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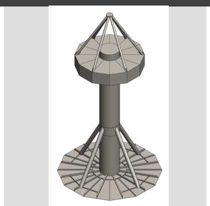
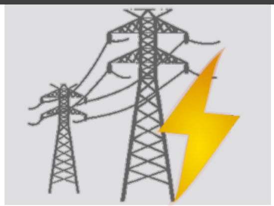
Sandia National Laboratories

Wave Data Assimilation in Support of Wave Energy Converter Power Prediction





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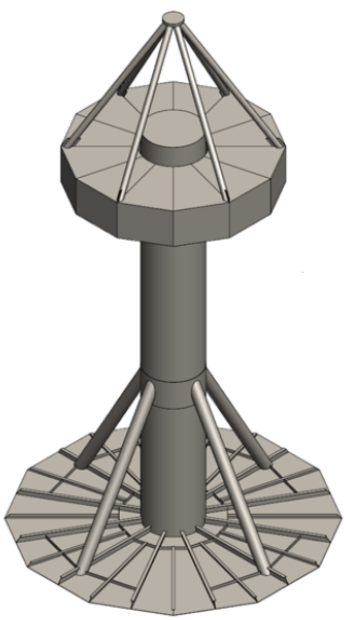
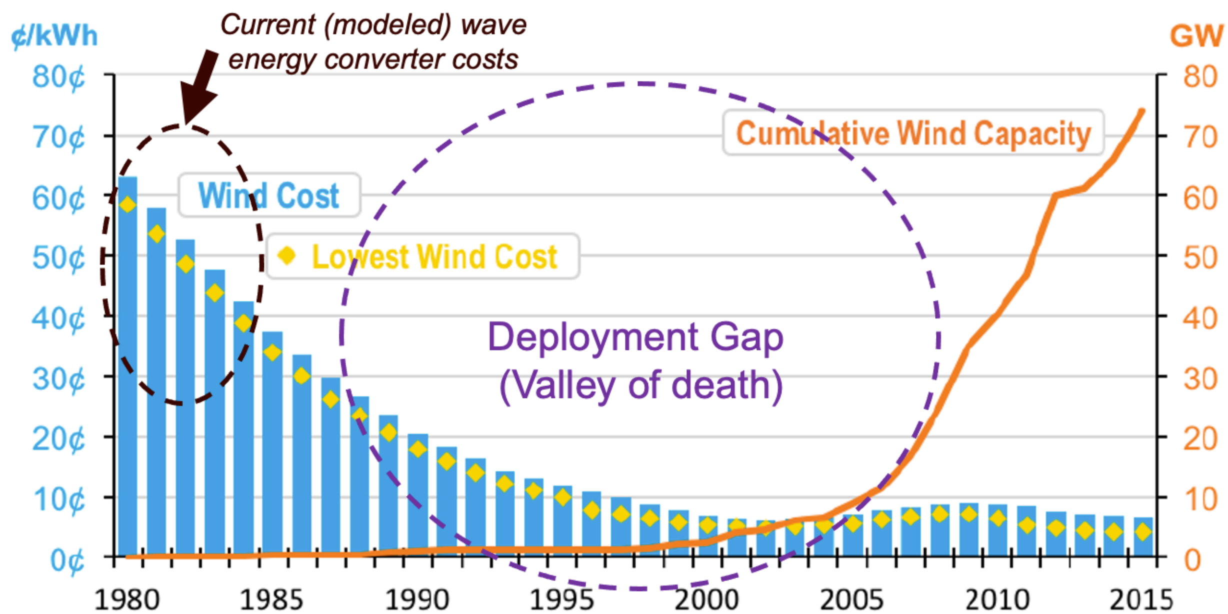
Background

- Wave energy is an **emerging renewable energy source**, particularly promising for remote (coastal & islanded) communities and military bases
- **Grid integration** and **efficient array power production** are major **deployment barriers** (see deployment gap in wind energy for example)
- ***Major hurdle:*** *accurate wave energy production forecasts for smart grid integration → removing deployment barrier to avoid gap*

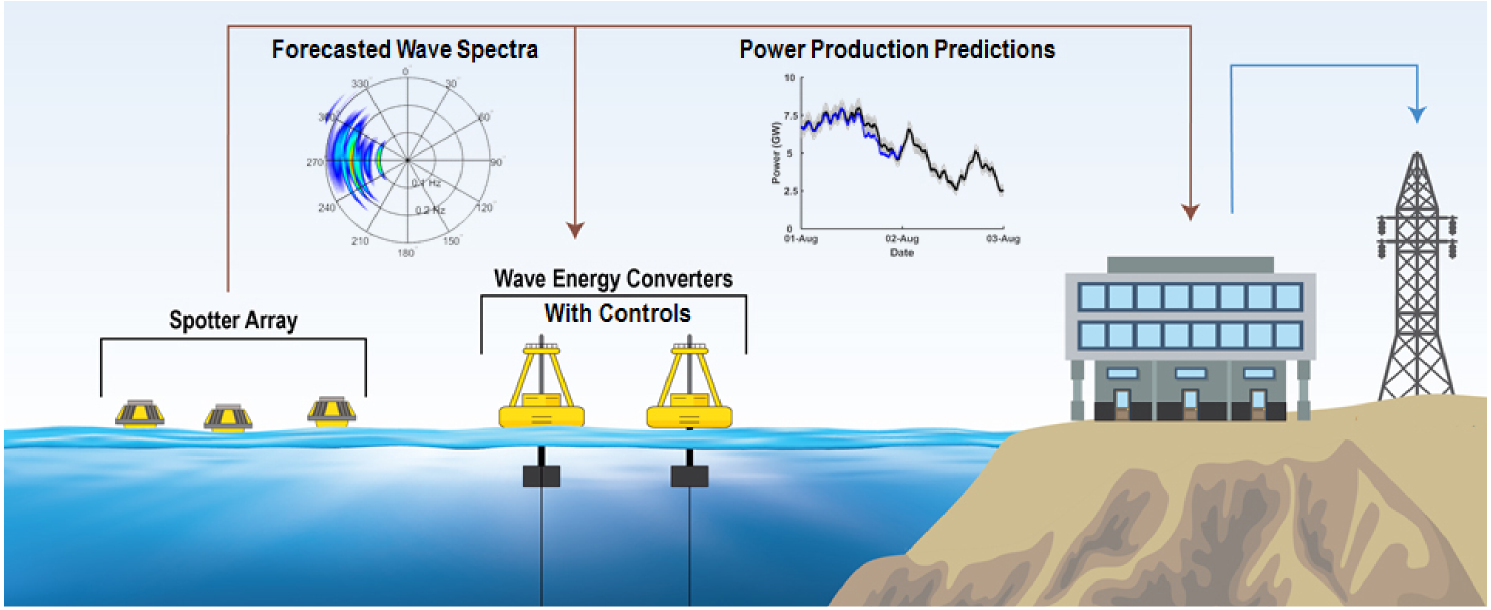




Reference for figure: Request for Information on a Draft Marine and Hydrokinetics (MHK) Program Strategy, December 21, 2016
Reference for historical U.S. Wind Costs and Deployments: DOE Revolution Now Report -http://energy.gov/revolution-now

Background

- **Existing nearshore wave forecast models** do not use real-time data assimilation and often have **significant errors** on an hour-by-hour basis
- **Real-time data assimilation has been shown to significantly improve the forecast** based on applications in other areas (also shown in 2018 exploratory project)
- In addition, wave forecasting, operational array controls, and grid integration **have not been coupled**, with unknown extent of uncertainty propagation
- This 'complete' power forecast will balance energy variability on grids for energy resiliency and security

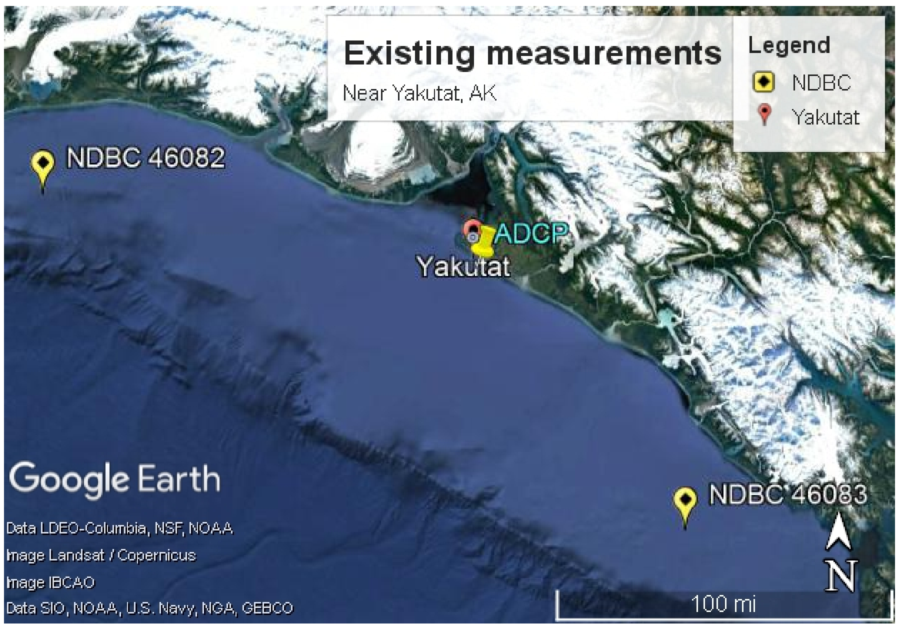


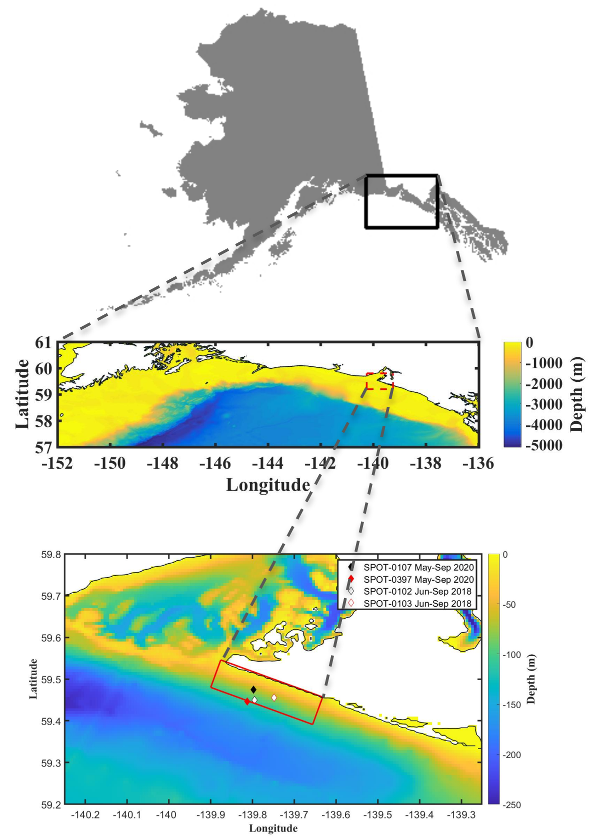
Modeling Tasks

- *Task 1: Incoming Wave Energy Forecasting*
  - Maximize and quantify improvements to wave forecasting using data assimilation (Ensemble Kalman filter) and constrain baseline forecast
- *Task 2: Wave Farm Operational Controls*
  - Utilize incoming wave energy forecasting on a short-term (10-20 minute) sea state basis to implement a WEC array operational controls model
- *Task 3: Grid Integration/Energy Storage*
  - Create an integrated Energy Storage System (ESS) control architecture for optimization of WEC array integration into microgrid
- *Task 4: Wave-to-wire Forecast Integration*
  - Scenario testing to explore optimization within forecasting uncertainty bands of WEC array operational controls and energy storage system characteristics

Wave Energy Forecasting

- Maximize and quantify improvements to wave forecasting using data assimilation (Ensemble Kalman filter) and constrain baseline forecast
- Case study: Offshore of Yakutat, Alaska, where the community is reliant on diesel energy generation; average annual wave energy could provide more electricity than Yakutat's electrical demand.





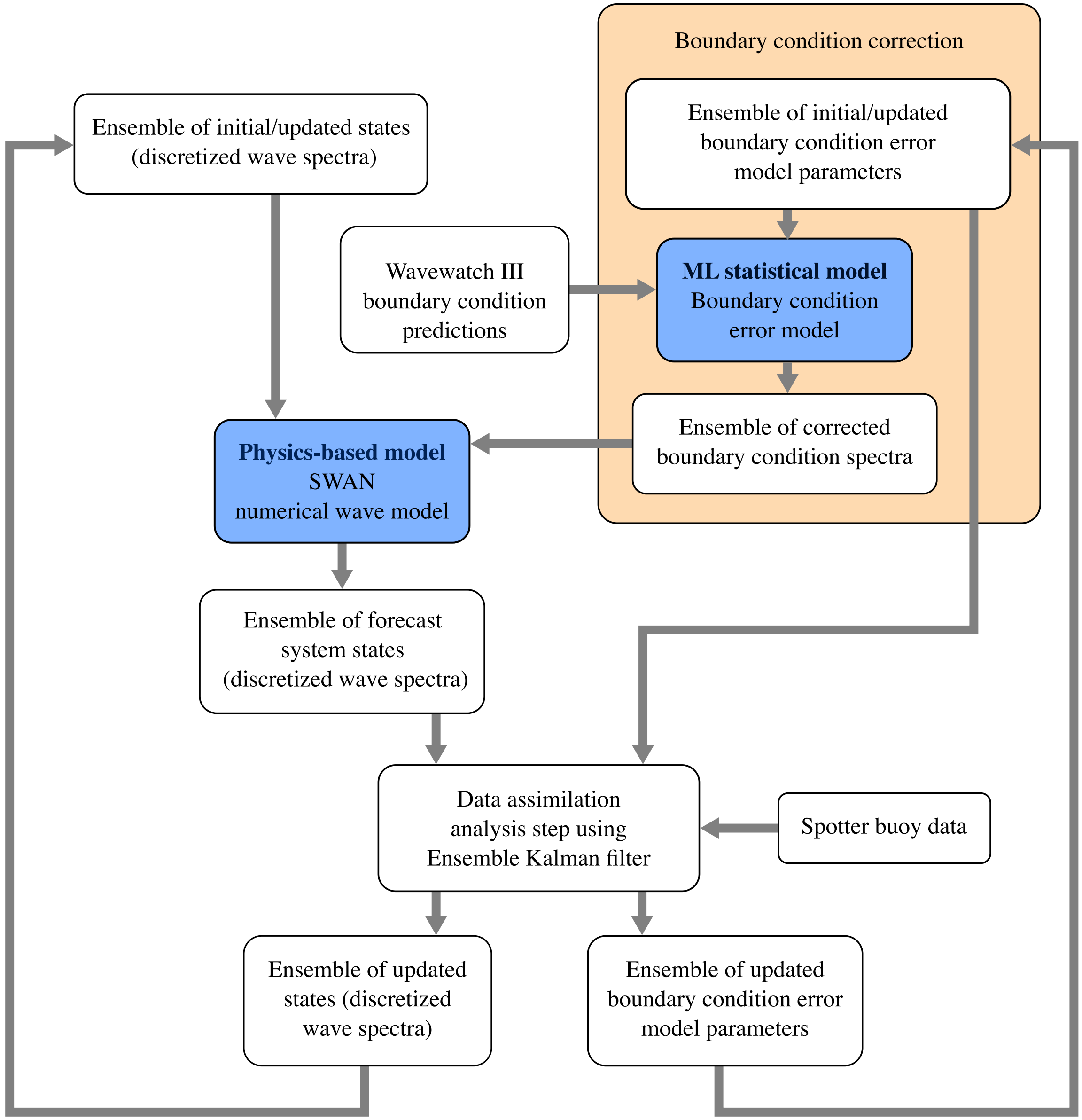
Wave Energy Forecasting

- We are achieving significant improvements to numerical wave forecast accuracy by updating the boundary conditions (obtained from Wavewatch III simulations) using:
  - Time-varying (as opposed to static) statistical discrepancy model
  - Ensemble Kalman filter for data assimilation/model calibration

- Examining significant wave height data from NDBC station 46082 (~100 miles east of Yakutat, AK) in comparison to Wavewatch III predictions for the month of September, 2019:

Model	Forecast window (hours)			
	12	24	48	72
Wavewatch III	16%	16%	16%	16%
DA with static BC correction	13%	15%	17%	18%
DA with time-varying BC correction	10%	11%	13%	14%

Wave Energy Forecasting



Wave Energy Forecasting

- Data assimilation combines the knowledge gained from the following two equations:
  - Model equation: $\boldsymbol{u}_{k+1} = \psi\,(\,\boldsymbol{u}_k\,,\,\boldsymbol{S}_k\,)$
    $\boldsymbol{u}_k \coloneqq$ State vector (discretized wave spectra, or summary statistics thereof, over the domain)
    $\psi \coloneqq$ Forward model operator (discretized in space, time, and spectral frequency and direction)
    $\boldsymbol{S}_k = \boldsymbol{S}\,(\,\omega, \theta, x, y, t_k\,) \coloneqq$ Stochastic boundary conditions (discretized wave spectra over the boundary)
  - Measurement equation: $\boldsymbol{d}_k = h\,(\,\boldsymbol{u}_k\,,\,\boldsymbol{\varepsilon}_k\,)$
    $h \coloneqq$ Measurement operator
    $\boldsymbol{\varepsilon}_k$ = Measurement error
- The solution is a probability density function (PDF) of the state vector, conditional on past observations: p $(\,\boldsymbol{u}_k \mid \boldsymbol{d}_1\,, \ldots, \boldsymbol{d}_k\,)$
- Numerical solution:
  - Forward (physics-based) model:
    - SWAN: Physics-based numerical wave model
    - Predicts random, short-crested wind-generated waves in coastal regions and inland waters
  - Data assimilation:
    - Ensemble Kalman filter (Evensen, 1994):
    - Ensemble of Monte Carlo system trajectories, propagated in time using original model operator, ψ
    - Relies on Gaussian closure of prior and likelihood PDFs (conjugacy) to arrive at conditional PDF p $(\,\boldsymbol{u}_k \mid \boldsymbol{d}_1\,, \ldots, \boldsymbol{d}_k\,)$
    - Small ensemble generally is sufficient (due to saturation)
    - Gaussian closure leads to small errors in cases involving frequent assimilation of data
  - Joint state-and-parameter inference:
    - Boundary condition spectra are corrected using a machine-learning (ML) models
    - ML model parameters jointly inferred using EnKF via state vector augmentation

Wave Energy Forecasting

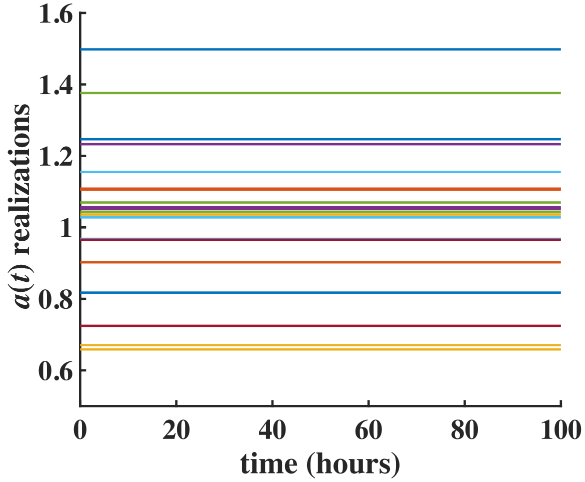
- Pre-specified BC spectra are corrected, within a data assimilation framework, using a statistical multiplicative correction factor:

$$S_{\text{corrected}}(\omega, \theta, x, y, t) = a(t) \cdot S_{\text{WWIII}}(\omega, \theta, x, y, t)$$

Static error model (1 DoF: α)

(constant in time)

$$a(t) = \alpha$$

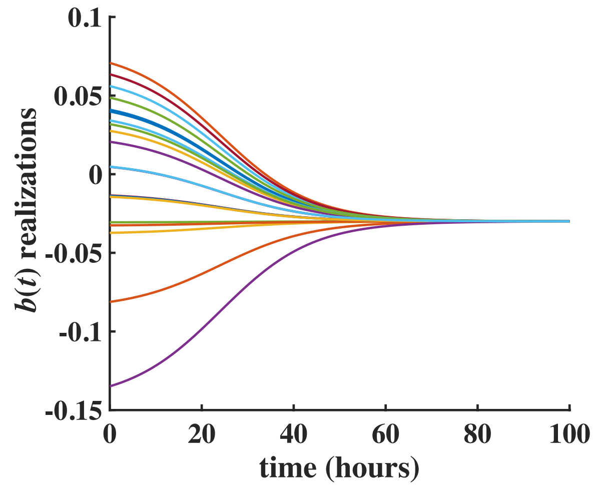


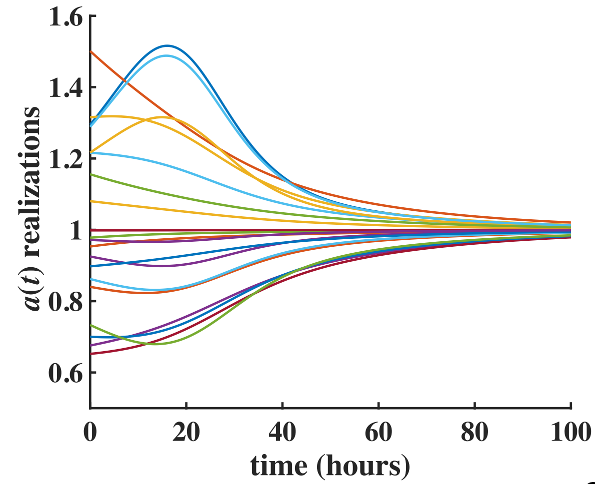
Time-varying error model (2 DoFs: α and β)

(captures varying error trends in time)

$$a(t) = \exp\left[\alpha \cdot \exp\left(b(t) \cdot (t - t_{\text{ref}})\right)\right]$$

$$b(t) = (\beta + 0.03) \cdot 0.5 \cdot \left(1 - \tanh\left(0.05 \cdot (t - t_{\text{ref}} - 24)\right)\right) - 0.03$$

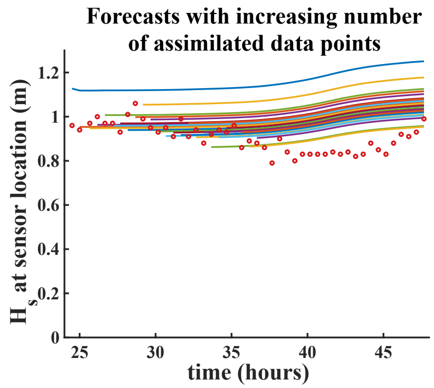


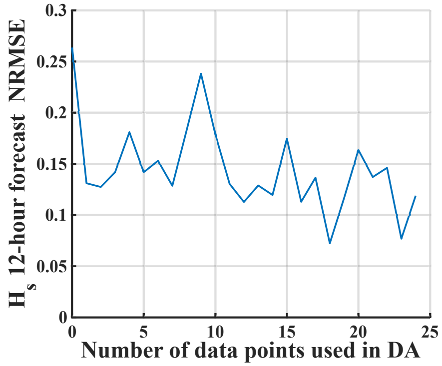


Wave Energy Forecasting

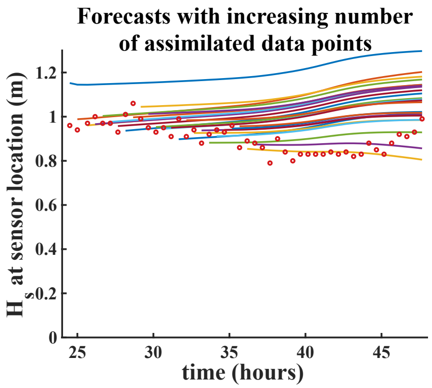
- We apply the ensemble Kalman filter to provide significant wave height predictions at the Spotter location for July 1st, 2018 (test case)
- **Over 12 hour period:** Significant wave height **NRMSE** reduced from **25-30%** (without data assimilation) to **~13%** (for static error model) and **~10%** (for time-varying error model) having assimilated 15 or more data points

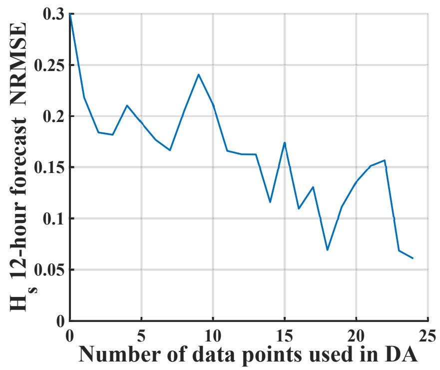
Static error model





Time-varying error model

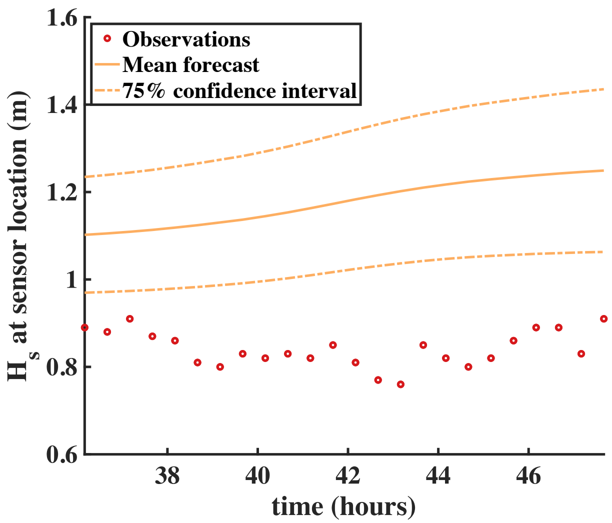




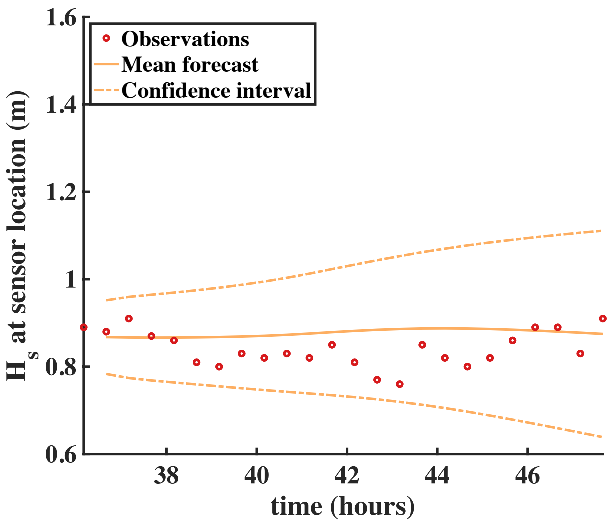
Wave Energy Forecasting

- It is important to consider uncertainty in addition to the mean result in order to determine confidence in the forecasts.
- Data assimilation reduces both the bias (data misfit) as well as the variance in predictions. In the absence of data assimilation:
  - The forecast trends away from the measured data
  - The true behavior is not encapsulated by the confidence interval

Without data assimilation



With data assimilation



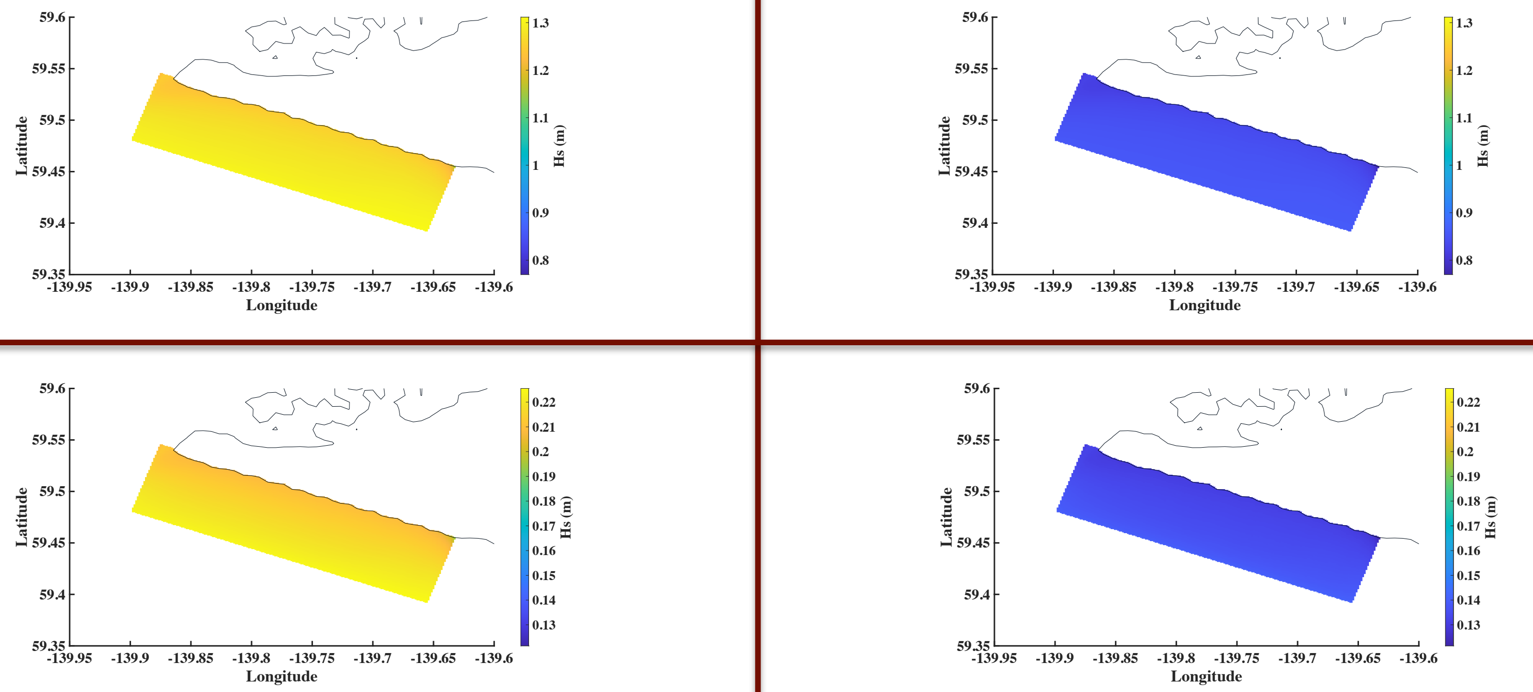
Wave Energy Forecasting

- Data assimilation updates the state over the entire domain based on data from one location:
  - There is a reduction in forecast wave height over the entire domain (bringing it closer to ground truth)
  - In addition, the standard deviation in the wave height (reflecting the uncertainty in the forecasts) is significantly reduced over the whole domain

Without data assimilation | **With data assimilation**

Mean prediction

Predictive uncertainty



Wave Energy Forecasting

- Next step: Allow for the assimilation of yet another data point/summary statistic (relating to first order moment of wave spectra) through another multiplicative term:

$$S_{\text{corrected}}(\omega, \theta, x, y, t) = a_1(t) \cdot S_{\text{WWIII}}(a_2(t) \cdot \omega, \theta, x, y, t)$$

Time-varying error model (4 DoFs: α_1, α_2, β_1 and β_2)

(increased flexibility: ability to nudge 0 and 1st-order spectral moments)

$$a_1(t) = \exp\left[\alpha_1 \cdot \exp\left(b_1(t) \cdot (t - t_{\text{ref}})\right)\right]$$
$$b_1(t) = (\beta_1 + 0.03) \cdot 0.5 \cdot \left(1 - \tanh\left(0.05 \cdot (t - t_{\text{ref}} - 24)\right)\right)) - 0.03$$

$$a_2(t) = \exp\left[\alpha_2 \cdot \exp\left(b_2(t) \cdot (t - t_{\text{ref}})\right)\right]$$
$$b_2(t) = (\beta_2 + \gamma_1) \cdot 0.5 \cdot \left(1 - \tanh\left(\gamma_2 \cdot (t - t_{\text{ref}} - \gamma_3)\right)\right)) - \gamma_1$$

- γ_1 through γ_3 are hyper-parameters that dictate amount of temporal "memory" present in frequency scaling factor $a_2(t)$
  - To be obtained through offline parametric/optimization studies

Summary

- Incorporating data assimilation for wave predictions significantly improves the forecasted significant wave height over a twelve-hour period where the boundary conditions did not represent the observations well.
- The improved data assimilation methodology, incorporating more flexible ML models for updating BCs, outperformed the constant-in-time correction.
- Predictive error in significant wave height was reduced and tighter confidence intervals were observed.
- A tighter confidence interval of power generation forecasts reduces the need for storage and helps to maximize efficiency of a microgrid.
- The data assimilation implementation will be tested on more recent data over longer time periods.
- Furthermore, we will incorporate data sources relating to other bulk parameters (summary statistics) with the potential for further gains in accuracy and precision of predicted wave spectra.