FORECASTING WAVE-ENERGY PRODUCTION BY COMBINING MODEL ENSEMBLE BLENDING WITH MACHINE LEARNING FORECASTING

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Abstract

Integration of renewable-energy resources into the electricity grid demands accurate forecasting of energy production capacities. Recently, significant effort has been undertaken to quantifywave energy because it is renewable, environmental friendly, abundant, and often close to population centers. However, a major challenge is the ability to quickly and accurately predict energy-generation potential, which for wave-energy converters requires wave-condition forecasting. Accurate forecasting of wave conditions is a challenging undertaking that typically involves solving the spectral action-balance equation on a discretized grid with high spatial resolution, typically demanding high-performance computing infrastructure. Moreover, current operational wave forecasting systems exhibit substantial errors with wave-height RMSEs of 40 to 60 cm typical, which limits the reliability of energy-generation predictions thereby impeding integration with the distribution grid. To address these shortcomings, over 40,000 runs of the physics-based Simulating WAves Nearshore (SWAN) model on a refined grid generated training data for a machine-learning model, which, when properly trained, can be used to predict wave heights with an RMSE below 9 cm, but that run in a fraction of a second [1]. Next, these machine-learning models were included in a statistical learning-aggregation technique that combine forecasts from multiple, independent models into a single "best-estimate" prediction of the true state [2]. The learning-aggregation technique uses past observations and past model forecasts to calculate a weight for each model. An appropriately weighted ensemble model outperforms individual ensemble members when forecasting wave conditions with perturbed inputs. By integrating ensemble forecasting with an extremely lightweight forecasting model and a statistical learning-aggregation technique, this study provides

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a complete real-time forecasting framework that leverages all available data from observations while accounting for uncertainties in model forcing data. These more accurate wave-condition forecasts can be used to make 48-hour predictions of energy production from an array of wave-energy converters.

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