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Please fill in your manuscript title.	Wave Data Assimilation In Support Of Wave Energy Converter Power Prediction: Yakutat, Alaska Case Study

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Abstract

Integration of renewable power sources into grids remains an active research and development area, particularly for less developed renewable energy technologies such as wave energy converters (WECs). WECs are projected to have strong early market penetration for remote communities, which serve as natural microgrids. Hence, accurate wave predictions to manage the interactions of a WEC array with microgrids is especially important. Recently developed, low-cost wave measurement buoys allow for operational assimilation of wave data at remote locations where real-time data have previously been unavailable.

This work includes the development and assessment of a wave modeling framework with real-time data assimilation capabilities for WEC power prediction. The availability of real-time wave spectral components from low-cost wave measurement buoys allows for operational data assimilation with the Ensemble Kalman filter technique, whereby measured wave conditions within the numerical wave forecast model domain are assimilated onto the combined set of internal and boundary grid points while taking into account model and observation error covariances. The updated model state and boundary conditions allow for more accurate wave characteristic predictions at the locations of interest.

Initial deployment data indicated that measured wave data from one buoy that were assimilated into the wave modeling framework resulted in improved forecast skill for a case where a traditional numerical forecast model (e.g., Simulating WAves Nearshore; SWAN) did not well represent the measured conditions. On average, the wave power forecast error was reduced from 73% to 43% using the data assimilation modeling with real-time wave observations.

Introduction

To operate a power system (grid) efficiently and reliably, a 'smart grid' will be critical to effectively balance the variation of renewable energy sources. Real-time data assimilation is commonly used in fields such as meteorology and oceanographic circulation modeling to improve model forecast skill. However, there have been very few data assimilation implementations into operational wave models. The availability of scientific grade measurement data from recently developed Spotter buoys (https://spoondriftspotter.co/, Raghukumar et al. 2019) allows for operational assimilation of wave data at remote locations where real-time data have previously been unavailable. The Spotter buoy is solar-

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powered, utilizes GPS technology for wave measurements, and the Iridium satellite communication network, which allows for long-term deployments anywhere in the word. Real-time wave measurements delivered to a user dashboard consist of wave bulk parameters such as significant wave height, peak and mean wave periods, and directional moments.

Nearshore wave models such as Simulating Waves Nearshore (SWAN), typically have systematic errors that significantly affect the accuracy of incoming wave energy (to a hypothetical wave energy converter farm). Typical normalized root mean square error (NRMSE) values are on the order of 20% for significant wave height (H_s) and 5-10% for energy period (T_e) (Dallman et al. 2014, Garcia-Medina 2014). The wave power is a function of the significant wave height squared multiplied by the energy period, and therefore errors in H_s are made worse when predicting wave power. This results in a typical RMSE values of 50-60% for omnidirectional wave power (J).

Incoming wave energy characteristics combined with device and array performance, and efficiencies (including controls), allows for prediction of the electricity to be produced and incorporated into a microgrid. Therefore, it is important to quantify the uncertainties and expected errors of the wave model so that the propagation of these errors through a full wave to grid scenario/model can be achieved. This work focuses solely on the wave forecasting error reduction, with additional work under way to optimize the data assimilation methods and sensor needs, and to incorporate the full scenario of electricity from wave energy converters onto the grid.

Methodology

The area of interest for this case study is the area offshore of Yakutat, Alaska. The coastal geography and offshore bathymetry in the area is shown in Figure 1. The baseline model setup for this analysis is taken from the University of Alaska, Fairbanks (UAF) study (Tschetter et al. 2016), which included a 10-year wave model hindcast. The coarse model domain is shown in Figure 1 and the first 'fine' model domain, termed 'F1' is shown in Figure 2. An additional, finer model domain, termed 'F2' was set up for the current study to implement data assimilation, which is outlined in Figure 2.

Offshore of Yakutat, deployment operations limited the deeper Spotter buoy (SPOT-0102) deployment location to about 3 nautical miles offshore, which in turn determined the extent of this research's model domain considered for data assimilation. The nearshore domain setup for data assimilation (F2) is shown in Figure 2, which is rotated by 20 degrees to be approximately parallel to the shore. The two Spotter buoys were deployed at 72m and 99m depth (Table 1), and are signified in Figure 2.

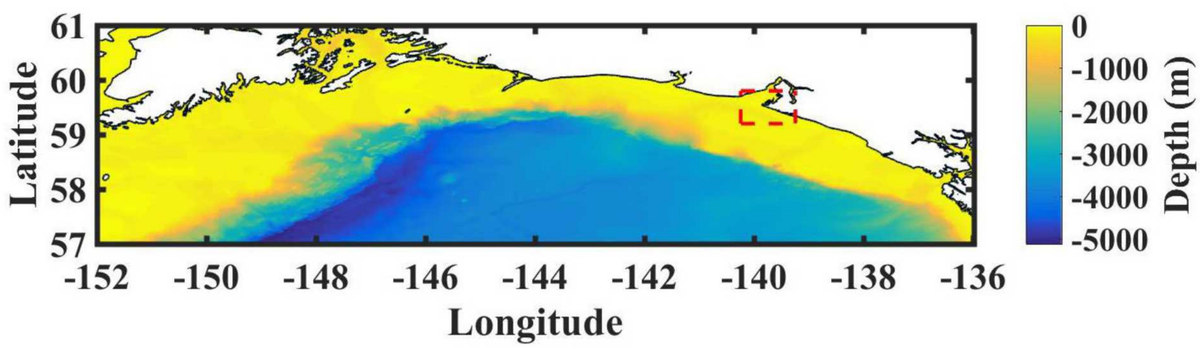

Figure 1. Coarse SWAN domain bathymetry. The outline of the F1 SWAN domain is indicated by the red dotted line.

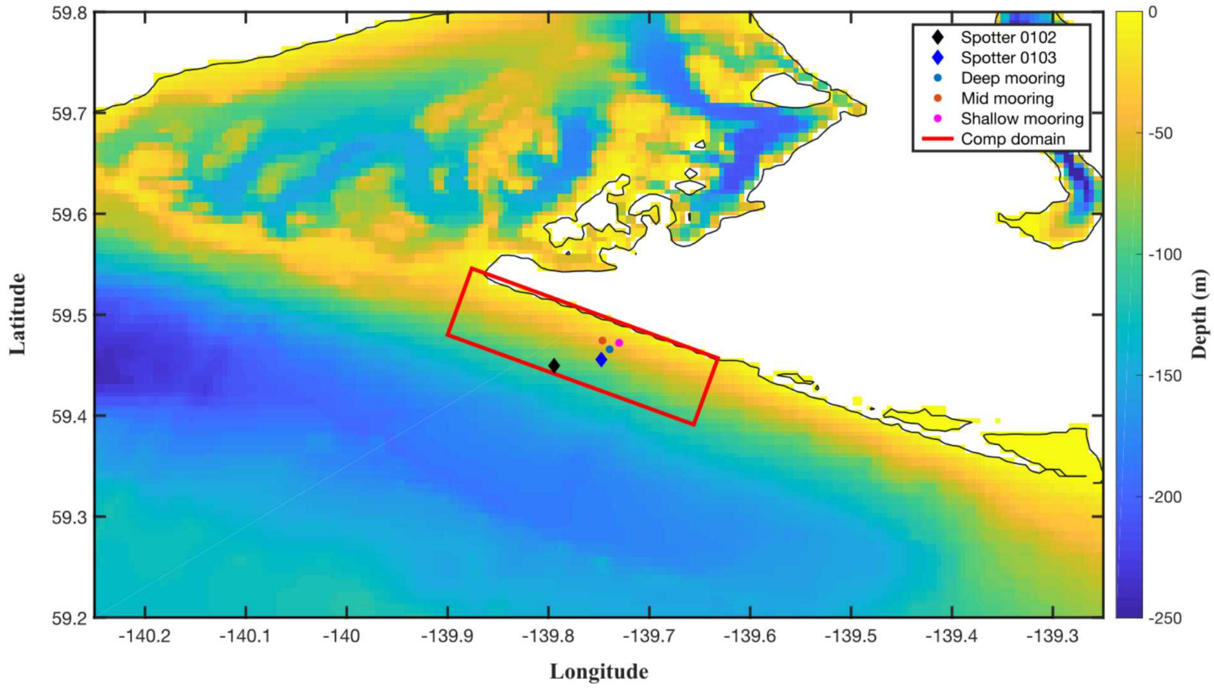

Figure 2. F1 SWAN domain showing the F2 SWAN domain and the location of the measurements.

Table 1. Deployed Spotter buoy locations and depths.

Buoy	**Depth**	**Latitude**	**Longitude**
SPOT-0102	99 m	59.4494	-139.7952
SPOT-0103	72 m	59.4555	-139.7485

Various data assimilation techniques are available for use, but in the context of dealing with large-scale nonlinear dynamical systems, the Ensemble Kalman filter (EnKF) and its many variations are some of the most-widely used methods for sequential data assimilation. EnKF extends the widespread Kalman filter (KF) method, appropriate for linear models with normally distributed measurement and model errors, using an ensemble step for the forward integration of error statistics and the traditional update equation in KF. The EnKF has been employed to assimilate data within a number of different contexts including operational weather as well as ocean current forecasts. One attractive and simple alternative to EnKF is optimal interpolation (OI) in which background error statistics are not extracted from the ensemble of (SWAN) model runs, but are pre-specified ahead of time. Although OI is more appropriate for statistical modeling, an ensemble optimal interpolation (EnOI) method has been developed as a simplification of the EnKF in which the background error statistics are extracted from an ensemble of long-term forecasts (performed prior to data assimilation). EnOI provides a suboptimal solution, in contrast to EnKF, since the error statistics do not adjust to the state of the system and the data assimilated. However, EnKF is more computationally intensive, requiring an ensemble of forward model integrations as opposed to just one for EnOI.

In this study, two data assimilation methods were initially considered, being the aforementioned EnKF and EnOI. However, strong cross-correlations across the entire state space were observed from numerical runs of the SWAN model, suggesting that a small ensemble for EnKF would suffice in this context. It was found that an ensemble of 10 to 20 model runs is sufficient to capture the error in the state of the system. Therefore, we relied upon an EnKF ensemble size of 10 for all results included in this report. For the source of uncertainty in our computational model, we implemented a simple stochastic model for the boundary conditions. This was achieved via amplitude modulation of the provided boundary condition (BC) spectra over space and time using a single factor with a log-normal prior probability density function having mean of 1 and a standard deviation of 0.15. The standard deviation was chosen based on numerical experiments using synthetic data to provide sufficient levels of uncertainty in the system state for data assimilation purposes, while not being too large as to result in forecasts with low confidence.

For this study, only significant wave height was considered for data assimilation, and data were assimilated from the SPOT-0102 buoy near the border of the computational domain (Figure 2). In the update step of EnKF, wave spectra over the domain were updated based on the difference in significant wave height between the model and the buoy data at the buoy location. The significant wave height is calculated as the square root of the zeroth spectral moment of the energy spectra. Therefore, the square of the ratio of the significant wave height from the initial model output and the buoy are used. The factor used in amplitude modulation of BC spectra was also updated using data assimilation by augmenting the state vector (significant wave height at all computational nodes) with that factor. In a data assimilation context, we are thus performing joint state and parameter inference. Since the assimilation of data reduces the uncertainty in the BC spectra scaling factor over time, we artificially inflate the variance to maintain a standard deviation that is 15% of the mean value (see Khalil et al., 2015 for a discussion on artificial inflation of parameter variance in data assimilation).

Initially, the data assimilation was set up and tested using synthetic data at a single time instance. A specific wave sea state condition was set as 'truth', and boundary conditions were set as an offset from this truth condition. Next, the computational framework was extended to incorporate the recorded buoy data and extended the SWAN runs to longer term forecasts that can incorporate a range of past measured data into the data assimilation.

The buoy data are available real-time through an application programming interface (API) and can be accessed through the dashboard on the manufacturer's website. The framework was also set up to continue forecasting whether data are available or not. It checks at regular intervals if data are available, and if so, interpolates the data to the nearest 10th minute forecast interval, and incorporates the data when updating the state and BC scaling factor. For this initial study, cases were evaluated after data were collected, but run in forecasting mode. Setting up the framework to be completely operational (independent of a user initializing parts of the model framework intermittently) would require more effort, but the framework has been established.

Results and Discussion

A one-day timeframe at the start of the buoy deployment was considered (July 1 00:00 – July 2 00:00). This case focused on a time period when the forecast is not tracking the data well, and it is expected that data assimilation can improve the accuracy.

Twelve-hour significant wave height forecasts with and without data assimilation are compared to determine longer term forecast improvement. Figure 3 shows the mean forecast without data assimilation, and the confidence interval represents two standard deviations, calculated from the results of the ensemble of forecasts. It is important to consider uncertainty in addition to the mean result in order to determine confidence in the forecasts. The mean and confidence interval (obtained as mean plus/minus 2 standard deviations) for the forecasts with data assimilation is shown in Figure 4. The forecast without data assimilation trends away from the measured data, particularly starting at about July 1, 12:00, where the data are not encapsulated by the confidence interval. However, the forecasts with data assimilation correctly adjust to the downward trend of H_s, and the data are fully encapsulated within the confidence interval (which is narrower in contrast to that obtained without data assimilation).

Overall the forecast skill is greatly improved over this time period, with NRMSE lowered from about 27% to an average of 16%.

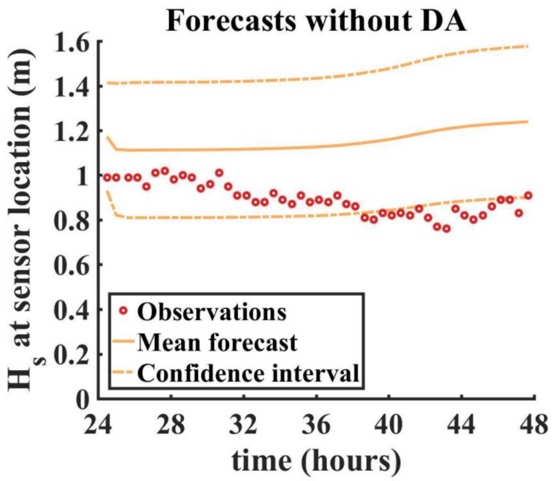

Figure 3. Forecasts without data assimilation (DA) starting at July 1, 00:30 at the SPOT-0103 buoy location. The confidence interval of the ensemble members is represented by the dotted line.

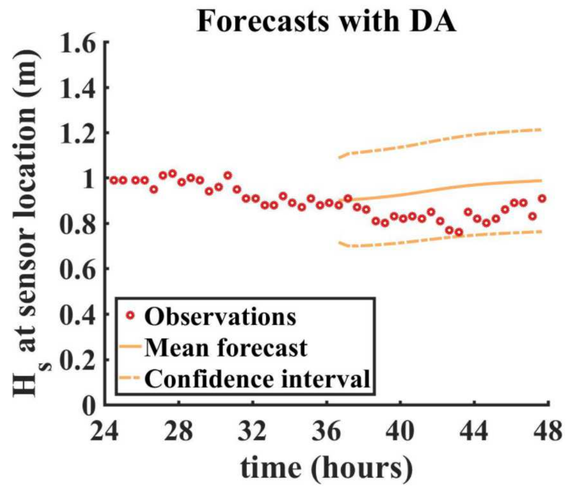

Figure 4. Forecasts starting at approximately July 1, 12:30 using all assimilated data from July 1, 00:30 to approximately July 1, 12:00. The confidence interval of the ensemble members is represented by the dotted line.

Although the focus has been the change to forecasted results at the nearshore buoy, SPOT-0103, the changes over the entire computational domain can be visualized as well. As seen in Figure 5 (mean H_s without data assimilation) and Figure 6 (mean H_s with data assimilation), there is a reduction in forecasted wave height over the entire domain, which maps to the change in forecast at the SPOT-0103 location shown in Figure 3 and Figure 4. In addition, the standard deviation of the ensemble of forecasted runs (reflecting the uncertainty in the forecasts) is significantly reduced over the whole domain (results omitted for brevity).

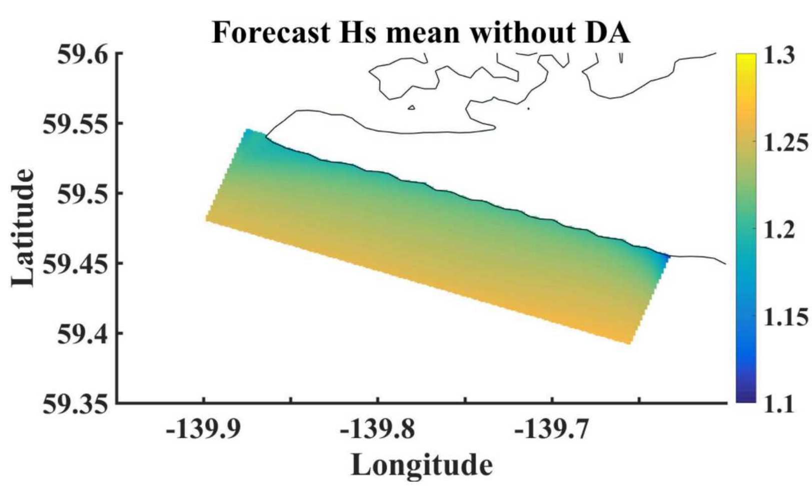

Figure 5. The mean forecast results without data assimilation (DA) at the final computational timestamp is shown over the whole computational domain.

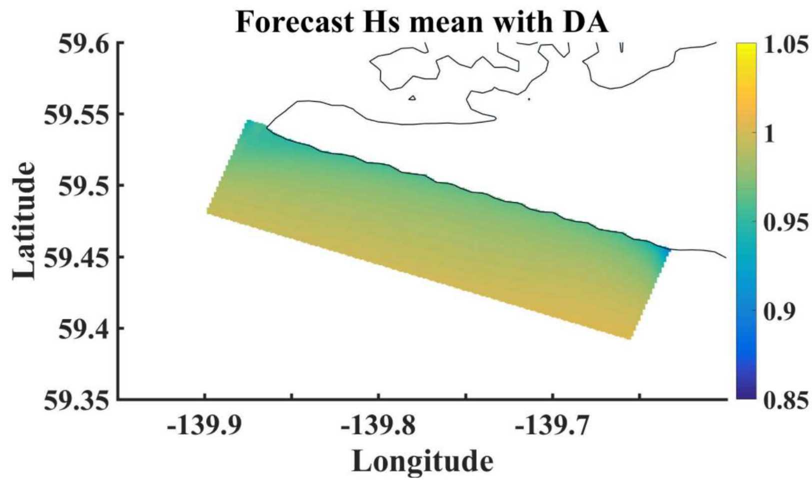

Figure 6. The mean forecast results with data assimilation (DA) at the final computational timestamp is shown over the whole computational domain. Note that the colorbar axis limits are different than in Figure 5.

From the results described above, it is clear that data assimilation is effective for long-term forecasts (i.e., more than one step) when the incoming boundary condition forecast is not capturing the wave characteristics well. Furthermore, data assimilation provides updated information over the entire computational domain of interest (not just a single measurement location) using sparse (in this case at one location) data. This provides more accurate sea state information for controls of WEC devices and the entire array (e.g., for increased power and power smoothing).

This initial study, utilizing the ensemble Kalman filter (EnKF) for data assimilation with just significant wave height data at one measurement buoy, showed substantial improvement in forecasting skill over a period of 12 hours for the case where the boundary conditions did not track the data well. The key variable for forecasting WEC power production is the incoming omnidirectional wave power (the wave resource), J. Wave power is a function of wave height squared, therefore improvements to H_s result in even greater reductions in the NRMSE for J. For the 12-hour forecast starting at July 1, 12:00 the NRMSE for J is 73% without DA, and an average of 43% with DA.

Conclusions

This initial study showed a significant decrease in error for both significant wave height and wave power. There are several areas of additional research that could further improve the robustness and accuracy of the forecasts obtained from the data assimilation framework established in this project. Additional buoy deployments, increased complexity in the data assimilation, and evaluating the benefits of additional sensors are areas that are currently being explored. The data assimilative wave forecasting framework will provide a useful development tool for the integration of WECs into electrical grids.

Acknowledgement

This paper describes objective technical results and analysis. Any subjective views or opinions that might be expressed in the paper do not necessarily represent the views of the U.S. Department of Energy or the United States Government.

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