CPSC 486 - Project

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April 2025

1 Abstract

Wave energy presents a promising and consistent renewable energy source, but its use highly depends on accurate wave forecasting to optimize Wave Energy Converters (WECs). Traditional physics-based models like SWAN offer physically grounded predictions but are computationally intensive and increasingly challenged by climate-driven variability. While pure machine learning (ML) models improve efficiency, they often lack physical fidelity and generalizability. This study proposes a hybrid approach that combines the strengths of both methods using a Bayesian Neural Network (BNN) trained on SWAN-simulated wave data. With the application of variational inference, the model captures the physical wave dynamics while quantifying both aleatory and epistemic uncertainty, enhancing prediction robustness. Literature review highlights the evolution of ML in ocean forecasting, and the various approaches that have already been studied. Results indicate the hybrid BNN achieves high accuracy and significant computational savings, demonstrating the viability of physics-informed machine learning for real-time, reliable wave energy modeling.

2 Introduction

Wave energy is one of the most promising sources of renewable energy, offering a consistent and dense form of power from the energy of ocean surface waves. Unlike solar and wind energy, which are more subject to daily and seasonal fluctuations, wave energy is generally more predictable and less intermittent, making it a great option for diversifying a clean energy portfolio. To harness this energy wave energy converters (WECs) are designed to capture the motion of waves and convert it into usable electricity. These devices come in various forms each with their own unique interaction with the ocean environment. However, the performance and survivability of WECs are highly sensitive to the characteristics of the surrounding wave field.

Accurate wave energy modeling is extremely important in optimizing the operation and control of WECs. Forecasts of wave height, period, and direction allow operators to tune device parameters to maximize energy extraction. Also within renewable energy systems there has been a rise of reinforcement learning techniques that optimize efficiency of grids by calculating energy production by source as the day fluctuates. Traditional physics-based models like SWAN have served as the foundation for these forecasts, but as deployment scales there is an increasing demand for models that are not only accurate but also computationally efficient. These needs are driving the development of hybrid and machine learning-enhanced approaches to wave energy forecasting.

3 Problem

The modern era of climate and ocean modeling has seen the rise of new techniques involving machine learning. Traditionally, climate simulations and weather forecasts relied on physics-based models, often written in languages like Fortran which simulate the fluid dynamics based on well establishes physical laws. Although these models are grounded in physical correctness, they are computationally expensive and often slow, especially when running over longer time scales. Additionally, with the major pattern shifts that have occurred as a result of climate change, these models struggle more and more to adapt.

One approach that was studied was the use of pure machine learning models, essentially models trained solely on historical climate/weather data that were then used for predictions. These models tend to be larger neural networks although multiple approaches have been studied. However, a major drawback of these models is that they struggle to accurately replicate physical conditions, therefore violating physical laws. In terms of ocean wave models, they struggle to replicate the physical behavior of ocean waves and their fluid properties. Particularly when extrapolating beyond conditions from the training data. Limiting these models performance in real-world scenarios.

To address these limitations, hyrbid approaches have gained traction. These methods combine the strengths of physics-based simulations with the flexibility and speed of machine learning. By using large datasets generated from traditional models, ML models can be trained to approximate certain components of the simulation while still respecting physical constraints. This project investigates a hybrid approach using variational inference and Bayesian neural networks to approximate the behavior of wave energy dynamics. Specifically the model is trained on output data from the

SWAN (Simulating WAves Nearshore) model, a well established physics based wave simulation tool. By leveraging SWAN generated data, the Bayesian model can be trained to predict wave behavior while also providing uncertainty estimates, making the predictions more robust and interpretable.This method aims to preserve the physical properties of traditional models while achieving improvements in efficiency from physics based models and accuracy from pure ML approaches. // The resulting model should offer gains in various dimensions: improved accuracy, faster runtime, and reduced model complexity. These improvements make hybrid ML-physics models a compelling path forward for future ocean wave energy modeling.

4 Literature Review

4.1 A review of machine learning and deep learning applications in wave energy forecasting and WEC optimization

This paper provides a comprehensive overview of the various pure ML techniques that have been applied in the field of wave energy. It acknowledges the already mentioned limitations of traditional physics based models such as high computational costs and poor capture of nonlinear behaviors. The authors explore how machine learning and deep learning can be used to improve both accuracy and efficiency of wave energy forecasting. The review delves into various models and their applications with emphasis on the potential of these pure ML approaches.

One recurring theme in this paper is the optimization of power take-off (PTO) systems in WECs. Accurately forecasting wave height (H_s), wave period (T), and wave direction (θ), is crucial for optimizing PTO parameters and improving energy extraction efficiency. The authors discuss the application of ML and DL models in predicting these wave parameters, which are essential for estimating wave power using the formula:

$$P = \frac{\rho g^2}{64\pi} H_s^2 T$$

where:

- P is the wave power per unit width (W/m),
- ρ is the water density (kg/m^3),
- g is the acceleration due to gravity (m/s^2),
- H_s is the significant wave height (m),
- T is the wave period (s).

The review provides a solid baseline and introduction to machine learning techniques in wave forecasting. Highlighting optimization techniques such as stochastic gradient descent along with supervised learning examples like SVM models, and neural networks for deep learnig approaches. The paper also shows how the combination of traditional numerical models to create hybrid systems leverages the benefits of multiple techniques. These approaches can lead to improved convergence rates and better forecasting accuracy

4.2 A Deep Learning Approach to Predict Significant Wave Height using Long Short-Term Memory

This paper presents a deep learning framework for forecasting significant wave height (H_s) in the Southwestern Atlantic Ocean. The authors use a Long Short-Term Memory (LSTM) model, a type of recurrent neural network trained using both ERA5 reanalysis data and buoy observations. The study focuses on seven locations along the Brazilian coast, considering four different lead times: 6, 12, 18, and 24 hours. It also analyzes the influence of additional variables such as wind speed and wave period on the model's performance. The LSTM model's performance is evaluated using the Mean Absolute Percentage Error (MAPE), defined as:

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100\%$$

where:

- A_t is the actual value at time t,
- F_t is the forecasted value at time t,
- n is the number of observations.

The results showed that the LSTM model achieved an accuracy of approximately 87% when compared to real buoy data, demonstrating its potential as an alternative to computationally expensive physical models and as an alternative to reanalysis data. The study concludes that data-driven methodologies like LSTM can provide efficient and accurate forecasts of significant wave height.

4.3 A machine learning framework to forecast wave conditions

This paper presents a hybrid approach to ocean wave forecasting. The study focuses on the Monterey Bay area, utilizing the Simulating WAves Nearshore (SWAN) model to generate a comprehensive dataset of wave conditions, including significant wave height

(H_s) and characteristic wave period (T). By running thousands of SWAN simulations with varying input conditions—such as wind speed, ocean currents, and boundary wave conditions—the authors created a robust training dataset the machine learning model.

This paper's framework integrates a multilayer perceptron (MLP) neural network by training it on the SWAN data to predict The machine learning framework employs multilayer perceptron (MLP) neural networks trained on the SWAN-generated data to predict H_s and T across the study domain. The performance of the MLP models is evaluated using the Root Mean Square Error (RMSE), defined as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

where:

- y_i represents the observed values,
- $\hat{y}_i$ denotes the predicted values,
- n is the number of observations.

The results show that the MLP model can replicate SWAN-simulated wave heights with an RMSE of approximately 9 cm and accurately identify over 90% of the wave periods in the test datasets. Additionally, the computational efficiency of this approach is high as it requires less than 0.1% of the computation time compared to the SWAN simulations. This reduction in computational cost highlights the potential of machine learning frameworks for real-time wave forecasting, offering both speed and accuracy.

4.4 A Hybrid Machine Learning Approach to Wave Energy

This paper presents a method for forecasting wave energy by combining multiple machine learning techniques. Due to the complex and nonlinear nature of ocean wave dynamics, the study combines Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Kalman Filters (KF), and Wavelet Neural Networks (WNN) to enhance prediction accuracy and reliability. This hybrid approach aims to leverage the strengths of each individual model: ANFIS for handling uncertainty and approximate reasoning, KF for refining predictions over time, and WNN for capturing both time and frequency information in the data.

The performance of the hybrid models is evaluated using metrics such as Mean Absolute Percentage Error (MAPE) and Normalized Root Mean Square Error (nRMSE), defined as:

$$\text{MAPE} = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|$$

$$\text{nRMSE} = \frac{\sqrt{\frac{1}{n} \sum_{t=1}^{n} (A_t - F_t)^2}}{\bar{A}}$$

where:

- A_t is the actual value at time t,
- F_t is the forecasted value at time t,
- n is the number of observations,
- $\bar{A}$ is the mean of the actual values.

The results demonstrated that the hybrid models outperform individual models in forecasting wave energy parameters, achieving lower MAPE and nRMSE values. This indicates improved accuracy and reliability, making the hybrid approach a promising tool for applications in wave energy conversion and management.

4.5 Phase-resolved Real-time Ocean Wave Prediction with Quantified Uncertainty Based on Variational Bayesian Machine Learning

This paper shows an approach to ocean wave forecasting that uses variational Bayesian machine learning techniques. The authors address the need for accurate and real time predictions of ocean wave elevations which are important for the efficiency of wave energy converters (WECs). Traditional linear wave theories often provide overly conservative estimates of the predictable zone (the time period over which wave predictions remain reliable). In contrast, the proposed method uses Bayesian neural networks to model the more complex, nonlinear wave dynamics while also quantifying both aleatory (inherent randomness) and epistemic (model-related) uncertainties. As this paper was the most referenced in my approach, I will breakdown their methodology

4.5.1 Data Collection and Handling

For this study, Wave tank experiments were conducted to collect the high-resolution time-series data of wave elevations. Sensors were placed to measure wave elevations at specific locations, providing the input and output pairs for model training and validation.

The collected data was then processed, including normalization and segmentation, to prepare it for training the machine learning model.

4.5.2 Variational Bayesian Neural Network (BNN) Framework

The core of the methodology is a Bayesian Neural Network trained using variational inference. Unlike traditional neural networks that provide point estimates, BNNs model the posterior distribution over the network's weights, allowing for uncertainty quantification in predictions.

4.5.3 Bayesian Inference Objective

The training objective is to approximate the true posterior distribution $p(\mathbf{w}|\mathcal{D})$ with a variational distribution $q(\mathbf{w})$, where w represents the network weights and $\mathcal{D}$ denotes the training data. This is achieved by minimizing the Kullback-Leibler (KL) divergence between $q(\mathbf{w})$ and $p(\mathbf{w}|\mathcal{D})$:

$$\mathrm{KL}(q(\mathbf{w})\|p(\mathbf{w}|\mathcal{D})) = \int q(\mathbf{w}) \log \frac{q(\mathbf{w})}{p(\mathbf{w}|\mathcal{D})}\, d\mathbf{w}$$

Evidence Lower Bound (ELBO)

Minimizing the KL divergence is equivalent to maximizing the Evidence Lower Bound (ELBO), defined as:

$$\mathrm{ELBO} = \mathbb{E}_{q(\mathbf{w})}[\log p(\mathcal{D}|\mathbf{w})] - \mathrm{KL}(q(\mathbf{w})\|p(\mathbf{w}))$$

Here, $p(\mathcal{D}|\mathbf{w})$ is the likelihood of the data given the weights, and $p(\mathbf{w})$ is the prior distribution over the weights.

4.5.4 Uncertainty Quantification

The BNN framework allows for the decomposition of predictive uncertainty into:

- **Aleatory Uncertainty**: Captures the inherent noise in the observations.
- **Epistemic Uncertainty**: Represents the uncertainty in the model parameters due to limited data.

By sampling from the variational posterior $q(\mathbf{w})$, the model generates a distribution over possible predictions, allowing for the quantification of both types of uncertainty.

4.5.5 Predictable Zone Determination

The methodology introduces an approach to determine the "predictable zone," which is defined as the time period over which wave predictions remain reliable. Unlike traditional methods that assume linear wave theory, this approach uses the BNN's uncertainty estimates to identify exactly where predictions meet the predefined confidence threshold.

4.5.6 Model Evaluation

The model's performance was assessed using metrics such as Root Mean Square Error (RMSE) and the length of the predictable zone. Analyzing the results showed that the proposed method outperforms traditional linear wave theory and deterministic machine learning models in both accuracy and the extension of the predictable zone.

5 Methodology

The first step of my approach is to utilize the SWAN model to generate wave parameter. Specifically the wave height, period, and direction for a 1 year period using wind and bathymetry data.

I downloaded the bathymetry data from GEBCO (General Bathymetric Chart of the Oceans) and wind data from CDS Climate Store, specifically the ERA5 reanalysis data

Theorem 1 (BNN-VI Framework). *Given:*

- *SWAN inputs* $\mathbf{x}_t^{SWAN} = [H_s, T_p, \theta_m] \in \mathbb{R}^3$
- *BNN likelihood* $p(y_t|\mathbf{x}_t^{SWAN}, \mathbf{w}) = \mathcal{N}\big(y_t \mid f_{\mathbf{w}}(\mathbf{x}_t^{SWAN}), \sigma^2\big)$
- *Prior* $p(\mathbf{w}) = \mathcal{N}(\mathbf{0}, \mathbf{I})$
- *Variational posterior* $q_\phi(\mathbf{w}) = \mathcal{N}(\mathbf{w} \mid \mathbf{m}, diag(\boldsymbol{\sigma}^2))$

The optimal variational parameters ϕ^* *minimize:*

$$KL\big(q_\phi(\mathbf{w}) \parallel p(\mathbf{w}|\mathcal{D})\big) = -ELBO(\phi) + \log p(\mathcal{D}) \tag{1}$$

where:

$$ELBO(\phi) = \underbrace{\mathbb{E}_{q_\phi}[\log p(\mathcal{D}|\mathbf{w})]}_{Data\ term} - \underbrace{KL\big(q_\phi(\mathbf{w}) \parallel p(\mathbf{w})\big)}_{Regularizer} \tag{2}$$

5.1 Proof Sketch

1. **Likelihood Gradient**:

$$\nabla_{\mathbf{w}} \log p(\mathcal{D}|\mathbf{w}) = \frac{1}{\sigma^2} \sum_{t=1}^{n} \big(y_t - f_{\mathbf{w}}(\mathbf{x}_t)\big) \nabla_{\mathbf{w}} f_{\mathbf{w}}(\mathbf{x}_t) \tag{3}$$

2. **KL Divergence** (Diagonal Gaussian):

$$\mathrm{KL}(q_\phi \parallel p) = \frac{1}{2} \sum_{i=1}^{d} \left(\log \frac{1}{\sigma_i^2} + \sigma_i^2 + m_i^2 - 1 \right) \tag{4}$$

3. **Reparameterization**:

$$\mathbf{w}^{(s)} = \mathbf{m} + \boldsymbol{\sigma} \odot \boldsymbol{\epsilon}^{(s)}, \quad \boldsymbol{\epsilon}^{(s)} \sim \mathcal{N}(\mathbf{0}, \mathbf{I}) \tag{5}$$

5.2 Gradient Calculations

$$\nabla_{\mathbf{m}} \mathrm{ELBO} \approx \frac{1}{S} \sum_{s=1}^{S} \nabla_{\mathbf{w}^{(s)}} \log p(\mathcal{D}|\mathbf{w}^{(s)}) \tag{6}$$

$$\nabla_{\boldsymbol{\sigma}} \mathrm{ELBO} \approx \frac{1}{S} \sum_{s=1}^{S} \left[\nabla_{\mathbf{w}^{(s)}} \log p(\mathcal{D}|\mathbf{w}^{(s)}) \odot \boldsymbol{\epsilon}^{(s)} \right] - \left(\boldsymbol{\sigma} - \frac{1}{\boldsymbol{\sigma}} \right) \tag{7}$$

5.3 Predictive Uncertainty

Corollary 1 (Uncertainty Decomposition)**.** *The predictive variance decomposes as:*

$$Var(y_*) = \underbrace{\frac{1}{S} \sum_{s=1}^{S} f_{\mathbf{w}^{(s)}}(\mathbf{x}_*)^2 - \left(\frac{1}{S} \sum_{s=1}^{S} f_{\mathbf{w}^{(s)}}(\mathbf{x}_*) \right)^2}_{Epistemic} + \underbrace{\sigma^2}_{Aleatoric} \tag{8}$$

5.4 Training Protocol

- **Optimizer**: Adam ($\eta = 10^{-3}$)
- **Batch size**: 128
- **Samples/gradient** (S): 10
- **KL annealing**: Linear warmup over 1k iterations

6 Results/Discussion

The Bayesian Neural Network (BNN) trained on SWAN-generated wave data showed great predictive performance across the evaluation dataset. Using wind and bathymetry inputs from ERA5 and GEBCO respectively, SWAN provided a reliable dataset over a one-year period, that captures both seasonal and directional wave dynamics. Our BNN not only reduced the Root Mean Square Error (RMSE) by approximately 18%, but also offered calibrated uncertainty estimates. This predictive variance, decomposed into epistemic and aleatoric components, revealed meaningful insights into the model's confidence. For example, higher epistemic uncertainty was observed during extreme events such as winter storms, indicating data sparsity in those regimes. In contrast, aleatoric uncertainty remained relatively constant, reflective of measurement noise in wave parameter estimation. The model's ability to provide phase-resolved predictions with uncertainty bounds makes it well-suited for various applications such as wave energy converter (WEC) where real-time forecast reliability is crucial. Additionally, the identified "predictable horizon," defined by a 95% confidence interval threshold, averaged 8–12 minutes ahead, offering a practical window for WEC optimization strategies. These results support the potential of hybrid physics-ML models for operational wave forecasting.

7 References

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