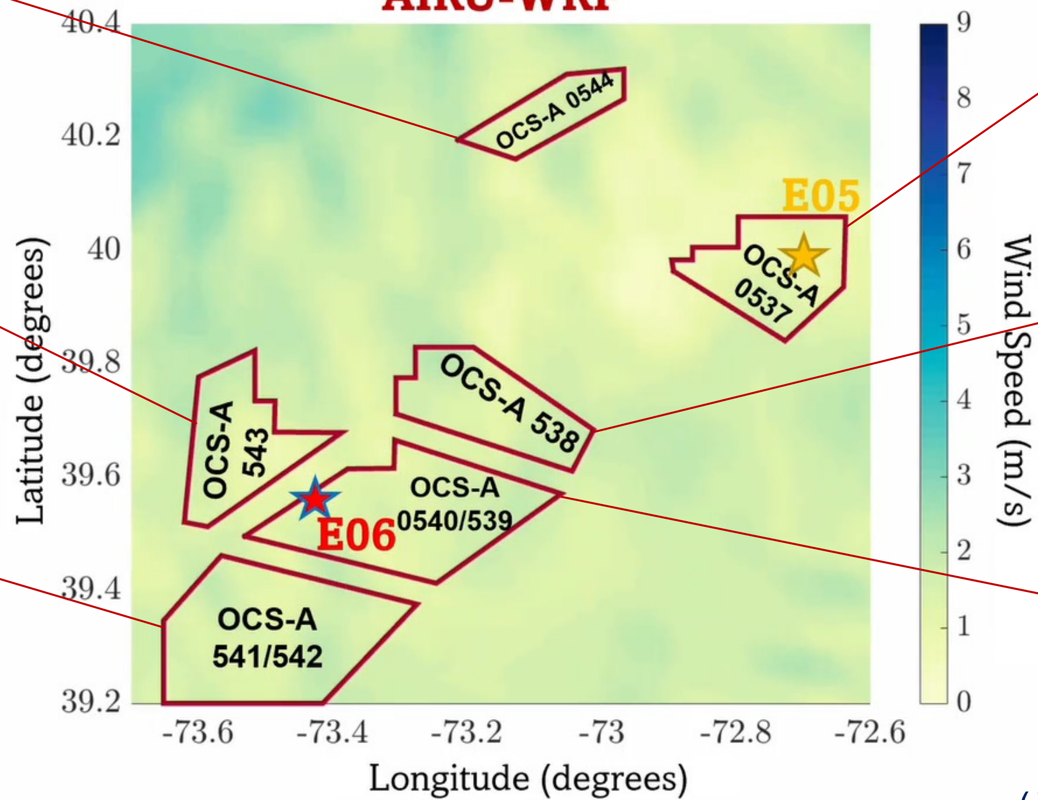
Result #3:
Filling the ML-Physics Chasm





Result #4: Filling the ML-Physics Chasm

Wind Field Forecast Maps via AIRU-WRF



MID-ATLANTIC OFFSHORE DEVELOPMENT

Joint venture of Shell & EDF Renewables

ATLANTIC SHORES offshore wind

Shell New Energies & EDF Renewables

InventivEnergy

InventivEnergy, LLC

OW OCEAN WINDS

Joint venture of EDPR & Engie

TotalEnergies

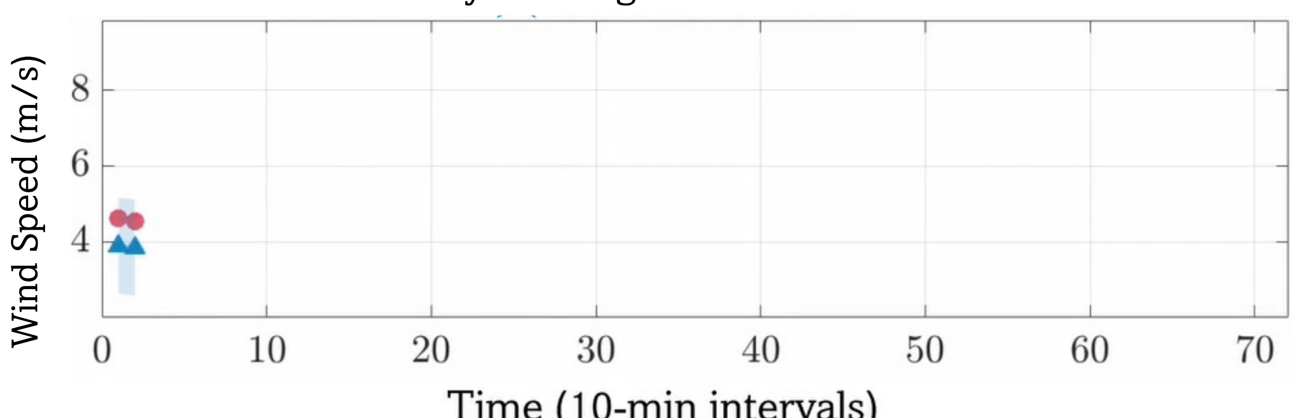
Attentive Energy (sub. of Total Energies)

RWE

nationalgrid

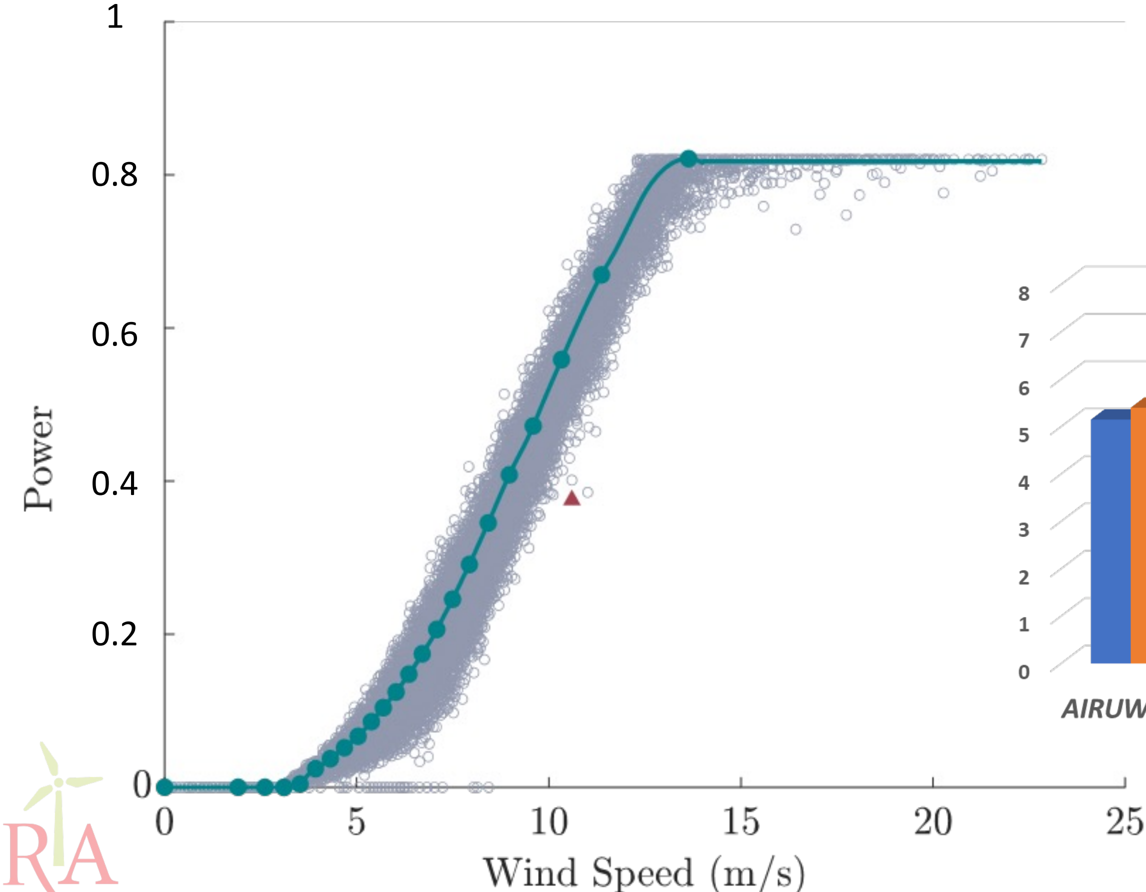
Bight Holding LLC (Joint venture of EWE & NE)

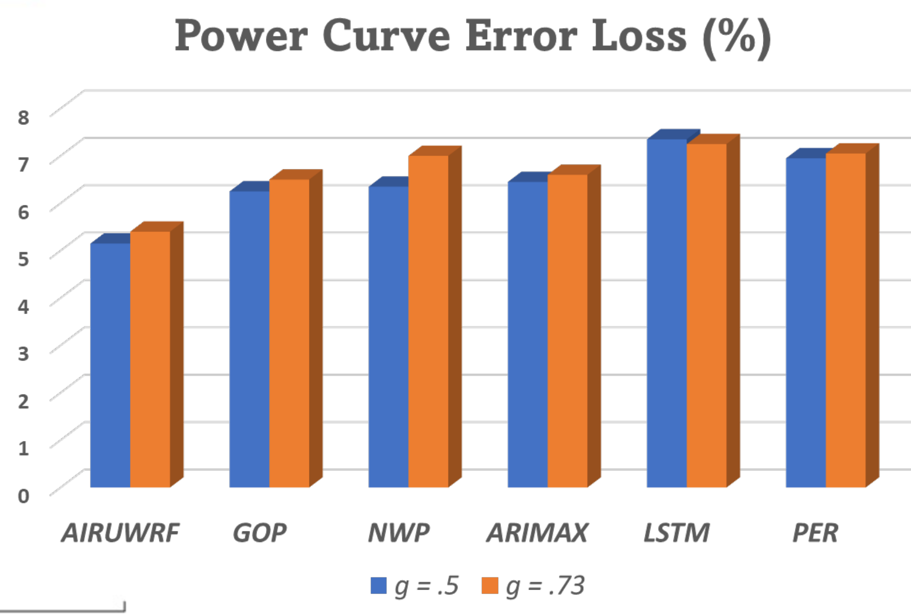
Currently showing forecasts at ★ **E06**



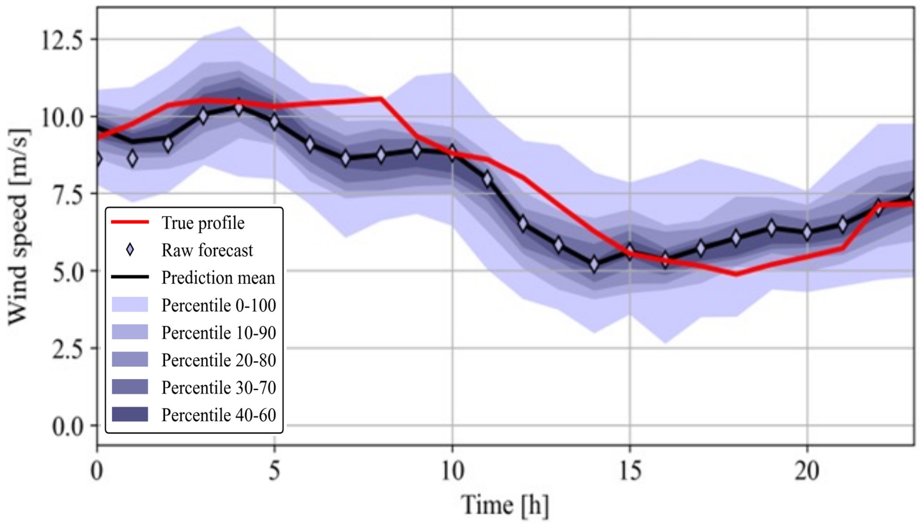
Result #5: From Wind Speed to Wind Power

- ✓ Statistical power curves from an operational wind farm (Ding, 2022)
- ✓ Evaluation using Power Curve Error Loss (Hering and Genton, 2010).

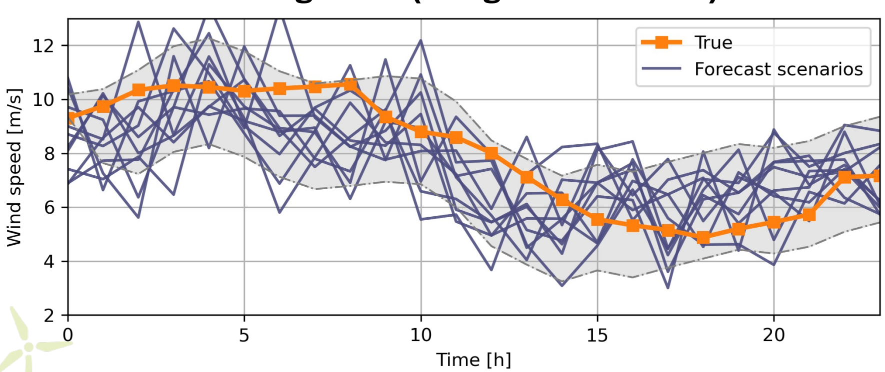




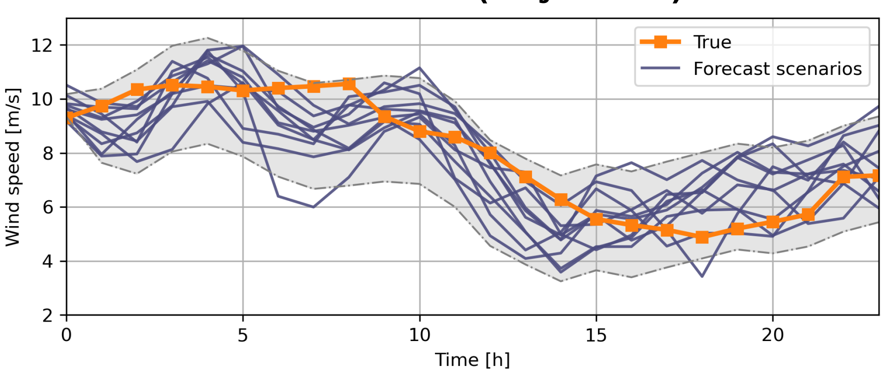
Result #6: Scenarios/Trajectories for Decision-Making Under Uncertainty



Correlations ignored (Marginal Densities)



Correlations considered (Trajectories)



Operations & Maintenance for Offshore Wind Farms

($\mathbb{C}_1$) High maintenance requirements

Transportation costs account for **30-70**% of offshore wind maintenance expenditures.

($\mathbb{C}_2$) Limited accessibility

56% of inaccessibility, with up to **6** days of consecutive in-access.

($\mathbb{C}_3$) 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"

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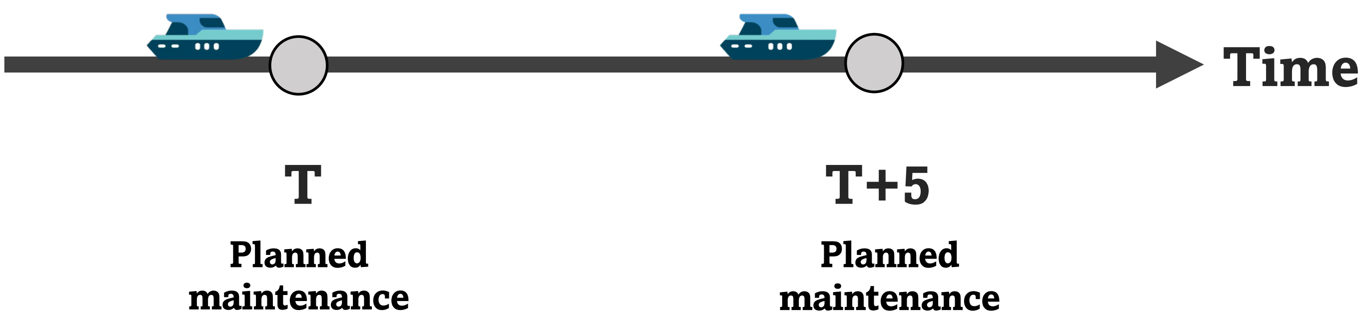
(1) Transportation-Based Opportunities

Grouping maintenance to maximize the utilization of transportation/crew resources

Total vessel rentals: 2



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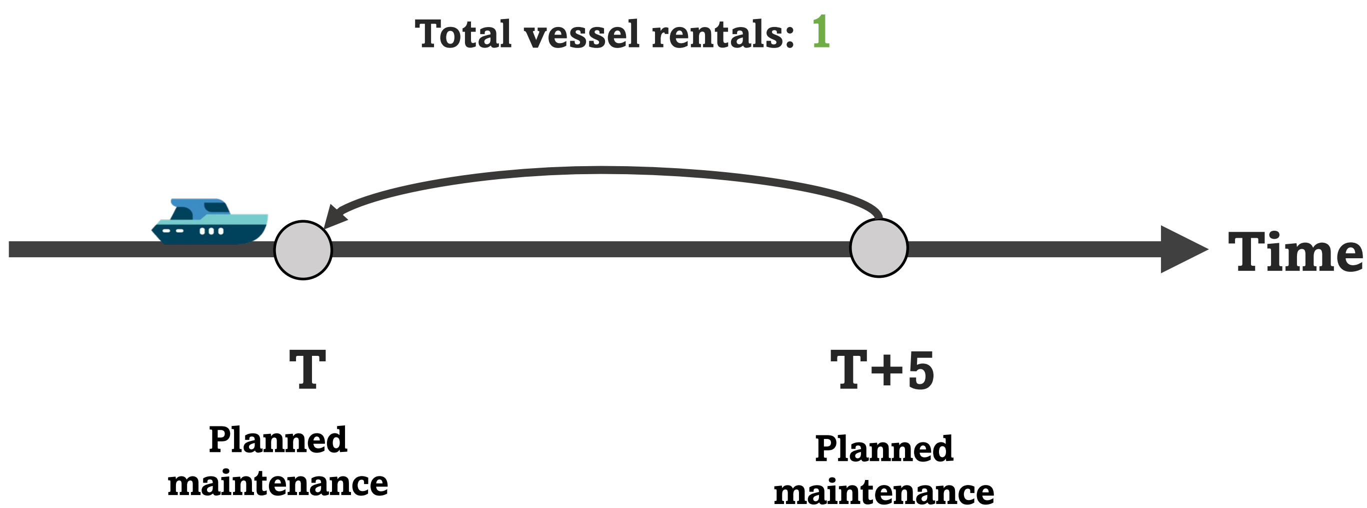
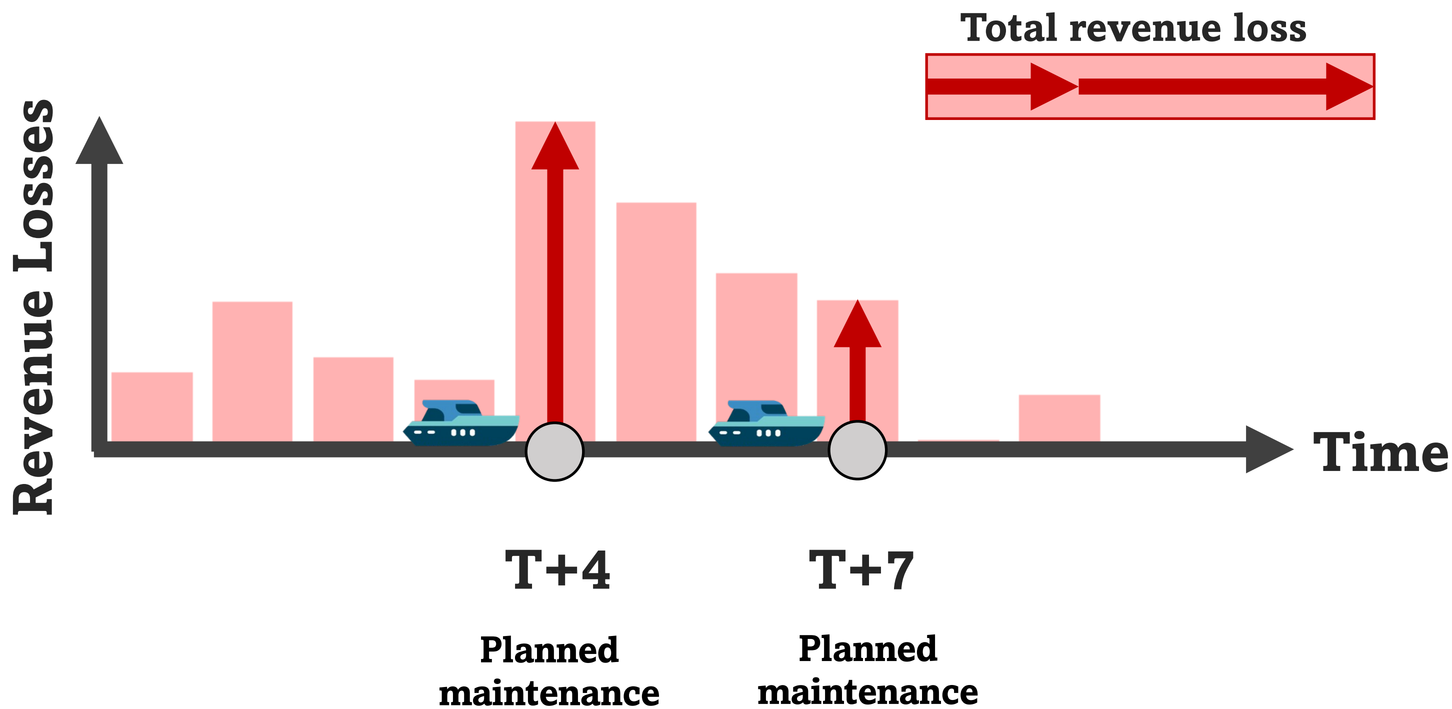


(2) Revenue-Based Opportunities

Grouping maintenance at times of minimal revenue losses



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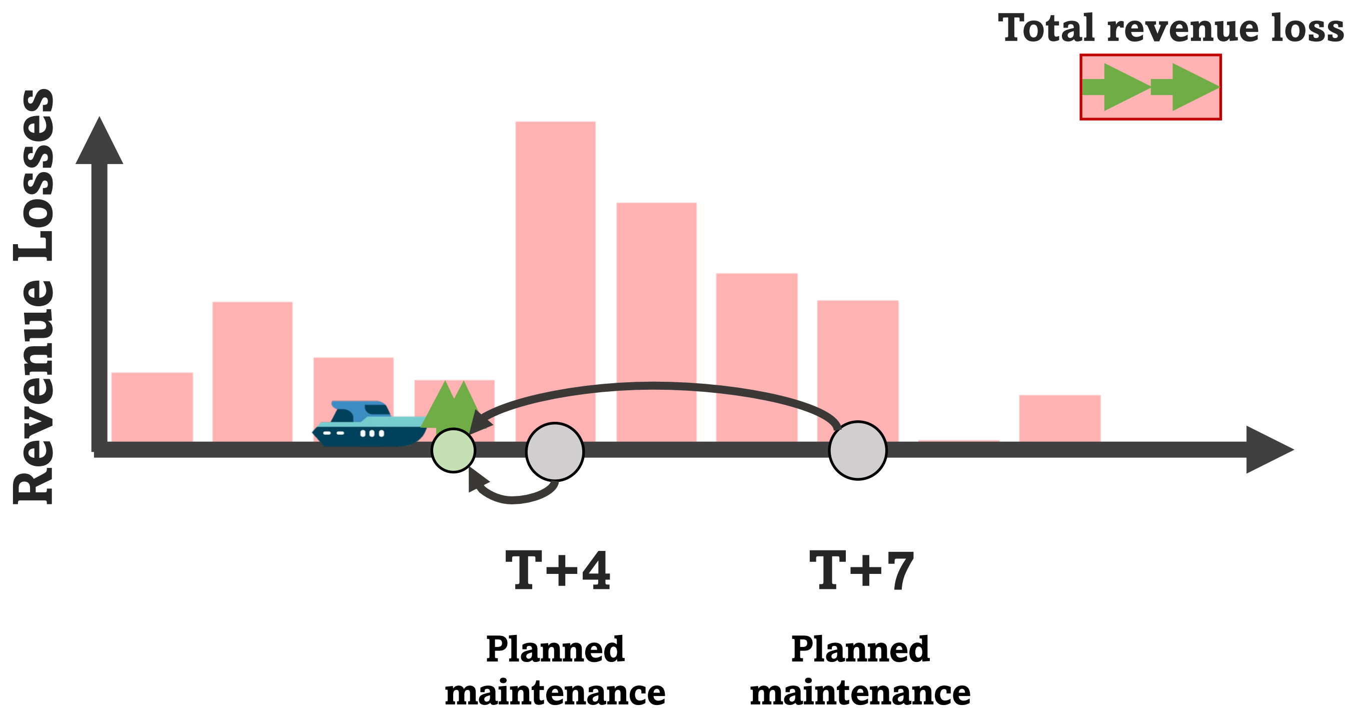
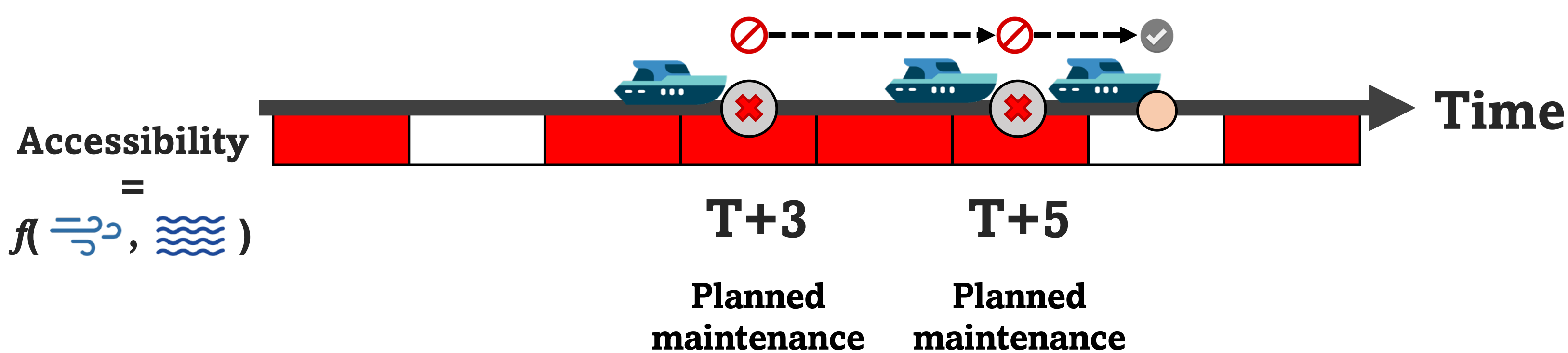


(3) Access-Based Opportunities

Grouping Maintenance at times of "open" access

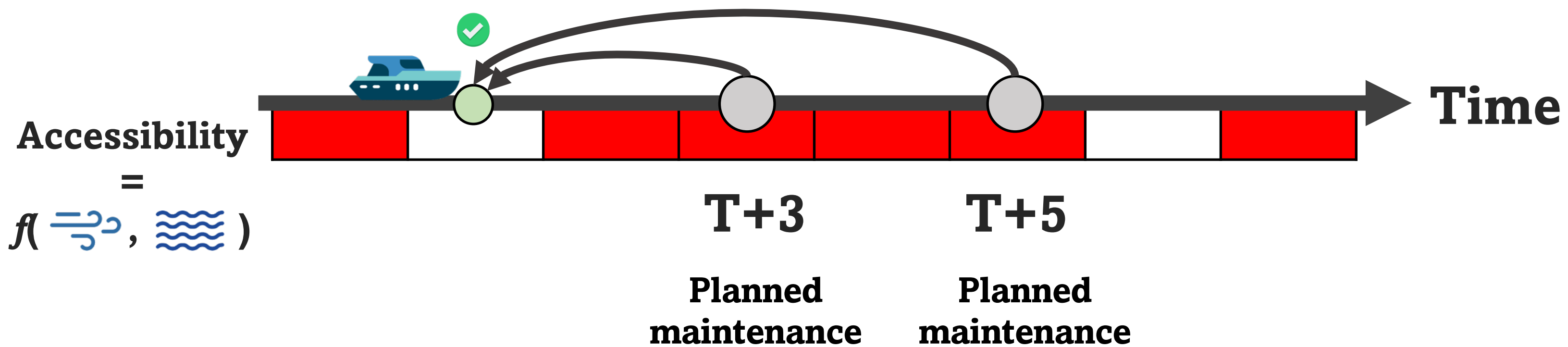
Vessel rentals: **3**
Risk of failure: **high**



(3) Access-Based Opportunities

Grouping Maintenance at times of "open" access

Vessel rentals: 1
Risk of failure: low



P. Papadopoulos, D. Coit, A. Aziz Ezzat, *Seizing Opportunity: Maintenance Optimization in Offshore Wind Farms Considering Accessibility, Production, and Crew Dispatch*, **IEEE Trans. on Sustainable Energy**, 2021.

$$\max \ \left\{ \overbrace{s + \sum_{d\in\mathcal{D}} l_d}^{\text{Total profit}} \right\}$$

$$s = \sum_{i\in\mathcal{I}, t\in\mathcal{T}} [\overbrace{\Pi_t \cdot p_{t,i}}^{\text{Hourly revenue}} - \overbrace{\mathrm{K}\cdot m_{t,i} - \Phi\cdot n_{t,i}}^{\text{Maintenance costs}} - \overbrace{\Psi\cdot x_{t,i}] - \Omega\cdot v - \mathrm{Q}\cdot q}^{\text{Transportation and Crew costs}}$$

Short-term PM decision var.

Short-term CM decision var.

Long-term PM decision var.

Long-term CM decision var.

$$l_d = \sum_{i\in\mathcal{I}} \left[\underbrace{\Pi_d \cdot p^L_{d,i}}_{\text{Daily revenue}} - \underbrace{\mathrm{K}\cdot m^L_{d,i} - \Phi\cdot n^L_{d,i}}_{\text{Daily Maintenance Costs}} - \underbrace{\Psi\cdot \tau_i(m^L_{d,i} + n^L_{d,i}) \right] - \Omega\cdot v^L_d}_{\text{Daily Transportation and Crew costs}} \quad \forall d\in\mathcal{D}$$

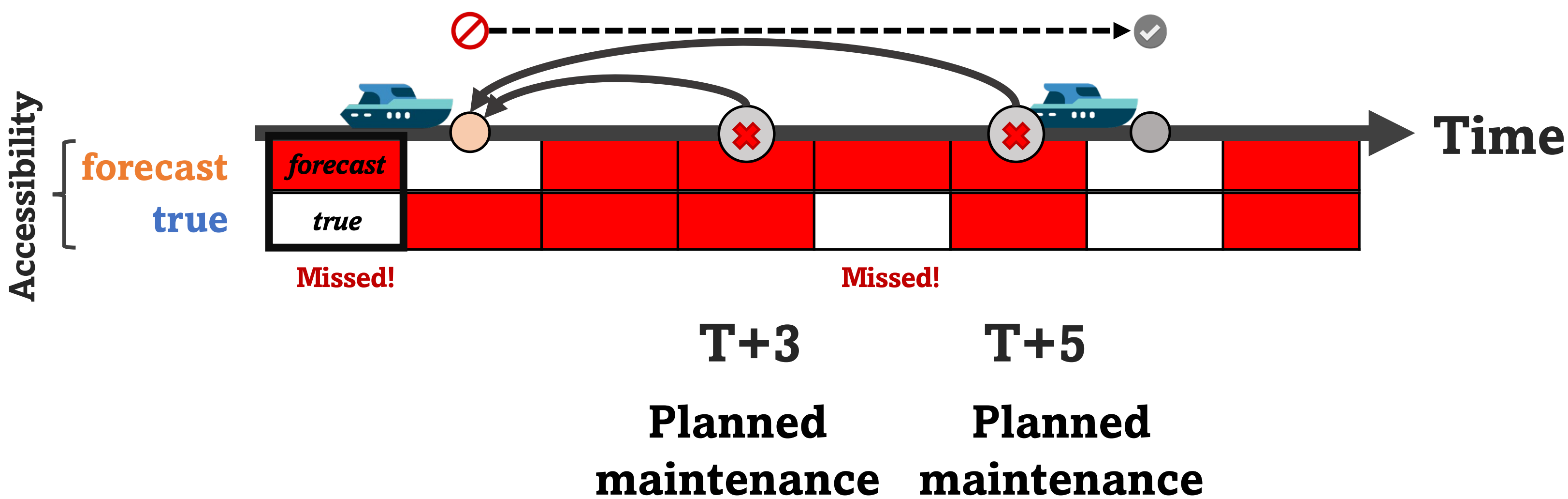
Method	# vessel rentals	vessel utilization (%)	total downtime (h)	production loss (MWh)	# PM actions	# CM actions	total cost ($K)	total cost reduction (%)
HOST	**6.8**	**83.7**	**131.8**	**312.6**	**9.9**	**1.2**	**118.9**	-
BESN	8.0	74.2	136.7	348.9	9.8	1.3	126.4	5.9%
PBOS	9.4	79.9	137.3	331.1	9.7	1.3	128.9	7.8%
TBS	13.3	63.7	156.3	504.0	7.2	3.9	182.4	34.8%
CMS	12.9	81.0	518.8	2624.3	0.0	11.0	412.5	71.2%

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**

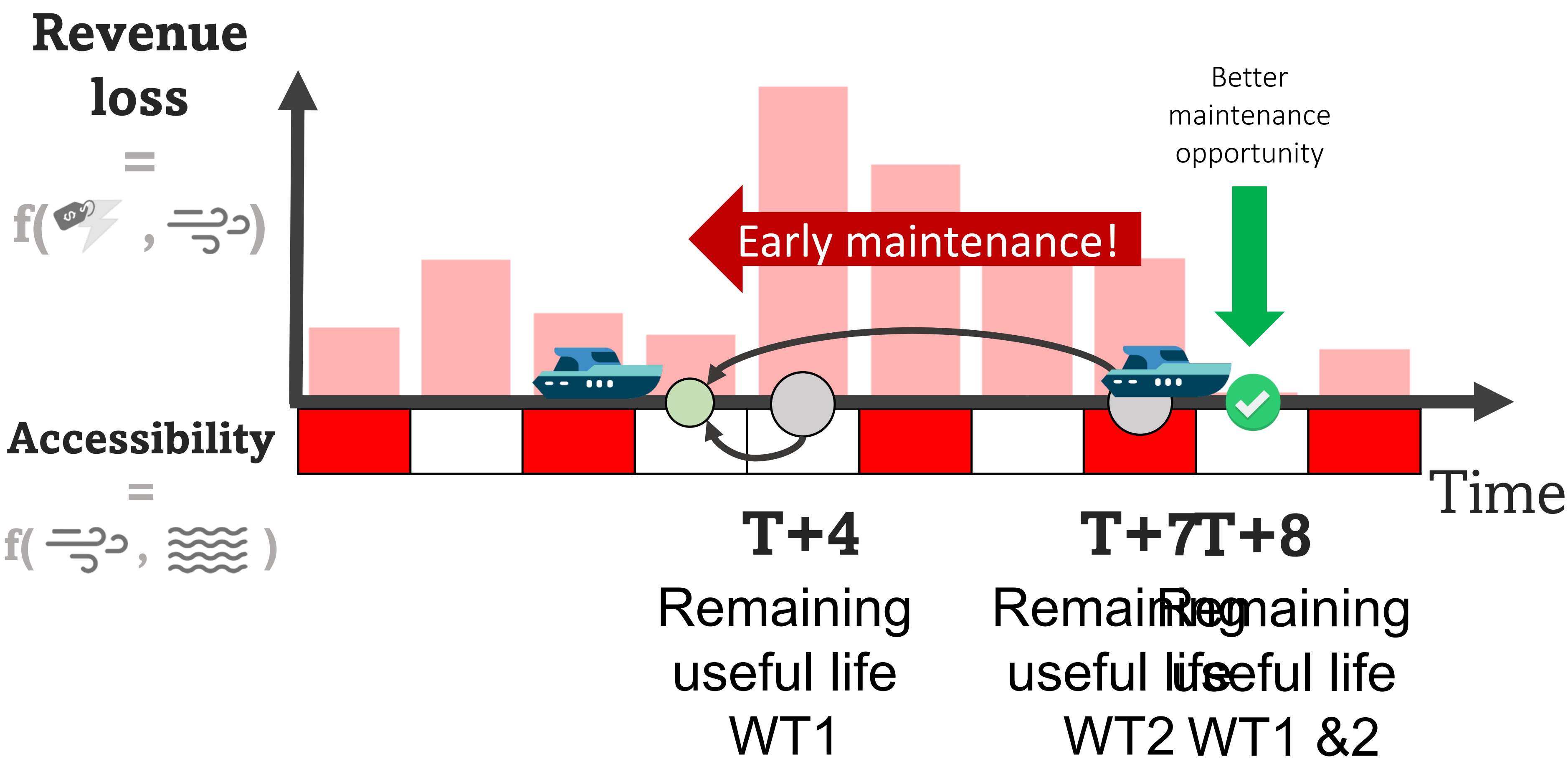


P. Papadopoulos, D. Coit, A. Aziz Ezzat, *STOCHOS: Stochastic Opportunistic Maintenance Scheduling For Offshore Wind Farms*, **IISE Transactions**, 2022.

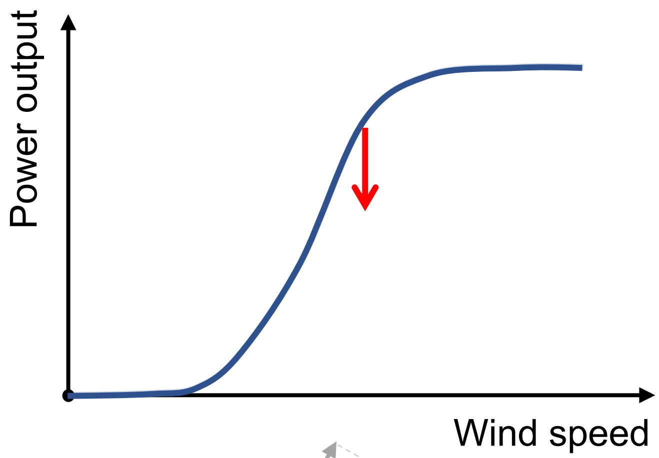
$$\max_{m_{t,i}, m^L_{d,i,s}, r, r^L_{d,s}} \Bigg\{ \overbrace{l^{STH}}^{\text{short-term profit}} + \overbrace{\sum_{d \in \mathcal{D}} l^{LTH}_d}^{\text{long-term profit}} \underbrace{- \frac{1}{N_S} \sum_{s \in \mathcal{S}} \Bigg[\overbrace{\sum_{i \in \mathcal{I}} (\mathrm{U}_s \cdot w_{i,s} + \mathrm{Y}_s \cdot b_{i,s})}^{\text{prolonged interruptions}} + \overbrace{\mathrm{C}_1 \cdot a^x_s + \mathrm{C}_2 \cdot a^q_s}^{\text{spot resource contracting}} \Bigg]}_{\text{stochastic penalty term}} \Bigg\}$$

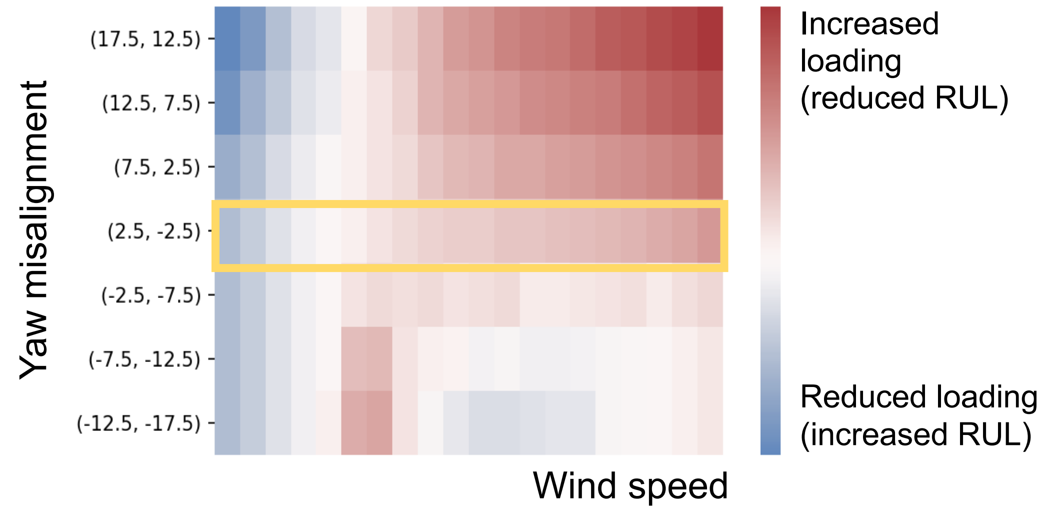
Metric	PK-HOST	STOCHOS	PF-HOST	TBS	CMS
Vessel rentals	2.36	**2.18**	2.26	4.92	6.72
Production loss (MWh)	101.21	**141.05**	154.59	597.68	1037.24
Revenue loss ($K)	5.10	**7.10**	7.83	29.85	51.64
Total PM tasks	5.00	**4.53**	4.48	2.35	0.00
Total CM tasks	0.00	**0.47**	0.52	2.65	5.00
Maintenance interruptions	0.66	**0.43**	0.64	1.23	1.83
Avg. total cost ($K)	38.92	**43.43**	45.00	86.90	127.91
Cost increase from opt ($K)	0.10	**4.60**	6.14	48.07	89.08
Median total cost ($K)	35.86	**39.69**	42.36	84.11	127.16

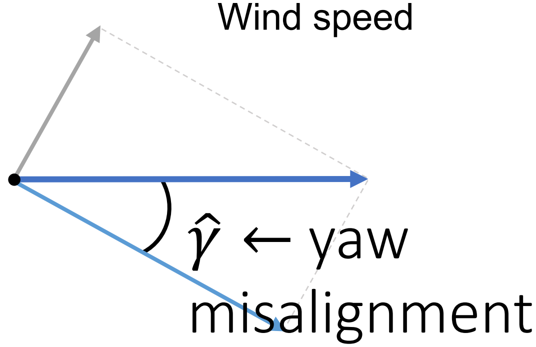
What if we could influence the degradation process of OSW turbines by controlling certain turbine settings?

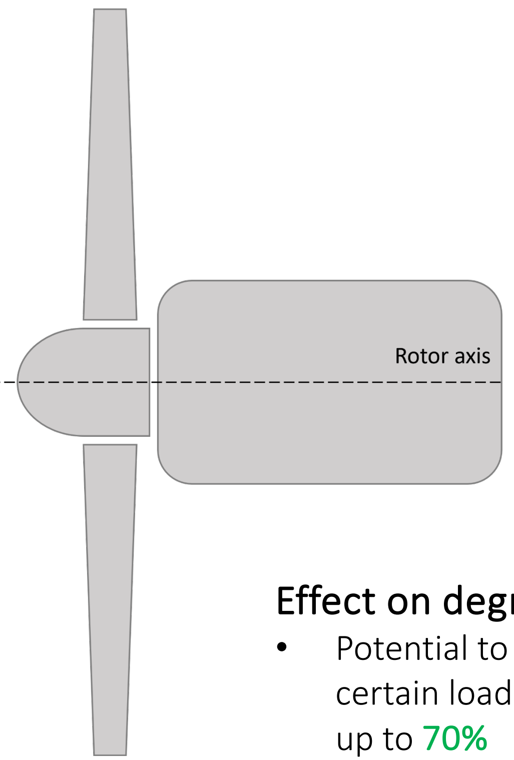


*Trade-off: **alleviate loading** and increase the RUL, at the cost of **reduced power production**, and vice versa*







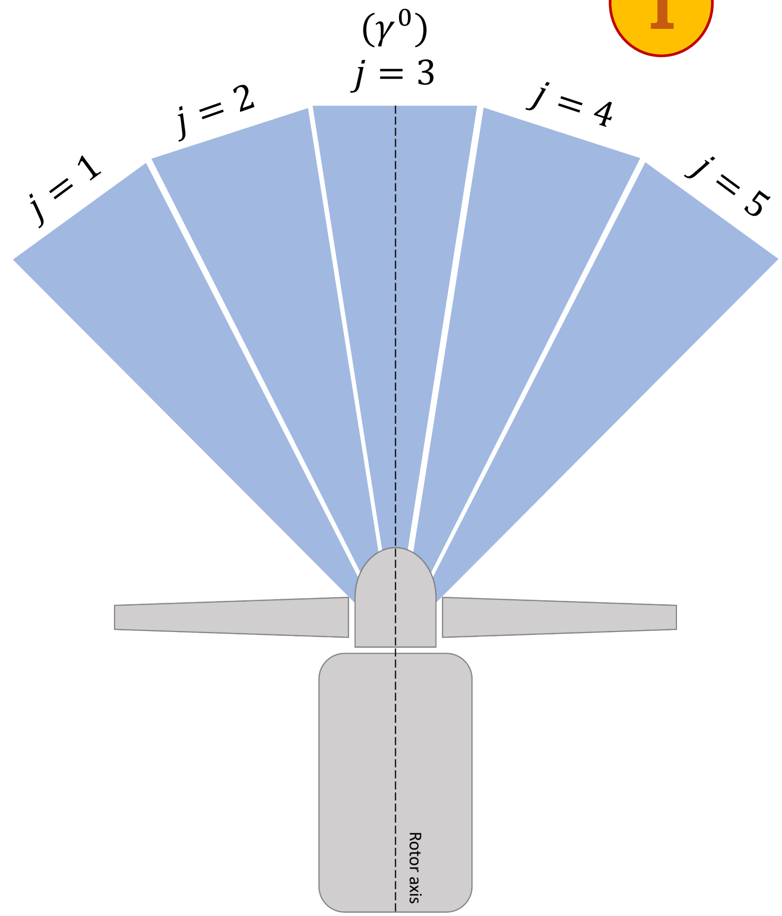


Perfect yaw alignment = 0 yaw misalignment

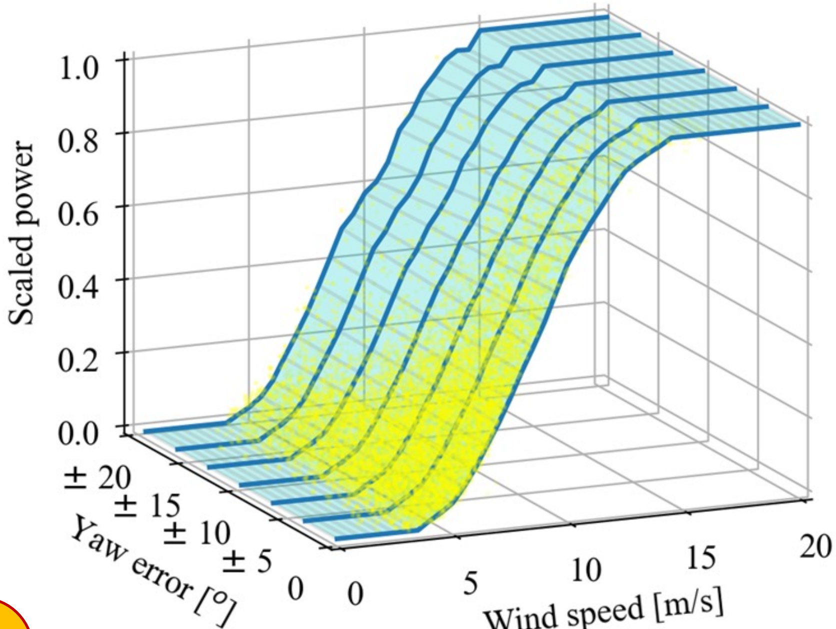
Effect on degradation

- Potential to alleviate certain load variations up to 70%

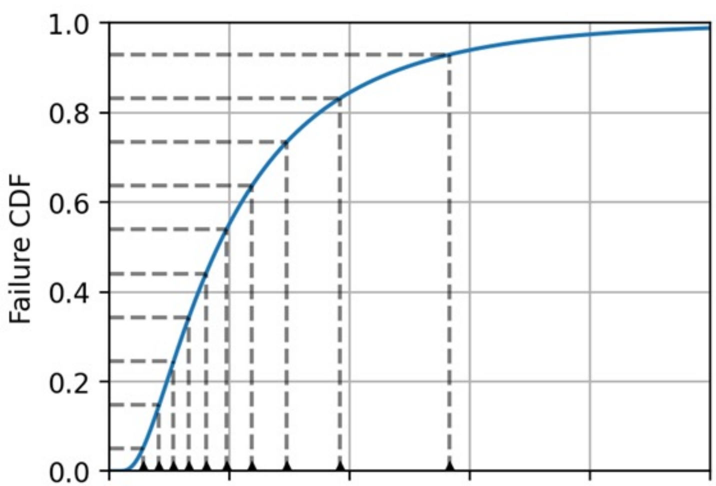
1 Discretizing yaw decisions



2 Yaw-Adjusted Wind Power Curves



3 Yaw-Dependent Degradation Modeling



$$\boxed{\lambda_{i,s}} = \boxed{\lambda^0_{i,s}} + \overbrace{\boxed{\zeta^0_{i,s}} \cdot \sum_{t\in\mathcal{T}} \left(\frac{1}{24} - \sum_{j\in\mathcal{J}} \boxed{\gamma_{t,i,j}} \cdot \boxed{F_{t,i,j,s}}\right)}^{\text{Day-ahead equivalent RUL gain/loss}}$$

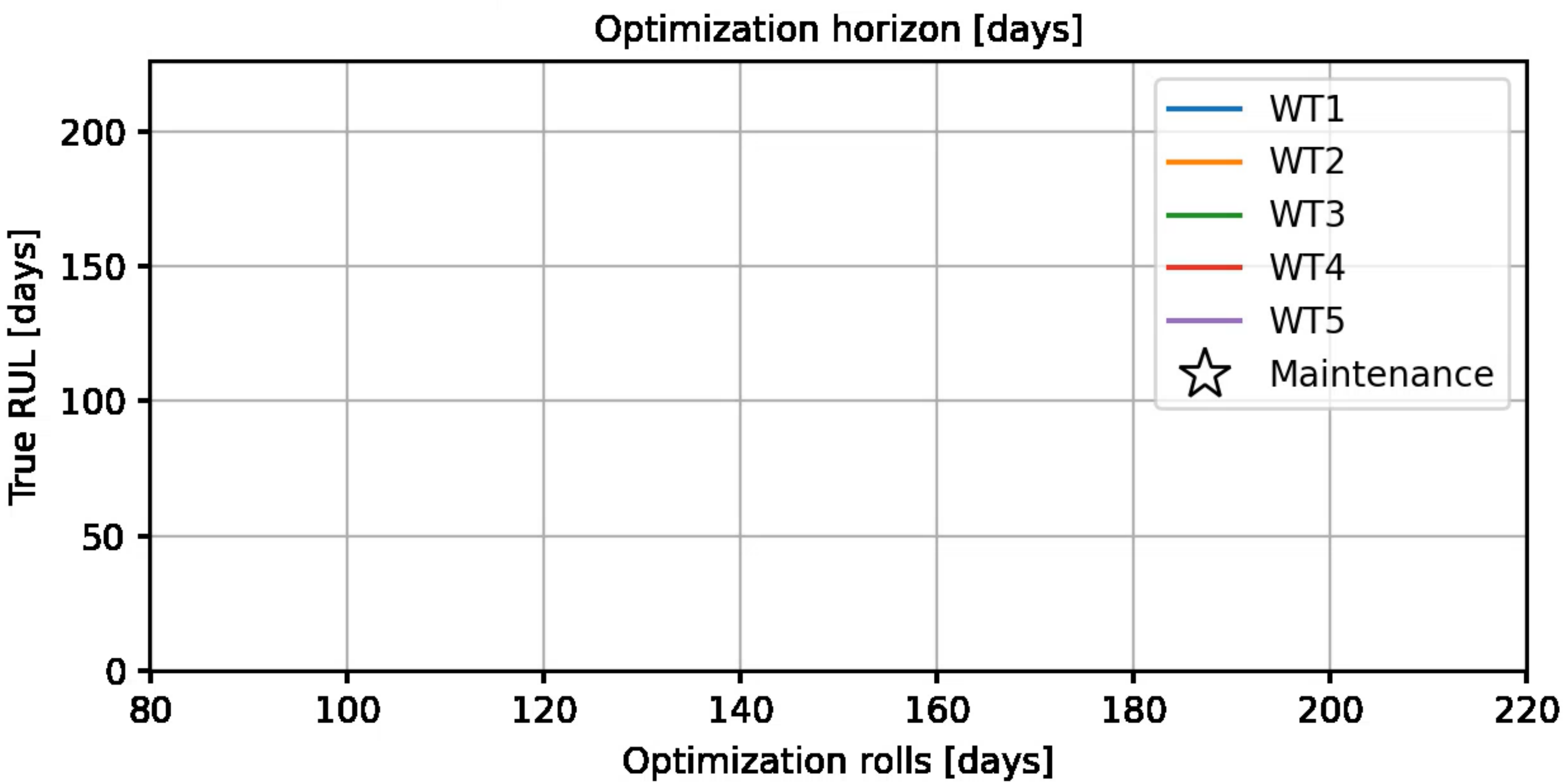
$$+ \underbrace{\sum_{d\in\mathcal{D}}\left[\boxed{\zeta^{0,L}_{d,i,s}}\cdot\left(1-\sum_{j\in\mathcal{J}}\boxed{\gamma^L_{d,i,j,s}}\cdot\boxed{F^L_{d,i,j,s}}\right)\right]}_{\text{LTH equivalent RUL gain/loss}}$$

P. Papadopoulos, F. Fallahi, M. Yildirim, A. Aziz Ezzat, POSYDON: Joint Production & Maintenance Optimization for Offshore Wind Farms, Under Review, 2023.

$$\begin{aligned}\max_{m_{t,i},\gamma_{t,i,j}} \Bigg\{ & \overbrace{l^{STH}}^{\text{short-term profit}} + \overbrace{\sum_{d\in\mathcal{D}} l_d^{LTH}}^{\text{long-term profit}} - \frac{1}{N_S}\cdot\sum_{s\in\mathcal{S}}\sum_{i\in\mathcal{I}}\Bigg[\overbrace{\mathrm{U}_s\cdot w_{i,s}+\mathrm{Y}_s\cdot b_{i,s}}^{\text{prolonged interruptions}} \\ & \underbrace{-C^{\lambda}\cdot\Bigg(\overbrace{\lambda_{i,s}}^{\text{RUL gain}} - \overbrace{\lambda^0_{i,s}\cdot\sum_{t\in\mathcal{T}} m_{t,i} - \sum_{d\in\mathcal{D}}(\lambda^0_{i,s}-d)\cdot m^L_{d,i,s}}^{\text{cycle days lost due to early maintenance}}\Bigg)}_{\text{end of horizon cost}}\Bigg]\Bigg\}\end{aligned}$$

Metric	POSYDON	STOCHOS	DET	TBS	CMS
Cost (K$)	**159.3**	273.8	398.4	715.0	1215.4
Revenue loss (K$)	**74.4**	121.6	283.5	475.8	999.2
Production loss (GWh)	**1.5**	2.5	5.8	9.7	20.8
Downtime (days)	**11.0**	21.3	32.5	52.0	102.5
Cycle days unused/task	**11.2**	8.9	2.9	17.5	0.0
Preventive tasks	**12**	15	7	12	0
Corrective tasks	**0**	3	4	8	14
Vessel rentals	**7**	14	11	28	20
Attempts per rental	**2.0**	1.3	1.2	1.1	1.1
Successes per rental	**1.7**	1.3	1.0	0.7	0.7

How Maintenance Actions are Grouped:



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Left to right: Feng Ye, Althea Miquela, Aziz Ezzat, Yating Fang, Petros Papadopoulos

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

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