Machine Learning for Low-Cost Offshore Modelling

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The EPSRC Supergen ORE Hub funded **Ma**chine **L**earning for Low-**C**ost **O**ffshore **M**odelling (MaLCOM) project has demonstrated a system that uses historical wave model data to provide spatial wave data from in-situ point measurements. By using machine learning of spatial-correlations in a long-term physics based model, the project has created a low computational-cost surrogate model that offers a higher level of accuracy than physics-based models alone. In essence this integrates in-situ measurements and historical model runs to achieve the spatial coverage of the model and the accuracy of the in-situ measurements. Once operational, the system requires very little computational power, meaning that it could be deployed to a mobile phone, operational vessel, or autonomous vessel to give continuous data. As such, it makes a significant change to the availability of met-ocean data with potential to revolutionise data provision and use in marine and coastal settings.

The work is motivated by the importance of accurate wave data for the design and operation of offshore renewable energy (ORE). Weather delays during installation, inspection, operation, and maintenance contribute significantly to project costs. For example, Wikinger Wind Farm incurred additional costs of over £17 million during installation, due to decisions based on inaccurate forecasts[1]. Accuracy in short-term forecasting allows operators to correctly identify and use weather windows, ensuring the health and safety of crews and avoiding unnecessary delays. As such, nowcasting and short-term forecasting is critical for operational decisions[2,3].

WP1 of the project gathered data that aligns with operational data sets widely used by industry. This comprised a 30 year hindcast regional SWAN wave model developed at the University of Exeter[4] and data from wave buoys operated as part of the Channel Coastal Observatory (CCO) initiative.

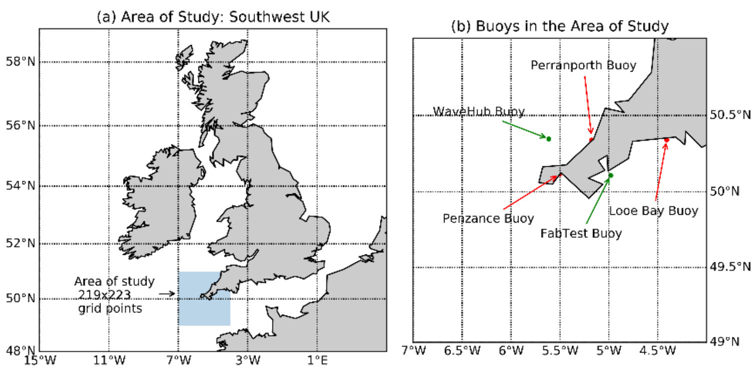

Figure 1 The region of interest considers the waters around Cornwall in the UK ranging from 4°W to 7°W in longitude, and 49°N to 51°N in latitude. Five wave buoys are used with the three red points (Penzance, Looe Bay, and Perranporth) representing buoys used as inputs for the spatio-temporal model, and the two green points (WaveHub and FabTest) representing the buoys used for validating the model outputs and benchmarking the proposed model framework.

WP2 developed the numerical framework for developing the surrogate wave model. Various sensitivity analyses were used to find optimal operational systems based on significant wave height, mean wave direction, mean zero-crossing period, and peak wave period. Three distinct models were developed (Figure 2);

- Spatial model based on a random forest algorithm, which learns the correlation between input locations and the rest of the model domain
- Short-term temporal modelling based on an LSTM system that predicts up to 24hrs based on recent data

- A spatio-temporal model that combines the two systems to provide a short-term spatial forecast.

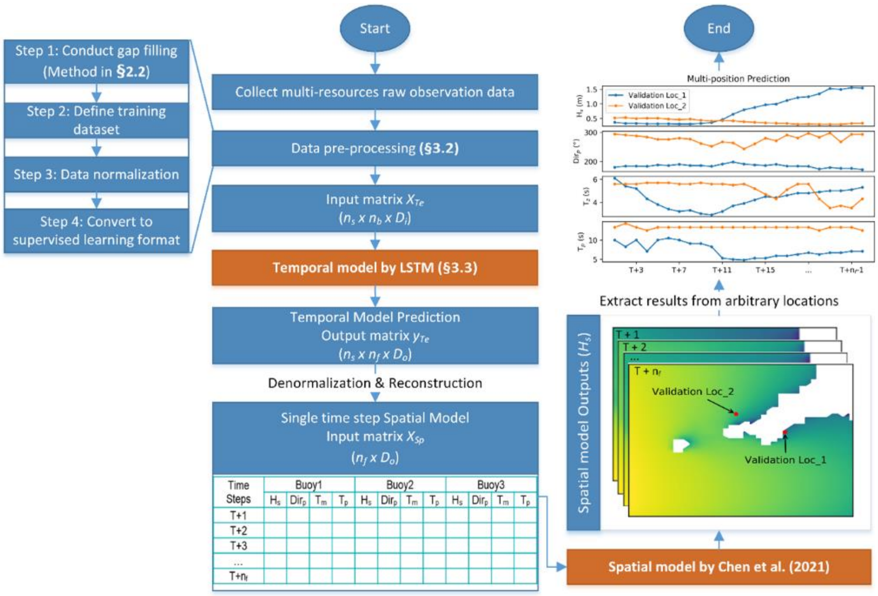

Figure 2 Spatio-temporal wave prediction model flowchart. Orange boxes highlight the temporal and spatial model that are the key novelty developed through this project. Section numbers refer to those in our publication introducing the full framework in Chen et al. 2022.

WP3 ran benchmarking studies on these models and found;

- A random forest can successfully be trained using a hindcast model and run using in-situ measurements to provide nowcasts;
- LSTM networks can be used to predict wave parameters at a fixed location; and
- Coupling the RF based spatial surrogate with the LSTM temporal predictions enables spatio-temporal forecasts of wave parameters.

Of particular note, the spatial surrogate model proved more accurate than the equivalent computational model (Figure 3 and Table 1), despite a significantly reduced computational requirement. This is in part due to the use of accurate in-situ data to drive the model and highlights the potential benefit of an integrated measurement-model system.

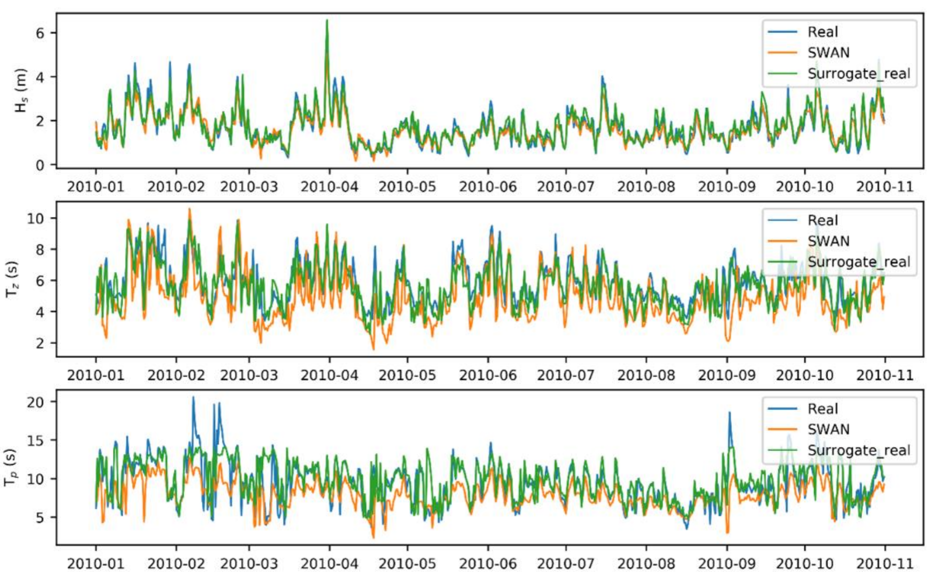

Figure 3 Comparison of four wave parameters in the year 2010 between SWAN output, the surrogate model output with real data input, and buoy observations at Wave Hub. Blue curves represent real buoy data, the orange and green curves represent SWAN and surrogate model outputs, respectively. The time-step for both sets of output was consistent with data plotted every 12 hours.

Table 1 Model Performance between the surrogate model and SWAN in 2010

		R^2	RMSE	NRMSE
H_s	SWAN	0.8521	0.3218	19.01%
	Surrogate	0.9067	0.2556	15.10%
T_z	SWAN	-0.0257	1.3903	23.71%
	Surrogate	0.7205	0.7258	12.38%
T_p	SWAN	0.2263	2.4852	26.26%
	Surrogate	0.5558	1.8831	19.89%

Results from the coupled spatio-temporal model were compared with historical operational forecast provided by the UK Met Office (UKMO). This is a leading marine forecast. At Wave Hub, the surrogate system showed similar uncertainties. However, the UKMO model results indicated more stable accuracy, while the accuracy of the proposed model framework reduced with forecast time (Figure 4)

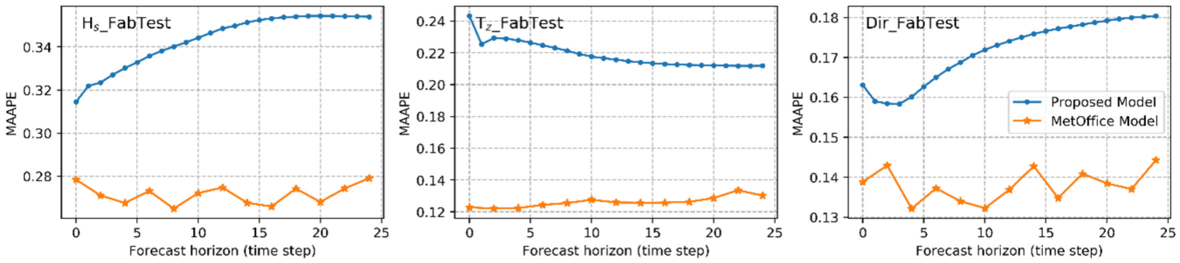

Figure 4 Accuracy against forecast horizon of present framework and Met Office operational forecasting model compared at FabTest buoy location for 2020.

Notably, at the FaBTest site, both the proposed model framework and the UKMO model were less accurate at FabTest than at WaveHub. However, the proposed model framework is consistently less accurate (i.e. higher errors) than the UKMO model for H_s and T_z over the forecast time horizon. This was related to limitations in the training data, particularly for waves in the English Channel. This outcome highlights the importance of adequate and accurate training data for the surrogate system.

This project was led by the University of Exeter and collaborated with the UK Met Office, James Fisher Marine Services, EIVA A/S, and Sofar Ocean to develop this forecasting framework, demonstrate it, and benchmark it in UK waters. A particularly exciting outcome was the short-term forecasting of wave parameters at a comparable accuracy level to physics-based forecasts, but at a fraction of the computational expense. The investigators have generated and published a framework for machine learning driven wave forecasts. It is anticipated that the framework can be effectively applied in marine operations planning during installation, operations, and decommissioning at offshore renewable energy sites improving vessel planning through more accurate estimates of site access. The outcomes have also highlighted the suitability of this system for integrating mobile, autonomous measurements and satellite measurements, which offers a promising avenue for further research.

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