Artificial Neural Networks for High-Fidelity Maximum Power Forecasting in Wave Energy Converters

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***Abstract*— This study investigates a machine learning-based framework for power output estimation and optimization of a Wave Energy Converter (WEC) across diverse sea state conditions. The methodology integrates simulation-driven data generation with artificial neural networks (ANN) modeling to identify optimal time shifts that maximize energy production. A WEC system, derived from the U.S. Department of Energy's Reference Model 3 (RM3) and modified with a slider-crank mechanism, is implemented in WEC-Sim and tuned using a reactive control strategy. A total of 990 distinct sea state scenarios are simulated to train multiple ANN architectures. The optimal configuration is selected based on performance metrics and validated using two randomized test datasets excluded from training. The best-performing model, validated against these datasets produced from simulations using WEC-Sim, achieved an average error of approximately 1% in maximum power point tracking, demonstrating potential for real-time implementation in control hardware.**

***Index Terms*—Artificial neural networks, Wave energy conversion, Maximum power point tracking, WEC-Sim.**

I. Introduction

Ocean wave energy holds significant promise as a renewable source for clean electricity, yet its commercial deployment remains constrained by high costs, technical hurdles, and ecological concerns [1]. As global interest in sustainable energy grows, wave energy stands out for its vast untapped potential. However, wave energy conversion systems require further development, particularly in accurately estimating and optimizing power output amid the nonlinear and variable nature of ocean waves. Machine learning (ML) techniques offer scalable, adaptive solutions for improving real-time power prediction and enhancing overall system efficiency [2].

Recent research has demonstrated the potential of ML techniques to improve wave energy forecasting and optimize Wave Energy Converter (WEC) performance. These data-driven approaches enable refined control strategies and component design by leveraging large-scale oceanographic datasets [3]. Complementing these algorithmic advances, initiatives such as the U.S. Department of Energy's Reference Model Project have introduced open-source benchmarks to standardize the evaluation of marine energy technologies [4].

Prior studies have applied various ML methodologies to WEC power forecasting. For instance, the authors in [5] compared multiple ML algorithms for short-term power prediction, while Shadmani et al. provided a comprehensive review of ML and deep learning techniques for wave energy forecasting and WEC optimization [3]. Reference [6] employed a supervised ML framework to estimate long-term wave energy at sites with limited short-term data, and the authors in [7] developed a multi-layer artificial neural network to forecast short-term wave-induced forces. The work of [8] used generative adversarial networks for wave energy scenario generation in combination with other sources. In [9], a machine learning technique was applied to estimate power output from a Wave Energy Converter Power Take Off (WEC-PTO) system; however, the study focused on a non-standard WEC configuration and utilized a dataset that did not reflect realistic sea state conditions. Albeit, these studies primarily focus on forecasting, scenario generation, and control, with limited attention to the direct application of ML for maximizing power extraction—a critical aspect for real-time optimization of system parameters.

To address this gap, the present study introduces a machine learning-based Maximum Power Point Tracking (MPPT) framework tailored for WEC–PTO systems. MPPT algorithms are designed to dynamically adjust system parameters to optimize power output [9]. While conventional MPPT methods perform well under controlled conditions, they often falter in the face of oceanic variability and PTO constraints. By integrating ML techniques, this study aims to develop a more adaptive and responsive control mechanism capable of handling the stochastic nature of wave dynamics. The proposed framework utilizes real-world datasets capturing power outputs under irregular wave conditions and undergoes rigorous testing to validate its performance in practical scenarios. Through this comprehensive approach, the study contributes to the advancement of renewable energy technologies by demonstrating the efficacy of ML in enhancing the precision, adaptability, and reliability of WEC systems. Key aspects investigated herein are:

- Systematic exploration of various ANN architectures and training configurations were rigorously evaluated to develop an effective MPPT strategy tailored for WEC–PTO systems.
- Testing of the proposed models using real datasets representing diverse and irregular marine conditions, ensuring robustness and generalizability across a broad range of sea states.
- The selection of the best-performing ANN configuration was conducted, in achieving terms of average MPPT estimation error with the goal of achieving strong predictive accuracy and control precision.

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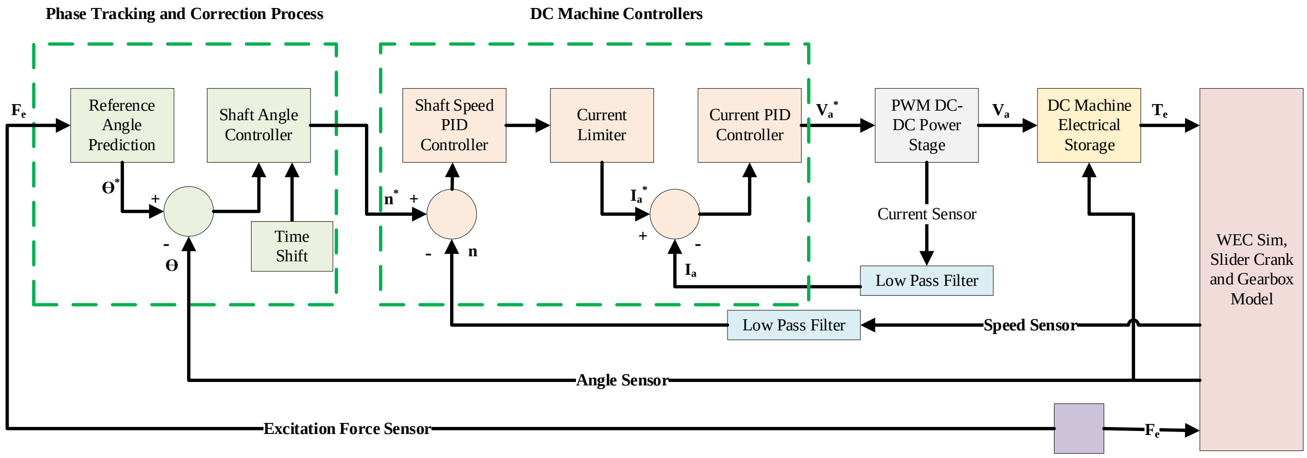

Figure 1. WEC Model Block Diagram.

- A modified WEC system based on the U.S. Department of Energy's Reference Model 3, incorporating a slider-crank mechanism, was simulated in WEC-Sim and tuned using a reactive control strategy to validate the practical applicability of the proposed approach.

II. Proposed Methodology

A. WEC Model Development

The WEC model employed in this study is derived from the U.S. Department of Energy's Reference Model 3 (RM3), incorporating a slider-crank mechanism as depicted in Figure 1. This configuration converts vertical heave motion into continuous unidirectional rotational energy, enabling more efficient mechanical-to-electrical energy conversion than traditional heaving buoy systems. To evaluate performance across a range of sea states, simulations are conducted using WEC-Sim, where a reactive control algorithm is applied to align the float's velocity with the wave excitation force, thereby improving energy capture efficiency. Prior scaling analyses [10] examined full-scale, half-scale, and one-third-scale WEC configurations, identifying the half-scale model as the most cost-effective in terms of Levelized Cost of Energy. Thus, this study adopts the half-scale configuration, featuring three degrees of freedom and an integrated mooring system.

B. Machine Learning Framework for MPPT

This study proposes a ML-based MPPT for a WEC–PTO system, where the resonance condition is defined by time shift and used as the control variable. A zero-time shift represents perfect phase alignment between wave excitation force and buoy velocity, maximizing energy capture, while negative and positive shifts indicate lagging and leading buoy responses, respectively. In [9], the authors implemented a feedforward ANN model that demonstrated high wave power estimation accuracy for both regular and irregular wave profiles, despite being applied to a non-standard WEC configuration and relying on a dataset that did not represent realistic sea state conditions. Here, another feedforward ANN model, shown in Figure 2, is developed to estimate power output under varying sea states using significant wave height, peak wave period, and time shift as inputs. The estimated power is then processed

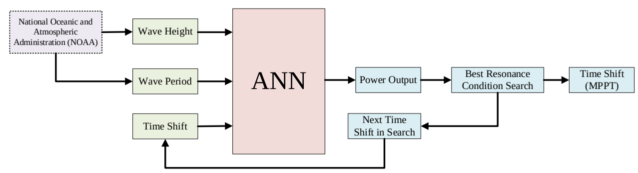

Figure 2. ANN Block Diagram for MPPT.

through a "Best Resonance Condition Search" module, which iteratively determines the optimal time shift to be applied to the shaft angle controller for maximum power extraction.

Data Generation: To evaluate WEC performance, a training dataset is constructed to span a wide range of realistic sea states and resonance conditions, defined by the phase relationship between wave excitation force and buoy velocity. Significant wave heights (H_s) ranged from 0.75–4.75 m in 0.5 m increments (9 values), while peak wave periods (T_p) varied from 3.5–12.5 s in 0.9 s steps (11 values). For each wave height–period pair, 10 resonance conditions are introduced through time shift values (−0.45 to 0.35 s), representing variations in phase alignment between excitation force and buoy response. This systematic combination yielded 990 unique scenarios, as shown in Figure 3, with corresponding power outputs computed using WEC-Sim to form a comprehensive dataset for training predictive models of WEC performance under diverse operating conditions. This study utilizes real-world oceanographic data from WaveWatch III and HYCOM for the North Carolina coast (depths <200 m) spanning July 2005 to December 2018. The dataset supports wave resource characterization via joint probability distribution (JPD) matrices, seasonal energy trends, and flux density mapping. A total of unique 990 sea state pairs capture over 96% of observed conditions in the underexplored North Carolina coast region.

ANN Training and Validation: The complete dataset generated from WEC-Sim (inputs: H_s, T_p, time shift; output: WEC power) is used to train multiple feedforward ANNs. Data are split: 70% for training, 15–25% for validation (varied in 5% steps), and the remainder for testing. The validation set guides training error minimization, while the test set provides an independent post-training assessment. Three

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two-hidden-layer architectures—(15 15), (20 20), and (25 25), denoting neurons per layer—are evaluated, each trained 20 times to capture variability from random initialization and convergence; resulting weight matrices are saved separately for later analysis. Networks employ sigmoid activation in the hidden layers and are trained using the Levenberg–Marquardt algorithm with Bayesian regularization to improve generalization and reduce overfitting [11]. Table 1 summarizes the configurations and training protocol.

ANN Model Evaluation and Selection: A total of 180 ANN configurations were evaluated based on mean squared error (MSE). Two randomized test sets as shown in Figure 4, each with 24 input cases sampled from the same parameter ranges used for training, are used for evaluation. For each case, the absolute error between estimated and actual power is computed employing (1), and the mean absolute error across each randomized set is calculated. Because the network with the lowest training MSE does not always give the most

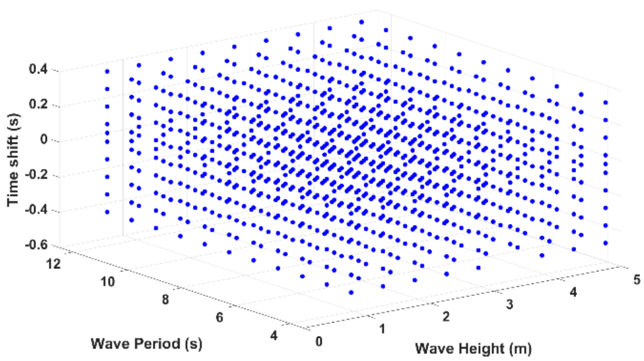

Figure 3. Training Dataset for ANN (Total 990 Input Pairs).

TABLE I. ANN Training Configurations

Parameter	Values/Settings
Training Set (%)	70
Validation Set (%)	15, 20, 25
Test Set (%)	Remaining set from (Training + Validation)
Hidden Layer Structures	[15 15], [20 20], [25 25]
Number of Runs	20 per configuration
Total Configurations	3 (validation & test subsets) × 3 (hidden layers) × 20 (runs) = **180 training runs**

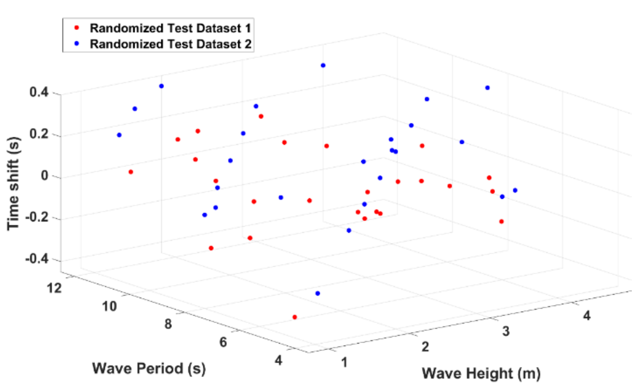

Figure 4. Randomized Test Dataset.

accurate predictions on an independent test dataset, several top-ranked ANN models (by MSE) are evaluated on additional randomized test sets to identify the best-performing model.

$$E_r = \left|\frac{Actual\ Power\ Output - Estimated\ Power\ Output}{Actual\ Power\ Output}\right| \times 100 \quad (1)$$

ANN-Based MPPT: To evaluate the estimation performance of the trained ANN models for MPPT, two sets of 24 randomized input cases (the same cases shown in Figure 4)—comprising significant wave height and peak period values—are processed through the WEC-Sim model to identify the time shifts that yield maximum power output. The brute-force approach systematically evaluates all possible solutions within a defined search space to identify the optimal outcome, relying on exhaustive computation rather than heuristic shortcuts. Here, a brute-force approach is employed, testing 17 discrete time shift values ranging from −0.45 s to 0.35 s in 0.05 s increments, and the time shift yielding the highest power is recorded as the ground truth for each case. Please note that the time shift range applied in the brute-force approach is identical to the range employed during the ANN model training. The top-performing ANN models—defined as the ANNs with the lowest average power estimation error—are then used to estimate both the optimal time shifts and corresponding output powers from the WEC-Sim model for the same 24 test cases in each randomized dataset. Equation (2) is employed to calculate the absolute error ($E_{r,MPPT}$) for the MPPT between the brute-force and the ANN model approach. The averaging of the absolute average errors across both datasets is then calculated for each configuration, and the one exhibiting the lowest overall mean error is designated as the optimal model.

$$E_{r,MPPT} = \left|\frac{P_{MPPT,Brute\_Force} - P_{MPPT,ANN}}{P_{MPPT,Brute\_Force}}\right| \times 100 \qquad (2)$$

where $P_{MPPT,Brute\_Force}$ is the maximum power at the optimal time shift identified by the brute-force approach, and $P_{MPPT,ANN}$ is the maximum power at the optimal time shift predicted by the ANN for each pair of wave height and peak period.

III. Simulation Results And Discussion

A total of 990 input data pairs were split into 70% for training, 15–25% for validation (in 5% increments), and the remainder for testing. Each configuration was evaluated 20 times. Based on the lowest MSE, the 10 best models with 5% test data and the three best models with 10% test data were selected for performance evaluation against two randomized

TABLE II. Performance of the 10 Best ANN Models (5 % Test)

Serial	MSE	Network
1	14828.98	Net_Train70_Val25_Hidden25--25_Run8
2	15568.48	Net_Train70_Val25_Hidden25--25_Run19
3	16281.02	Net_Train70_Val25_Hidden25--25_Run14
4	21937.39	Net_Train70_Val25_Hidden25--25_Run6
5	24159.26	Net_Train70_Val25_Hidden20--20_Run4
6	29717.28	Net_Train70_Val25_Hidden20--20_Run15
7	31675.69	Net_Train70_Val25_Hidden25--25_Run13
8	33552.30	Net_Train70_Val25_Hidden25--25_Run10
9	34684.46	Net_Train70_Val25_Hidden25--25_Run11
10	34748.33	Net_Train70_Val25_Hidden25--25_Run2

TABLE III. Performance of the 3 Best ANN Models (10 % Test)

Serial	MSE	Network
1	45457.63	Net_Train70_Val20_Hidden20--20_Run19
2	61918.73	Net_Train70_Val20_Hidden20--20_Run20
3	62013.10	Net_Train70_Val20_Hidden20--20_Run17

test sets. The selected models and their MSEs are presented in Tables 2 and 3. As the 5% test data configuration yielded lower MSEs, more models from this group were chosen for further analysis to identify the best-performing ANN. Of the top 24 ANN configurations with the lowest MSE, only 3 originated from the 10% test dataset, and none from the 15 % test dataset. Since the 5% test set consistently yielded lower MSEs, more models from this group are selected for further analysis to identify the best-performing ANN. In Tables 2 and 3, the network labeled *Net_Train70_Val25_Hidden25--25_Run8* corresponds to a configuration trained on 70% of the data, validated on 25%, with two hidden layers of 25 neurons each, and represents the 8th run out of 20 training iterations.

The average power estimation error for these test sets was computed using (1), and the performance of the top ANN configurations—based on both mean error and standard deviation (SD)—is depicted in Figure 5. The most accurate predictions were achieved by the model trained with a 70% / 25% / 5% data split and a hidden layer architecture of (25 25). Specifically, run 13 yielded the lowest error for the randomized test dataset 1, while run 14 performed best for dataset 2 (*Highlighted in Table 2*). This configuration resulted in estimation errors below 1.3% for dataset 1 and 1.89% for dataset 2, indicating strong generalization capability. For dataset 1, Figure 6 compares the WEC-Sim power output with the ANN-predicted values from the most accurate model, and Figure 7 presents the corresponding error histogram.

ANN-Driven MPPT Search: As previously noted, two randomized test datasets were utilized to identify the optimal ANN model. The six best-performing configurations—three from the 5% test dataset (Figure 6: Serial 3, Serial 7, and Serial 10) and three from the 10% test dataset—were selected based on their minimum power estimation error. The brute-force method was then employed, applying 17 discrete time shift values ranging from −0.45 s to 0.35 s in 0.05 s increments to each selected configuration. This process aimed to estimate the maximum power output corresponding to randomized input combinations of H_s, T_p and time shift. The MPPT estimation

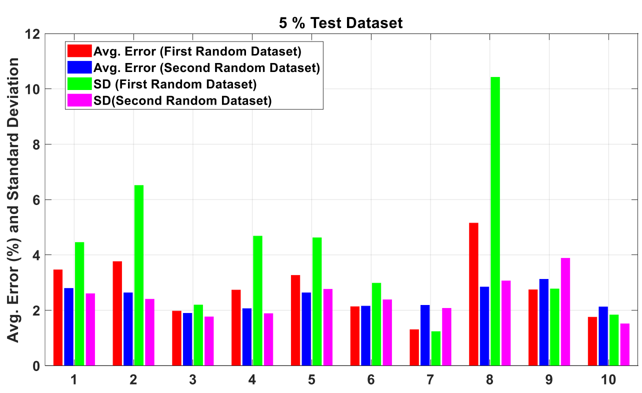

Figure 5. Average Error and Standard Deviation of the 10 Best ANN Models (5 % Test Split) on Randomized Test Dataset.

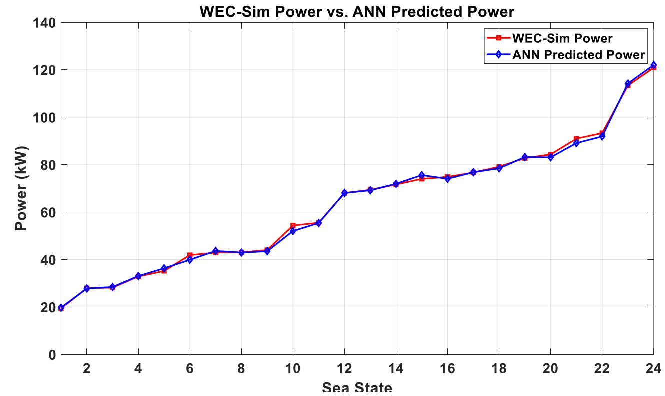

Figure 6. Power Comparison Between the WEC-Sim and ANN for Randomized Test Dataset – 1. ***ANN Model*:** 5 % Test Dataset with Lowest Average Error for Power Estimation.

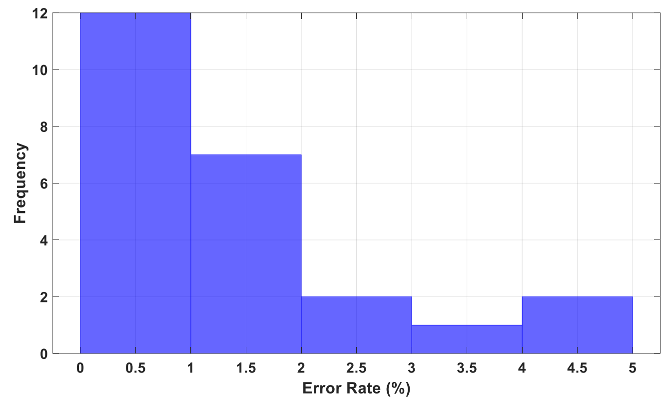

Figure 7. Error Histogram for Randomized Test Dataset – 1. ***ANN Model*:** 5 % Test Dataset with Lowest Average Error for Power Estimation.

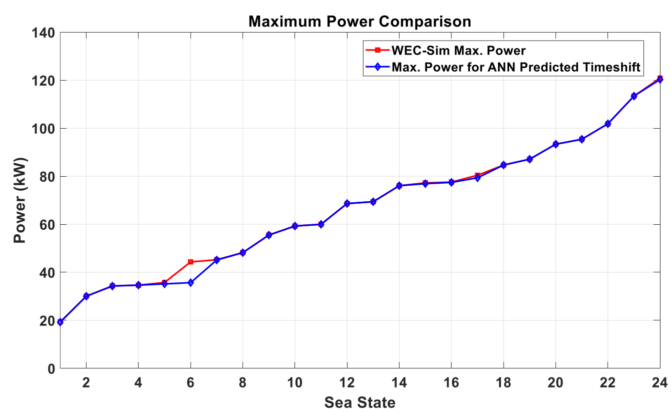

Figure 8. *Brute Force:* MPPT Comparison for Randomly Generated Dataset 1. ***ANN Model*:** 5 % Test Dataset with Lowest Average Error for Power Estimation.

scheme, when paired with the top-performing ANN model, achieved an average error rate of approximately 1% relative to WEC-Sim model results, demonstrating its suitability for real-time power estimation. A comparison between the WEC-Sim and ANN-based estimation results is presented in Figure 8.

To finalize the selection of the optimal ANN configuration, the mean of the absolute average errors across both randomized test datasets was computed for each top-performing model. The configuration with the lowest overall mean error was designated as the optimal ANN model. Figure

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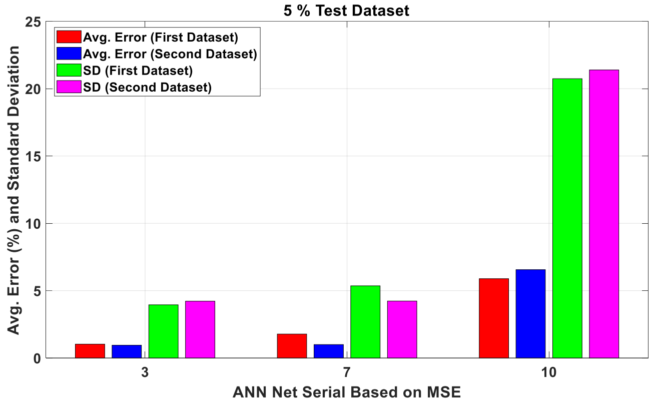

Figure 9. Performance of the Selected 3 Best ANN Configurations from 5 % Test Dataset.

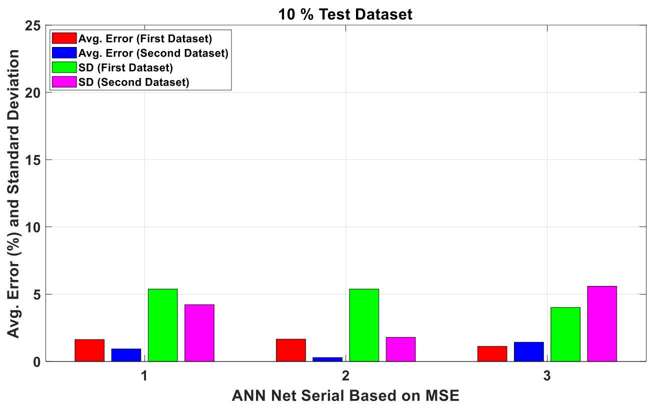

Figure 10. Performance of the Selected 3 Best ANN Configurations from 10 % Test Dataset.

9 shows the average error and SD for MPPT estimation using the selected configurations on the 5% test dataset, while Figure 10 presents the corresponding results for the 10% test dataset.

Among the evaluated ANN configurations, two models exhibited nearly identical mean average errors (within 1%) across both randomized test datasets. The first model, trained with a 70% training, 25% validation, and 5% testing split using a (25 25) hidden layer architecture (Run 14, designated as Serial 3 with the 5% test dataset), and the second model, trained with a 70% training, 20% validation, and 10% testing split using a (20 20) hidden layer architecture (Run 20, designated as Serial 2 with the 10% test dataset), both demonstrated high accuracy. While both models demonstrated high accuracy, Serial 3 in Table 2 consistently achieved lower standard deviation values and maintained stable performance across both test datasets. This statistical consistency, coupled with its minimal error rate, supports the selection of Serial 3 in Table 2 as the optimal ANN configuration for maximum power estimation in this study.

IV. Conclusion

This study demonstrates the effective application of ML for estimating and optimizing the power output of the WEC. By integrating simulation-driven data generation with ANN modeling, 990 unique sea state scenarios from the real-world North Carolina Coast were employed to train multiple ANN configurations. The optimal model was identified through performance evaluation on two randomized test sets and validated using a brute-force approach via the WEC-Sim model. Based on the results in this research, the following conclusion are advanced:

(a) Among 180 ANN configurations, the two-hidden-layer network with a (25 25) architecture, trained using the Levenberg–Marquardt algorithm with Bayesian regularization, achieved mean MPPT estimation errors below 1.3% and 1.9% across two independent randomized test datasets.

(b) The ANN-based estimator accurately reproduced physically simulated resonance conditions. The computation of optimal time shifts and corresponding maximum power outputs closely matched brute-force WEC-Sim computations across 17 discrete phase offsets, yielding an average deviation of approximately 1%.

(c) Compared to brute-force optimization method with the WEC-Sim model, however, the ANN-based MPPT provides instantaneous power estimation once trained. This enables integration into real-time WEC control systems for adaptive power optimization under stochastic ocean dynamics.

The proposed ANN-based MPPT framework can be embedded within onboard WEC control hardware to provide real-time power optimization without reliance on complex hydrodynamic computations. Its demonstrated accuracy (<1% error) makes it suitable for integration into supervisory control and data acquisition systems. The proposed ANN-based MPPT methodology shows strong potential for evaluating WEC deployment performance in coastal regions beyond the North Carolina coast. Future work will investigate advanced machine learning architectures to further enhance MPPT performance assessment for WEC-PTO systems.

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