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LDRD PROJECT NUMBER: 210648

LDRD PROJECT TITLE: Improved Wave Energy Production Forecasts for Smart Grid Integration

PROJECT TEAM MEMBERS: Ann Dallman[1], Mohammad Khalil[1], Kaus Raghukumar[2], Jeremy Kasper[3], Craig Jones[2], Jesse Roberts[1]

[1]Sandia National Laboratories

[2]Integral Consulting

[3]University of Alaska Fairbanks

ABSTRACT:

Integration of renewable power sources into electrical grids remains an active research and development area, particularly for less developed renewable energy technologies, such as wave energy converters (WECs). High spatio-temporal resolution and accurate wave forecasts at a potential WEC (or WEC array) lease area are needed to improve WEC power prediction and to facilitate grid integration, particularly for microgrid locations. The availability of high quality measurement data from recently developed low-cost buoys allows for operational assimilation of wave data into forecast models 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. Spoondrift wave measurement buoys were deployed off the coast of Yakutat, Alaska, a microgrid site with high wave energy resource potential. A wave modeling framework with data assimilation was developed and assessed, which was most effective when the incoming forecasted boundary conditions did not represent the observations well. For that case, assimilation of the wave height data using the ensemble Kalman filter resulted in a reduction of wave height forecast normalized root mean square error from 27% to an average of 16% over a 12-hour period. This results in reduction of wave power forecast error from 73% to 43%. In summary, the use of the low-cost wave buoy data assimilated into the wave modeling framework improved the forecast skill and will provide a useful development tool for the integration of WECs into electrical grids.

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INTRODUCTION:

To operate a power system (grid) efficiently and reliably, a 'dynamic paradigm' (Zhou et al., 2014), or a 'smart grid' will be critical to effectively balance the variation of renewable energy sources. This is particularly critical for microgrids. The three components to a dynamic paradigm are (1) dynamic system estimation (where the system is), (2) dynamic forecast simulation (where the system is going), and (3) dynamic contingency analysis (controls). Existing studies on these components explore WEC device dynamics and simulation based on bulk statistics of assumed wave dynamics, and the use of controls to maximize power output from WECs. These 'wave-to-wire' models (Penalba & Ringwood 2016) are specific to the hydrodynamics and Power Take-Off (PTO), e.g., generator, of individual devices, and only some consider grid requirements. Successful implementation of the dynamic paradigm (i.e., effective microgrid management) requires high temporal resolution and accurate forecasts at a potential WEC (or WEC array) location.

Real-time data assimilation is commonly used in fields such as meteorology and oceanographic circulation modeling. However, there have been very few implementations into operational wave models; in addition, to the best of our knowledge, none have been applied to real-time wave energy characterization or performance prediction. The availability of scientific grade measurement data from recently developed Spotter buoys (https://spoondriftspotter.co/, Raghukumar et al. 2018) allows for operational assimilation of wave data at remote, site specific locations where real-time data have previously been unavailable. Spotter buoys are compact (38 cm diameter), lightweight (<5.5 kg) surface-following devices that can be deployed using a small vessel or a kayak. The Spotter is solar-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 root mean square error (RMSE) 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).

Utilizing data assimilation can significantly reduce wave energy prediction errors, however further research is needed to optimize the methods for nearshore applications. Several studies have implemented data assimilation in larger regional wave models, often using sparse satellite or buoy data (e.g., Wittman & Cummings 2005, Chen et al. 2004, Hasselmann et al. 1997). For example, Chen et al. 2004 used a variational data assimilation method, which significantly improved the forecast accuracy in the first 12 hours. In a hindcast resource assessment study over a regional domain (the entire Black Sea), satellite data was used to improve modeled significant wave height

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values (Rusu 2015), with RMSE values reduced form 0.34m to 0.29m. A few studies have incorporated data assimilation in nearshore wave models used for port operation management. For example, in Almeida et al. 2016, the RMSE of H_S was reduced from approximately 0.4m to 0.25m at a location offshore of Portugal.

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 estimated. This work focuses solely on the wave forecasting error reduction, and recommends future work to optimize the data assimilation methods and sensor needs, and to incorporate the full scenario of electricity from wave energy converters onto the grid.

DETAILED DESCRIPTION OF EXPERIMENT/METHOD:

The area of interest for this case study is the area offshore of Yakutat, Alaska, where the community is reliant on 100% diesel energy generation. The community, however, is considering utilizing renewable electricity generation, in particular wave energy. The University of Alaska Fairbanks (UAF) has completed a resource assessment using measurements and numerical modeling (Tschetter et al. 2016). A regional wave model was used in order to characterize the regional wave climate, and identify promising installation sites for WECs. It was found that the average annual wave energy at the site is around 20 kW/m, and could provide more electricity than Yakutat's electrical demand.

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 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.

Typical water depths targeted by wave energy developers are around 50-100m. Hypothetical arrays of WECs for utility scale electricity generation could consist of dozens of devices, spaced several diameters apart to accommodate moorings and minimize interactions between devices (Neary et al 2014). An array could take up several square kilometers of ocean space, therefore, centering an array on ~70m (the SPOT-0103 nearshore buoy location) is a realistic assumption. 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.

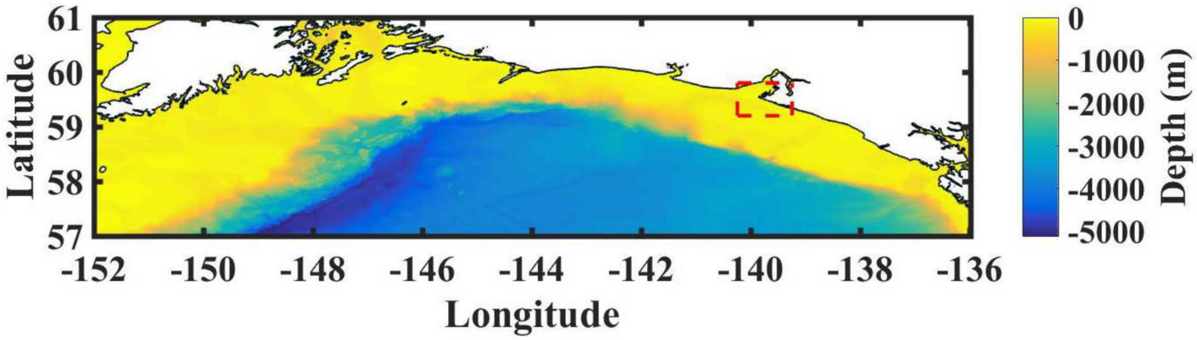

Figure 1. Coarse SWAN domain bathymetry. The outline of the F1 SWAN domain is indicated by the red dotted line.

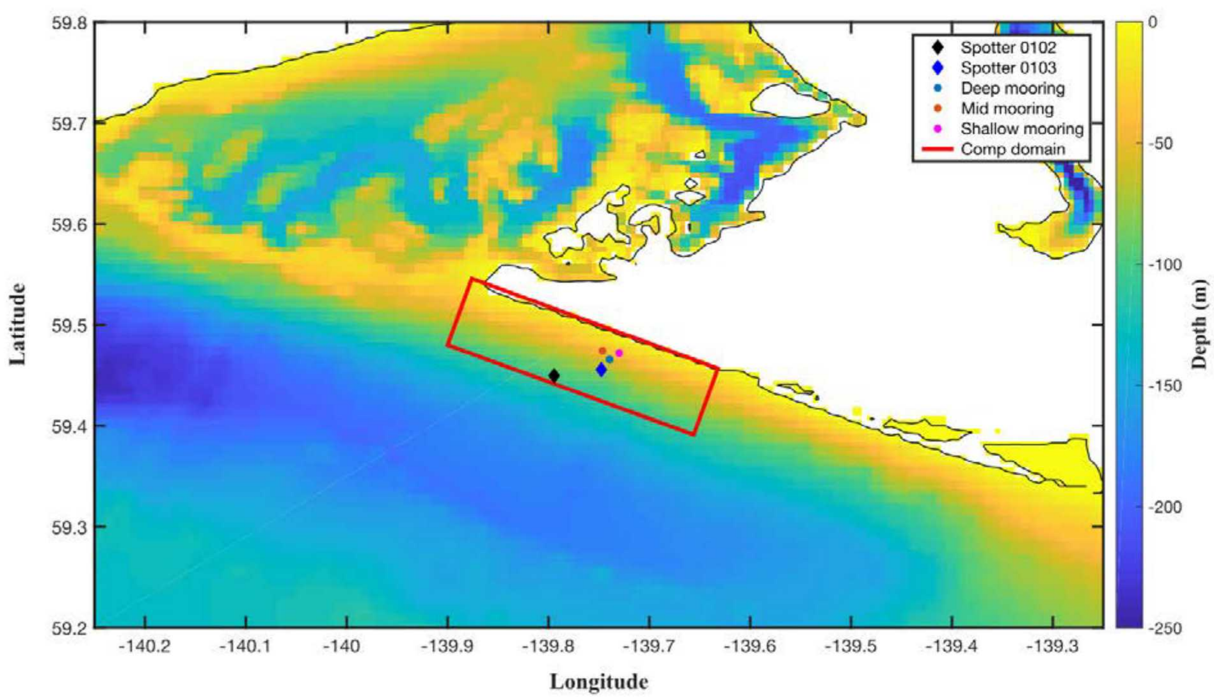

Figure 2. F1 SWAN domain showing the F2 SWAN domain and the location of the measurements.

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 normal 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 modelled as a log-normal random variable with mean of 1 and a standard deviation of 0.15. The standard deviation was chosen based on numerical experiments using synthetic data, chosen to provide enough uncertainty in the state to provide reasonable data assimilation results 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 was 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 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 amplitude modulation of BC spectra was also updated using data assimilation by augmenting the state vector (significant wave height at all computational nodes) with the factor used in amplitude modulation. In a data assimilation context, we are thus performing joint state and parameter estimation. 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 Matlab 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 is available real-time through an application programming interface (API) and can be accessed through the dashboard on Spoondrift’s website: https://spoondriftspotter.co/. A screenshot of the dashboard is shown in Figure 3. A Python script was written to access the API and download data over a specified time period. This can be run on a regular (operational) basis to continuously download the buoy data.

The Matlab framework was also set up to continue forecasting whether data is available or not. It checks at regular intervals if data is 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 was 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.

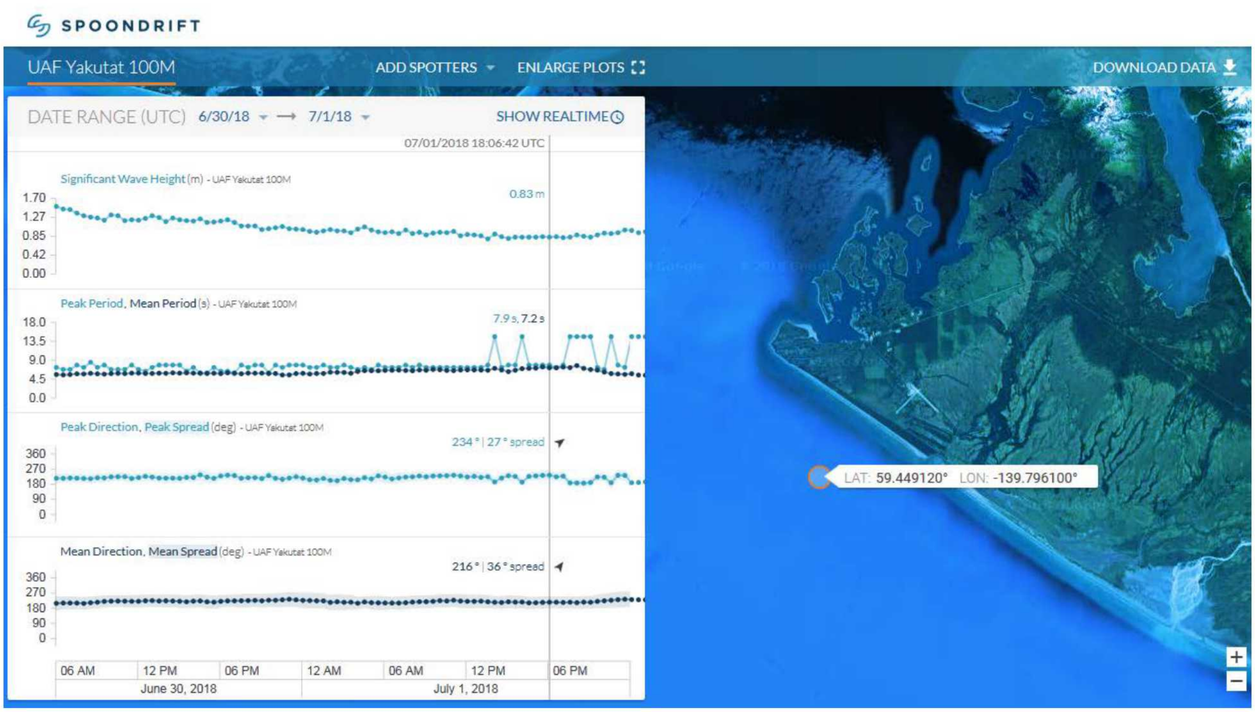

Figure 3. Spoondrift dashboard website with data access.

RESULTS:

A two-day timeframe at the start of the buoy deployment was considered (June 30 00:00 – July 2 00:00). The forecast without data assimilation is compared to measured SPOT-0103 buoy data at the 72m depth location (where an assumed WEC array would be located) in Figure 4. As expected, there are periods of time where the forecast is consistent with the data, and times when the forecast is missing a trend or peak/valley in the data.

The first 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. This data assimilation case starts on July 1. The H_s results of the ensemble of one-step forecasts with data assimilation are shown in Figure 5, and the mean of the ensemble members is shown in Figure 6. The mean of the ensemble members (Figure 6), is very consistent with the measured data and exhibits an effective correction/update at each time step.

Longer-term forecasts with increasing numbers of assimilated data points are shown in Figure 7 and a zoomed version is shown in Figure 8. The forecast without data assimilation from July 1, 00:30 is in blue, and is noticeably greater in value than the subsequent forecasts with data assimilation. Starting at July 1, 00:30, a forecast with one data point was assimilated, then a forecast starting at July 1, 01:00 with two data points were assimilated and so on. The final forecast uses approximately 12 hours of data (24 data points, available at approximately 30 minute increments). The spectra are updated at the boundary of the computational domain (system parameter estimation) along with the internal degrees-of-freedom (system state estimation), i.e., performing joint state and parameter estimation. Therefore, the assimilation of previous data results in updated forecasts that are more accurate, reflecting the updated BC spectra.

Twelve-hour significant wave height forecasts with and without data assimilation are compared to determine longer term forecast improvement. Figure 9 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 10. The forecast without data assimilation trends away from the measured data, particularly starting at about July 1, 12:00, where the data is not encapsulated by the confidence interval. However, the forecasts with data assimilation correctly adjust to the downward trend of H_s, and the data is fully encapsulated within the confidence interval (which is narrower in contrast to that obtained without data assimilation).

Starting at approximately July 1, 12:00, the normalized root-mean-square error (NRMSE) is calculated over the forecast interval for each of the forecasts shown in Figure 7 (varying the number of assimilated data points). The NRMSE is shown in Figure 11 where the first data point represents the forecast without data assimilation (zero data points used in DA). Note that data is available approximately every 30 minutes, so the last point on the plot represents about 12 hours of data being assimilated. The forecast using 9 data points has a jump in NRMSE because it is responding to the spike in measured data that can be seen in Figure 8. Besides that outlier, the other assimilated forecast NRMSE values remain around 15% or lower. The lowest NRMSE is at 23 data points with a value of 6.1%. Overall the forecast skill is greatly improved over this time period, with NRMSE lowered from about 27% to an average of 16%.

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 12 (mean H_s without data assimilation) and Figure 13 (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 9 and Figure 10. In addition, the standard deviation of the ensemble of forecasted runs (reflecting the uncertainty in the forecasts) is significantly reduced over the whole domain (Figure 14 and Figure 15).

The second case considered covered a time period where the forecast without data assimilation tracked the measured data well, starting at June 30, 01:30.

The one-step ensemble forecasts with data assimilation are shown in Figure 16, and the mean of the ensemble members is shown in Figure 17. Similar to the case above, one-step forecasts with data assimilation match well with the buoy data, and results in effective one-step corrections to the significant wave height.

However, due to the trend in the data over approximately 01:30 to 10:00, the forecasts with data assimilation vary quite a bit with each additional data point being considered in the assimilation (Figure 18 and Figure 19). As seen in Figure 20, the forecasts without data assimilation perform quite well, and the confidence interval includes nearly all of the measured data. Whereas in Figure 21, the forecasts with data assimilation also do well, and the confidence interval, which includes all the data, is tighter than without data assimilation. The NRMSE with each additional data point incorporated into the data assimilation is shown in Figure 22, where the case without data assimilation, and data assimilation with five or more points have similar results. For brevity the plots of mean and standard deviation of H_s over the domain are not shown. However, the results are similar to that found in the previous case (Figure 12 - Figure 15), where the standard deviation is reduced with data assimilation (as evidenced at the SPOT-0103 buoy in Figure 21).

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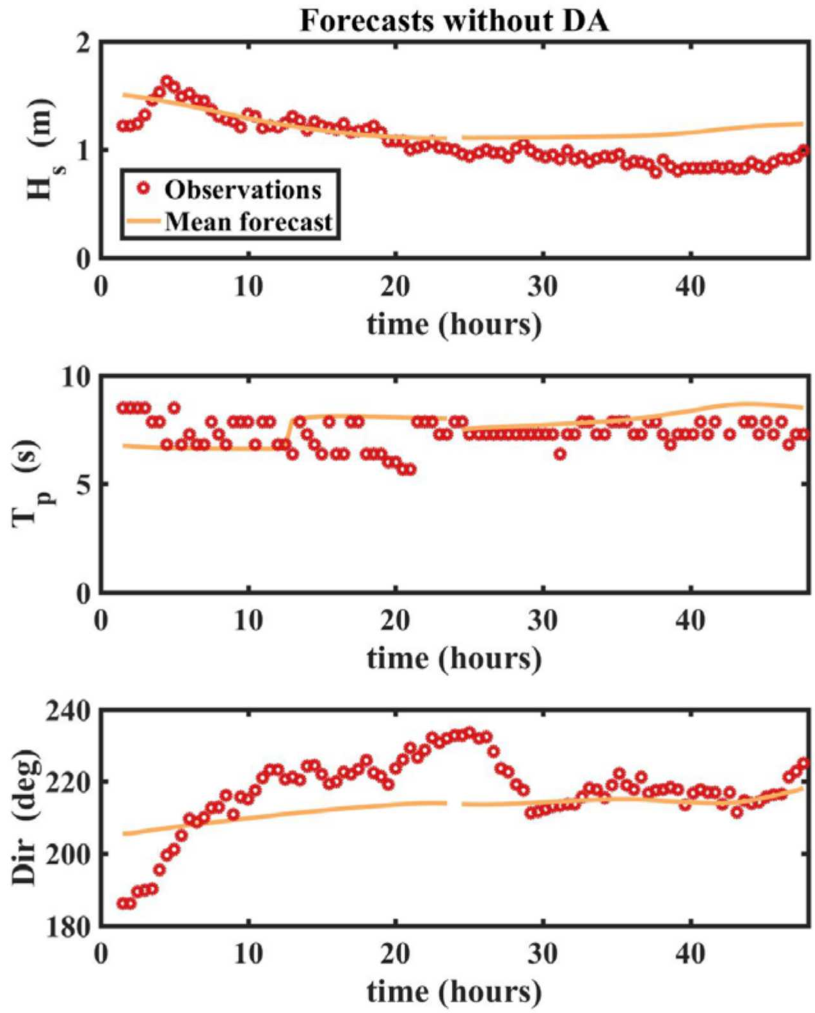
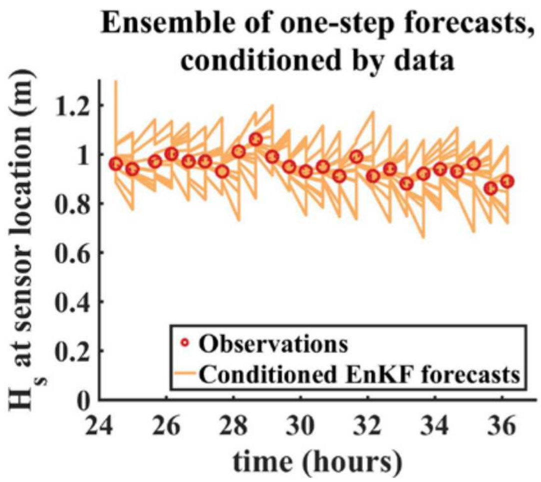


Figure 4. Mean forecast results compared to buoy observations starting at June 30, 01:30. The top figure shows significant wave height, H_s, the middle figure shows peak period, T_p, and the bottom figure shows wave direction (the direction the waves are coming from in degrees clockwise, where North is 0 degrees).



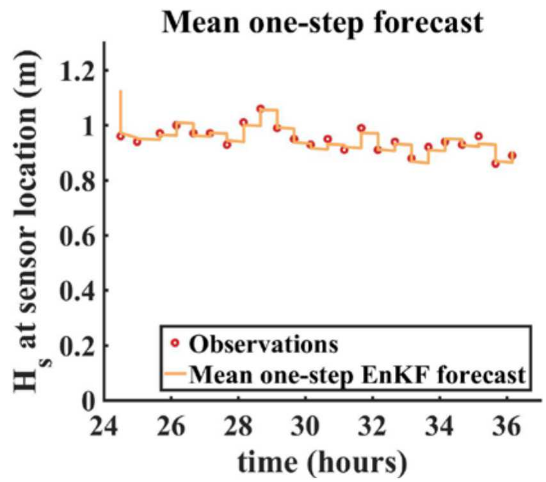


Figure 5. One-step ensemble of forecasted H_s with data assimilation starting at July 1, 00:30 at the location of the SPOT-0102 buoy that is used for data assimilation. Hour 24 refers to July 1, 00:00.

Figure 6. Mean of ensemble forecasts shown in Figure 5.

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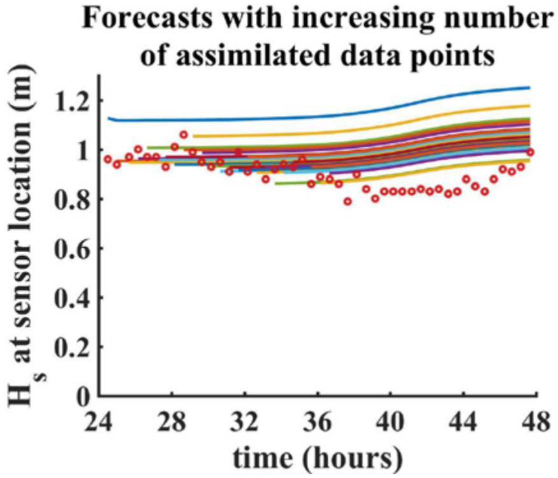

Figure 7. Forecasts with increasing number of assimilated data points, starting at July 1, 00:30.

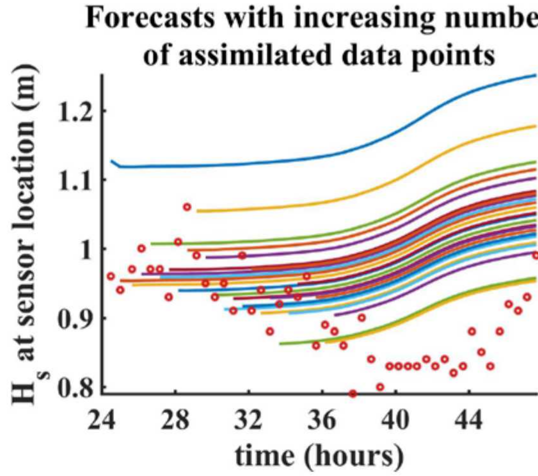

Figure 8. Zoomed in version of Figure 7 (Forecasts with increasing number of assimilated data points, starting at July 1, 00:30.)

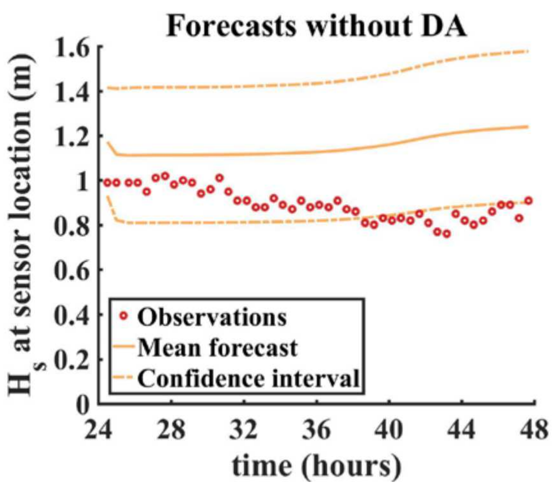

Figure 9. Forecasts without data assimilation (DA) starting at July 1, 00:30 at the SPOT-0103 buoy location. The confidence interval of the ensemble members is represented by the dotted line.

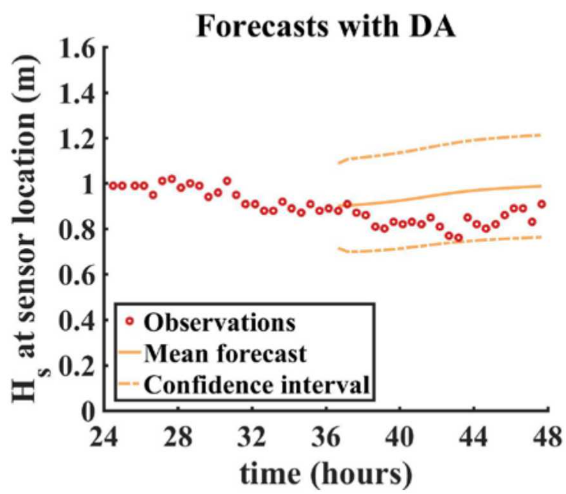

Figure 10. Forecasts starting at approximately July 1, 12:30 using all assimilated data from July 1, 00:30 to approximately July 1, 12:00. The confidence interval of the ensemble members is represented by the dotted line.

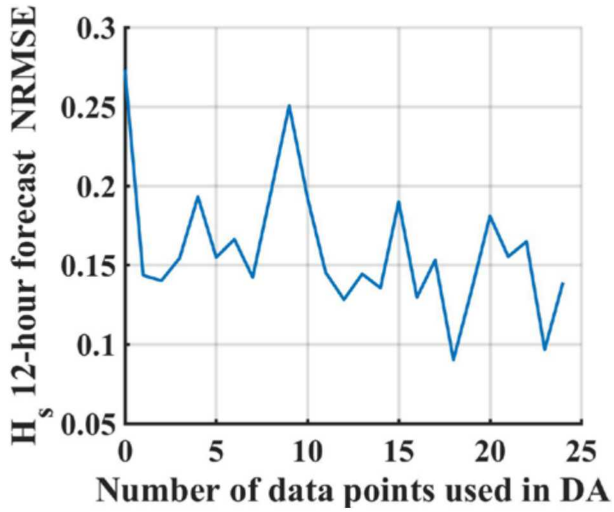

Figure 11. Normalized root mean square error for forecasts starting at July 1, 00:00 with increasing number of assimilated data points (DA represents data assimilation). Data points are in approximately 30-min intervals, therefore 24 points represents using about 12 hours of data.

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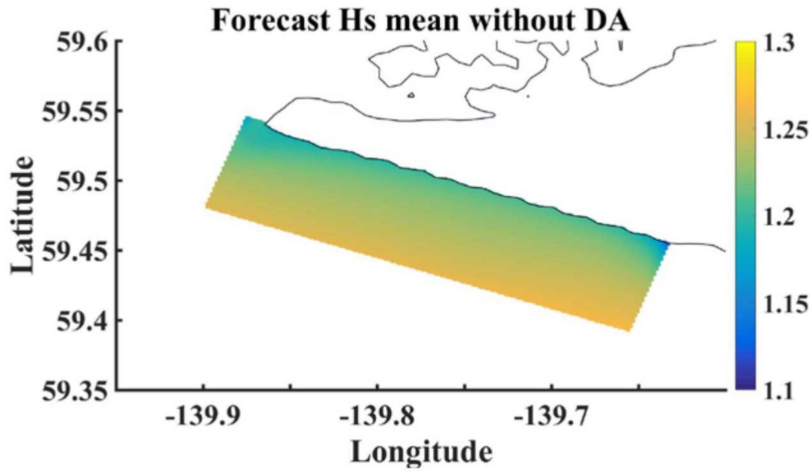

Figure 12. The mean forecast results without data assimilation (DA) at the final computational timestamp is shown over the whole computational domain.

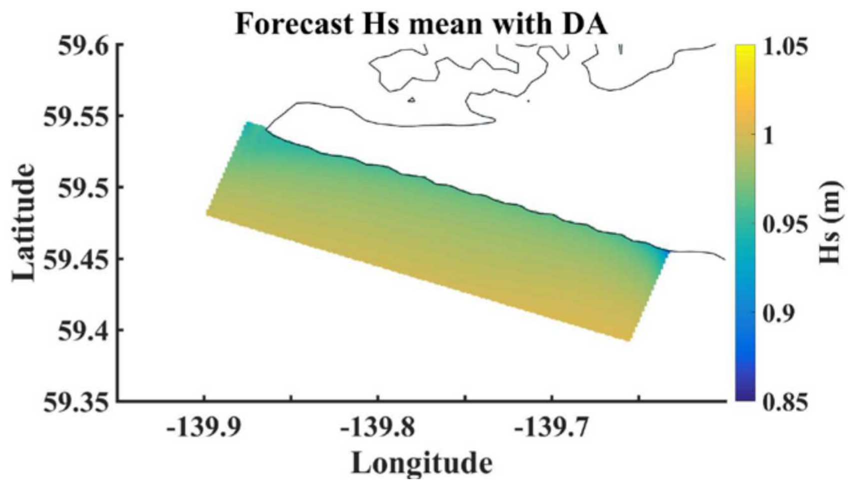

Figure 13. The mean forecast results with data assimilation (DA) at the final computational timestamp is shown over the whole computational domain. Note that the colorbar axis limits are different than in Figure 12.

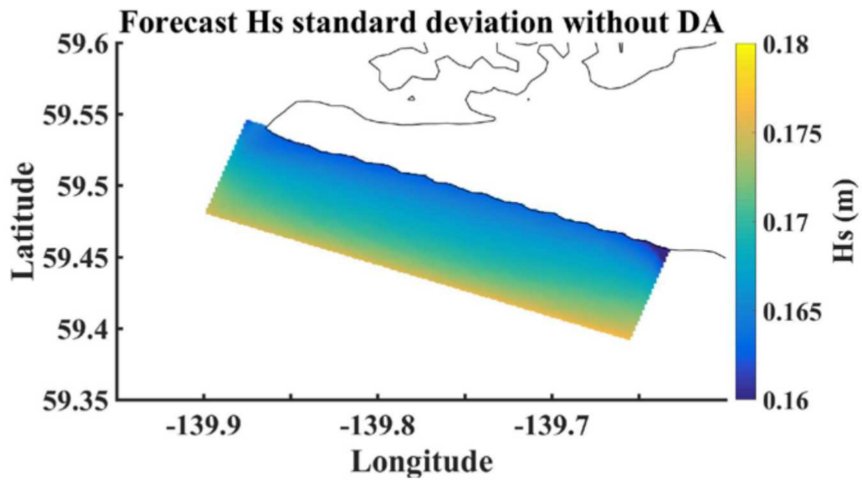

Figure 14. The standard deviation of the forecast results without data assimilation (DA) at the final computational timestamp is shown over the whole computational domain.

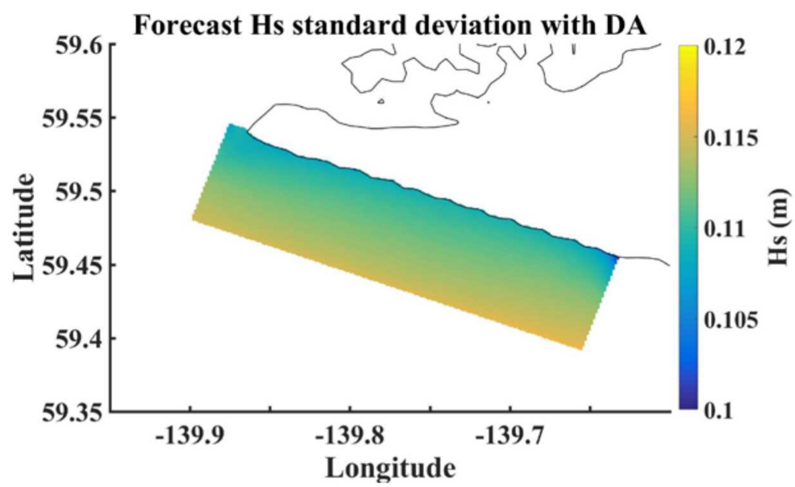

Figure 15. The standard deviation of the forecast results with data assimilation (DA) at the final computational timestamp is shown over the whole computational domain. Note that the colorbar axis limits are different than in Figure 14.

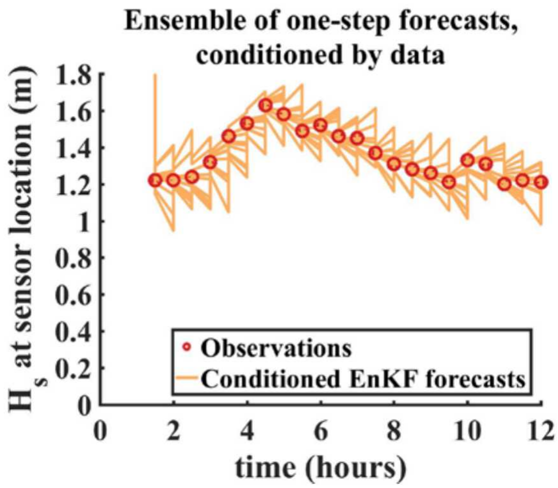

Figure 16. One-step ensemble of forecasted H_s with data assimilation starting at June 30, 01:30 at the location of the SPOT-0102 buoy that is used for data assimilation. Hour 0 refers to June 30, 00:00.

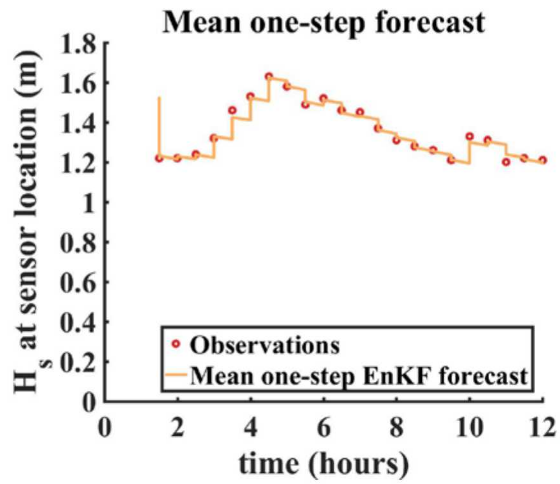

Figure 17. Mean of ensemble forecasts shown in Figure 16.

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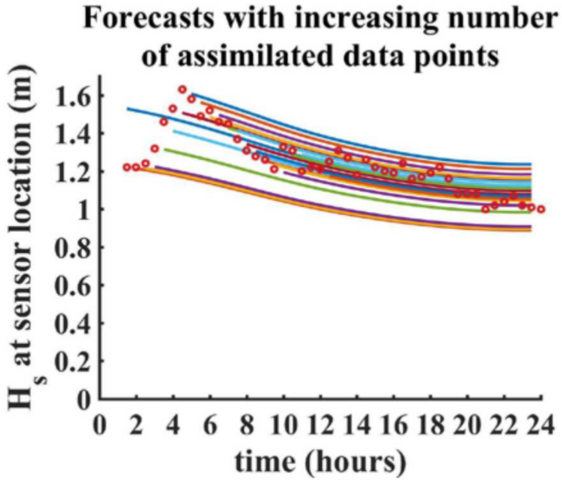

Figure 18. Forecasts with increasing number of assimilated data points, starting at June 30, 01:30 (the first available measured data point).

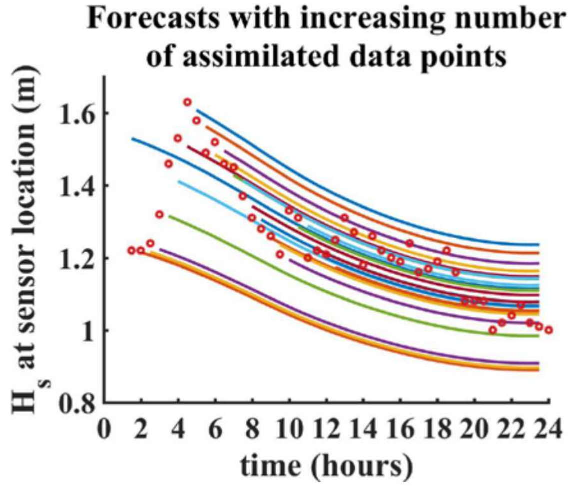

Figure 19. Zoomed in version of Figure 7 (Forecasts with increasing number of assimilated data points, starting at June 30, 01:30.)

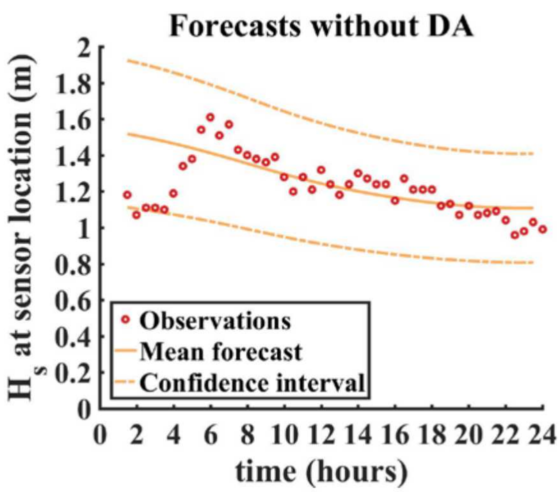

Figure 20. Forecasts without data assimilation starting at June 30, 01:30 at the SPOT-0103 buoy location. The confidence interval of the ensemble members is represented by the dotted line.

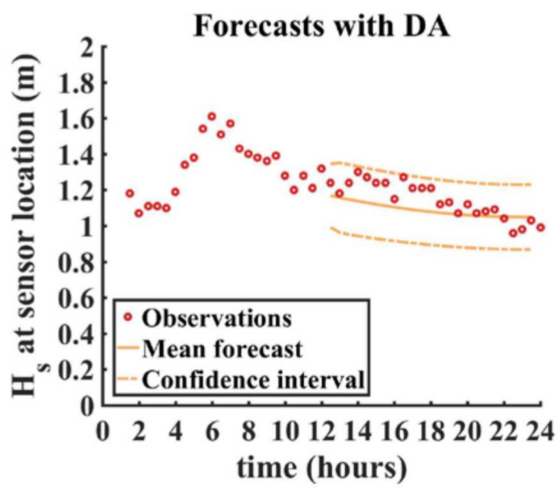

Figure 21. Forecasts starting at July 1, 12:00 using all assimilated data from July 1, 00:30 to approximately July 1, 12:00. The confidence interval of the ensemble members is represented by the dotted line.

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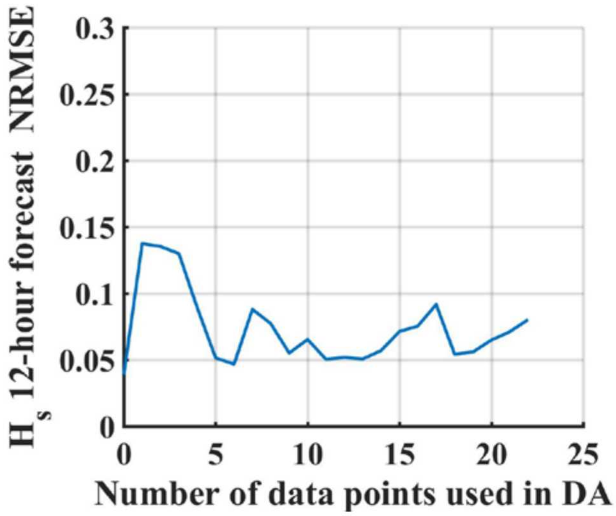

Figure 22. Normalized root mean square error for forecasts starting at June 30, 01:30. Data points are in approximately 30-min intervals, therefore 22 points represents using about 11 hours of data.

DISCUSSION:

From the results described above, it is clear that data assimilation is much more 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 also allows for more accurate hindcast analyses that can feed into the optimization of locations of individual devices within a commercial array (or at least the first row). In addition, it should be noted that the standard deviation of the ensemble of forecasts is significantly reduced when data assimilation is incorporated, resulting in more precise forecasts.

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), which is related to H_s and the energy period, T_e, through the deep water approximation:

$$J = \frac{\rho g^2}{64\pi} {H_s}^2 T_e \approx 0.49 {H_s}^2 T_e$$

where ρ is the density of sea water and g is the gravitational acceleration. Therefore, simply improving the wave height forecast significantly impacts the wave power forecast. Using the equation above to calculate J from the buoy and the forecasts results, the NRMSE for the 12 hour forecast starting at July 1, 12:00 is 73% without DA, and an average of 43% with DA.

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. These additional improvements would lead to a more viable commercial tool, and attract external investment in this area (for which Sandia would become a leader). These include:

- Considering that we are using a simple one degree-of-freedom stochastic model for the BC spectra (described above), it is reasonable to suggest that a more elaborate model that incorporates spatial and/or temporal correlations in those BC spectra would further improve the accuracy in forecasts. A reduced-order stochastic process modeling methodology utilizing Karhunen-Loève Expansions (e.g. see Khalil et al., 2014) can be leveraged to explore more complex stochastic models for the BC spectra.
- The level of uncertainty in the BC significant wave height was fixed (covariance inflation with a standard deviation equal to 15% of the mean value) based on offline experiments with data assimilation. Covariance inflation plays an important role in the EnKF as it maintains a level of uncertainty in the system state as the amount of

data assimilated increases. Manual tuning of the inflation parameters by trial and error is computationally expensive. As a remedy, we can (a) utilize adaptive online estimation or (b) obtain offline maximum likelihood estimates of the inflation parameters.

- As mentioned above, significant wave height data from the buoys was assimilated as a first step. We also focused on updating the significant wave height of the spectra across the computational domain. This decision allowed for a reduction in the computational demands of performing data assimilation. However, from an information-theoretic perspective, there is information that is being ignored in our current framework. As shown in Figure 4, there is potential for further improving the forecasted power by assimilating more spectral parameters (e.g., peak period T_p and peak wave direction D_p). As a next step, we would consider assimilating additional data while also updating other features of the solution space. A sensitivity study would be performed to understand the tradeoffs in forecast skill and computing resources required.
- Although the current framework for data assimilation relies upon EnKF, the framework is implemented to easily utilize a set of popular sampling-based techniques based on the particle filter. We propose to utilize such techniques as well as exploit recent developments towards the hybridization of EnKF and PF (e.g. see Khalil et al, 2015) to reduce sampling-based errors as well as capture non-Gaussian trends in the spectra. Such refinements would result in more accurate and robust predictions.
- Finally, this study incorporated data from one measurement buoy for data assimilation, with the error statistics compiled using the nearshore buoy, representative of a WEC array location. It is anticipated that further improvements to the forecast can be made with additional sensors, however the additional cost and complexity of the data assimilation implementation may outweigh the benefits, particularly when the domain is relatively small and the correlation throughout the domain is already high. It is likely that larger computational domains would benefit more from additional sensors. Therefore, a sensitivity study on the number and placement of measurement buoys is recommended.

ANTICIPATED OUTCOMES AND IMPACTS:

Increased forecast accuracy and lower uncertainty of incoming wave power to a WEC array will be critical to operating a microgrid. This project showed a case study where the forecasted significant wave height NRMSE was reduced from 27% to an average of 16%. The incoming wave power is a function of the square of significant wave height, making the reduction in wave power error even more substantial, from 73% to an average of 43%. In addition, the uncertainty of the ensemble of forecasts was reduced in all cases. This has major implications on the integration of wave energy into microgrids. The increased certainty and accuracy of forecasts provides greater confidence in the ability to correctly forecast electricity from a WEC farm into a microgrid.

As discussed above, there are several immediate next steps to progress the data assimilation research. To explore further increases in accuracy, the following steps were identified:

- explore more complex stochastic models for the boundary condition spectra,
- further investigation of the appropriate level of uncertainty to be specified in the boundary conditions,
- assimilate additional spectral parameters beyond significant wave height,
- consider particle filter and hybridizeation of EnKF and particle filter methods for the data assimilation,
- optimization of the number of measurement sensors and the size of the model domain,
- conduct sensitivity studies on all above items to consider computer resources and cost compared to the improvement to the forecast.

In addition, there are short term next steps to connect this improvement in the wave forecast with the ability to forecast the actual power production of a WEC array. This would include incorporating wave-to-wire models (including device and array controls algorithms, power production, and grid integration models) to understand uncertainty of power production forecasts.

In the longer term, there is a need for comprehensive research, not only in data assimilation applied to nearshore wave models, but also with respect to the WEC device and array controls, power production, and grid integration.

With the above in mind, Sandia supported an ARPA-E proposal led by project partner Integral Consulting Inc submitted to the OPEN2018 call (June 2018). This proposal focuses on the creation of a toolbox to incorporate wave forecasting using data assimilation, wave energy device and array performance with controls, and power output to a potential grid connection. However, if the project is funded, there is still much research to be done in all areas of the toolbox. For example, determining the optimal data assimilation methods and measured data locations (see bulleted list above), as well as researching, defining, and optimizing controls algorithms on representative devices and arrays (or on a variety of different WEC devices), and grid integration requirements (understanding fluctuations in the electricity produced and how much storage will be necessary). This is a substantial amount of research that would need to be funded from another source.

The inability to provide cost share severely limits Sandia's ability to lead such a proposal from this funding source, and even hinders participation on this type of proposal due to the lead organization needing to provide cost share for both their portion of the budget and Sandia's. Despite this, Integral recognizes Sandia's expertise in advanced controls algorithms, grid integration studies and controls, and data assimilation and proposed a substantial amount of the federal budget would go to Sandia.

There are plans to submit to the Energy & Homeland Security LDRD Investment Area next year for potential FY20 funding. This would incorporate scope beyond data assimilation alone; in fact, it would include WEC device and array controls as well as grid integration models. For this expanded scope, the core project team identified additional experts to be key team members for the proposed new research. The proposal leads will get feedback from LDRD committee members on the scope of the proposal to ensure it meets the needs of the investment area effectively and efficiently. The key area this proposal will address is strengthening the nation's energy security and resiliency, as well as innovative R&D for energy systems, preparing for increased penetration of renewables.

This project and potential follow on research has impacts to several Sandia programs and will position Sandia to lead future forecasting and grid integration research for the Department of Energy's Water Power Technologies Office (DOE WPTO). This is an area of research that has limited focus right now in the DOE WPTO portfolio due to the need to drastically reduce cost and improve performance of WEC devices as part of the initial commercialization thrust. However, power forecasting and grid integration are a larger part of their longer-term strategy (U.S. DOE 2016), and will likely be a greater focus area in the coming years. In addition, potential early customers of WEC technologies include military base operators located on or adjacent to the coast (e.g., Navy installations). The Navy has developed clean energy goals for its installations, and includes wave energy as a potential source in its Strategy for Renewable Energy (U.S. Navy 2012). Prior to committing to incorporate this new renewable energy source, a deep understanding of the mircogrid integration of WECs will be required.

Our growing expertise in renewable focused data assimilation research can also be applied to other Sandia programs, such as wind farm performance predictions presently funded by the Department of Energy's Wind Energy Technologies Office. Although much more headway has been made in weather forecasting, and many models include capabilities for 'nudging', smaller scale (microscale) models covering the area of a wind energy farm do not often use or have operational capabilities to incorporate data assimilation. However, it is very possible to greatly improve forecasting wind farm energy production through data assimilation that utilizes existing in situ meteorological towers and remote sensing instrumentation. This will lead to more efficient grid operations for existing and new wind farm installations.

CONCLUSIONS:

Incorporating data assimilation for wave predictions was found to significantly improve the forecasted significant wave height over a twelve-hour period where the boundary conditions did not represent the observations well. The NRMSE of significant wave height was reduced from 27% to an average of ~16%. The wave power is a function of the square of the significant wave height, therefore improvements in H_s result in even greater impacts on wave power, the variable of interest for grid integration. This has a major impact on grid requirements and cost savings. For this case, the reduction in wave power NRMSE is from 73% to an average of 43%.

When the forecasted model boundary conditions track the measured conditions well, data assimilation did not make a significant impact to the mean forecast skill (as expected). However, it should be noted that implementing data assimilation for both cases resulted in tighter confidence intervals for the significant wave height. A tighter confidence interval of power generation forecasts reduces the need for storage and helps to maximize efficiency of a microgrid.

Several recommended next steps detail opportunities for further improving wave forecasts. These include exploring more complex boundary condition models, optimizing the level of uncertainty in the boundary condition, assimilating additional spectral parameters beyond significant wave height, utilizing particle filter sampling or a hybridization of EnKF and particle filter, and finally exploring the benefits of additional measurement sensors and size of the model domain. Each of these steps will increase either computational effort or project cost (in terms of measurement purchases), and therefore sensitivity or trade-off studies are recommended to detail the improvements to the forecast compared to cost.

To realize a successful wave energy industry, the nation will require important improvements to the forecasting of incoming WEC farm wave conditions to meet critical grid integration demands, particularly for microgrid locations. The location in this study is a very relevant example of an area with high wave resource with a single source of power (currently a 100% reliance on diesel fuel). Research like this, that quantifies the accuracy and uncertainty levels of WEC power production will inform grid and storage needs, and increase confidence in and likelihood of successful commercialization of this lesser developed renewable energy technology.

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REFERENCES:

Zhou N, Huang Z, Meng D, Elbert S, Wang S, Diao R, “Capturing Dynamics in the Power Grid: Formulation of Dynamic State Estimation through Data Assimilation” PNNL-23213, March 2014.

Penalba M, Ringwood JV. A Review of Wave-to-Wire Models for Wave Energy Converters. Energies 2016;9(506).

Raghukumar, K., Spada, F., Chang, G., Jones, C., Janssen, T. (2018) “Performance characteristics of ‘Spotter’, a newly developed real-time wave measurement buoy. In review. Journal of Atmospheric and Oceanic Technology.

Dallman A, Neary V, Stephenson M (2014) Investigation of Spatial Variation of Sea States Offshore of Humboldt Bay, CA Using a Hindcast Model. Sandia National Laboratories, Albuquerque, NM. SAND2014-18207.

García-Medina G, Özkan-Haller HT, Ruggiero P (2014) Wave resource assessment in Oregon and southwest Washington, USA. Renew Energy 64:203-214.

Wittman P, Cummings J (2005) Assimilation of Altimeter Wave Measurements into Wavewatch III. Report NRL/PP/7320—04-0003.

Chen HS, Behringer D, Burroughs LD, Tolman HL (2004) “A Variational Wave Height Data Assimilation System for NCEP Operational Wave Models.” National Weather Service National Centers for Environmental Prediction. Technical Procedures Bulletin, Series No. MMAB/2004-04.

Hasselmann S, Lionello P, Hasselmann K (1997) An optimal interpolation scheme for the assimilation of spectral wave data. Journal of Geophysical Research, 102(C7):15, 823-836.

Rusu L (2015) Assessment of the Wave Energy in the Black Sea Based on a 15-Year Hindcast with Data Assimilation. Energies 8, 10370-10388.

Almeida S, Rusu L, Soares CG (2016) “Data assimilation with the ensemble Kalman filter in a high-resolution wave forecasting model for coastal areas.” Journal of Operational Oceanography 9(2):103-114.

Tschetter T, Kasper JL, Duvoy PX, “Yakutat Area Wave Resource Assessment” Alaska Center for Energy and Power, November 1, 2016.

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Neary VS, Previsic M, Jepsen RA, Lawson MJ, Yu Y-H, Copping AE, Fontaine AA, Hallett KC, Murray DK (2014) Methodology for Design and Economic Analysis of Marine Energy Conversion (MEC) Technologies. Sandia National Laboratories, Albuquerque, NM. SAND2014-9040.

Khalil, M, Sarkar, A, Adhikari, S, Poirel, D, "The estimation of time-invariant parameters of noisy nonlinear oscillatory systems." Journal of Sound and Vibration 344:81-100, 2015.

Khalil, M, Sarkar, A, "Independent component analysis to enhance performances of Karhunen-Loeve expansions for non-Gaussian stochastic processes: application to uncertain systems." Journal of Sound and Vibration 333:5600-5613, 2014.

U.S. Department of Energy (2016), Request for Information (RFI): Draft Marine and Hydrokinetic Program Strategy DE-FOA-0001721. Available at: https://eere-exchange.energy.gov/Default.aspx?Archive=1#FoaIdec253663-c0d2-4a05-942f-50c8975fcf58

U.S. Department of the Navy (2012) Strategy for Renewable Energy. http://www.secnav.navy.mil/eie/Documents/DoNStrategyforRenewableEnergy.pdf

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