International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Conference Proceedings: Volume: 05 ACME – 2026 DOI: 10.55041/ISJEM.ACME007
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

Machine Learning Enhanced Forecasting of Wave Energy for Optimized WEC Performance

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Abstract
Wave power, a renewable energy source that harnesses the ocean's dynamic forces, is very promising. The importance of accurate wave energy forecasting is growing as the globe works to incorporate renewable energy sources into the grid in order to maximize energy harvesting and grid integration. Recent developments in ML approaches, including DL, ensemble methods, and hybrid models for ocean wave energy prediction, are examined in this study. The complex non-linear dynamics of ocean waves are discussed, including how to predict energy flow, significant wave height (SWH), and wave period, as well as the pros and cons of various approaches. Also covered in depth is the rise of hybrid models—those that use both physical and ML components—as a means to improve prediction accuracy over more traditional methods. This study concludes with a discussion of potential future approaches, specifically focusing on how state-of-the-art technologies like as transformers, generative adversarial networks (GANs), and real-time data assimilation might enhance processing efficiency and prediction reliability.
Keywords—Wave energy; Energy forecasting; Machine learning; Energy harvesting; Wave energy forecasting; Hybrid models; Deep Learning

INTRODUCTION

One possible answer to the world's increasing need for renewable energy sources is wave power.items (1) and (2). Wave energy, which is generated by the ocean's kinetic forces, has a leg up on other renewable resources due to its consistent supply and great predictability [1]. Accurate wave energy forecasting is both necessary and the biggest challenge when it comes to optimizing wave energy converters (WECs) and ensuring their stable integration into the electrical grid [3]. Wave energy,

being one of the most abundant renewable resources, has the potential to significantly alter the global energy landscape [4]. However, precise forecasts of wave dynamics are essential to their usefulness, and these dynamics are inherently complex and diverse. Factors including wind speed, air pressure, tides, and seabed geology make it difficult to get accurate wave estimations in the ocean. Accurate predictions of energy output are essential for grid integration and efficient power generation; nevertheless, this uncertainty makes both of these tasks more challenging. New advances in ML and DL have allowed for more accurate wave energy forecasts. While traditional numerical models struggle with datasets that are high-dimensional and noisy, these models excel at capturing the non-linear and dynamic behavior of ocean waves. Hybrid approaches, which combine physical oceanographic models with data-driven ML algorithms, have also increased the accuracy of both short-term and long-term predictions.

BACKGROUND AND LITERATURE REVIEW

Wave energy forecasting is quickly becoming a must-have for renewable power systems. In the past, quantitative wave models like WW3, SWAN, and WAve Model (WAM) were used to forecast the properties of ocean waves [5]. One issue is that these models struggle with marine-specific datasets, which tend to be high-dimensional, sparse, and noisy. But since they can discover patterns and correlations in the data, ML models are fantastic at handling these complications[6][7]. Surfing Ocean Waves (A) Understanding ML's role in wave forecasting requires familiarity with the basic wave energy equations. Common ways to express the power density (P) of a wave are:

$$P = \frac{1}{16} \rho g H_s^2 T \quad (1)$$

where ρ represents the density of seawater (about 1025 kg/m3), Hs the height of the significant waves (the average height of the top third of the waves in meters), g the acceleration of gravity (9.81 m/s2), and T the duration of the wave energy (in seconds) [8]. A formula for the power of directionally integrated waves is as follows:

$$P = \frac{1}{16} \rho g^2 H_s^2 T \cos(\theta) \quad (2)$$

Because these parameters substantially impact WEC design and feasibility, precise prediction of wave height and period is critical for optimizing WEC operation and integration with power grids [4]. The efficiency of a WEC's power take-off mechanism and the wave properties determine the extent to which the device can extract power. When compared to conventional models, ML models perform better at accurately predicting Hs and T, which is crucial for improving WEC operations. Section B: Non-Linear Wave Resonance Wave prediction is difficult due of the ocean's non-linear nature. Models using variables, such the KdV (Korteweg-D)

$$\frac{\partial \eta}{\partial t} + c_0 \frac{\partial \eta}{\partial x} + \alpha \eta \frac{\partial \eta}{\partial x} + \beta \frac{\partial^3 \eta}{\partial x^3} = 0 \quad (3)$$

As a function of both space and time, the wave height is shown by (x,b), the wave speed is represented by $c0$, and the non-linear and dispersive coefficients β *and* β are given by [10]. Machine learning algorithms effectively capture these non-linearities by acquiring complex patterns that traditional equations would fail to notice. Deep Learning Models (Supervised ML) Section C Deep learning (DL), a subfield of ML, employs ANNs with many layers. All the layers work together to learn how to extract increasingly complicated attributes from basic input data, including images or time series. In the field of ocean wave energy forecasting, DL models excel in capturing the non-linear correlations among variables such wave heights, periods, wind speeds, and wave energy potential [11]. Top DL models include CNNs and LSTM networks, which stand for Long Short Term Memory. For energy flow and significant wave height (SWH) prediction, many research have used long short-term memory (LSTMs), a kind of recurrent neural network (RNN) that is well-suited to sequential data and resolves the vanishing gradient problem [15]. Their ability to capture long-term associations in time-series data is made possible by their recurring nature, making them ideal for short-term forecasts [11][12]. One noteworthy feature of the GI-BiLSTM (Gini Impurity Bidirectional LSTM) model is its capacity to predict SWH by including dependencies that span both past and future time steps. For both short- and long-term predictions, our model outperformed the competition, with RMSEs as low as 0.05 and 0.17, respectively [15]. Regional wave energy forecasting using satellite or buoy data is a good fit for concurrent neural networks (CNNs) because of their great spatial data processing capabilities. Combining convolutional neural networks (CNNs) with long short-term memory (LSTM) models has also increased prediction accuracy[11][16] by integrating geographical and temporal data. Hybrid models, such CNN-GRU (Gated Recurrent Unit), have substantially enhanced time series analysis for SWH forecasting [18].

TABLE I. SUMMARY OF DEEP LEARNING MODELS AND THEIR PERFORMANCE IN WAVE ENERGY FORECASTING

Model Type Used	Application	RMSE (m) / R^2 /MAPE	Ref
ICEEMDAN-ELM (Improved Complete Ensemble EMD with Adaptive Noise-ELM)	SWH forecasting	0.016 - 0.018 / 0.999 / -	[19]
ANNs	SWH prediction	0.23 / 0.842 / -	[20]
LSTM	SWH prediction	0.03 - 0.50 / - / 2.19 to 24.15%	[21]
Bayesian Neural Network (BNN)	Real-time wave prediction with uncertainty	0.279 m (Case #1), 0.699 m (Case #2)	[22]
Multi-Task Evolutionary ANN (MTEANN)	Short-term wave height and energy flux prediction	0.0987 to 0.25 (6h), 0.1822 to 0.4915 (12h)	[23]
Nested ANN (NANN)	SWH prediction	0.525 - 0.631 / 0.84 / -	24]
BDNN	SWH forecasting	0.069 - 0.0789 / 0.9564 / -	[16]
Prophet + LSTM (Hybrid Model)	Effective wave height prediction	0.204 - 0.212 / 0.914 to 0.930/-	[25]
PatchTST (Time-Series Transformer)	Long-term SWH prediction	0.65	[26]

Hybrid model combining VMD, RCMFE, and E-GRU	Multistep-ahead prediction of SWH	0.0984-0.0816 / 0.9726-0.9826/ 4.379-2.669%	[43]
Hybrid Intelligent Models (EN-1,EN-2)	Weekly mean SWH prediction	0.0736-0.0847/ 0.9850-0.9802 / 3.7107% - 2.2373%	[42]
CNN	SWH forecasting	0.444/ 0.911/8.55%	[46]
GWO-GMDH	Monthly Mean SWH Prediction	0.202/0.953/7.353%	[47]
ANN, LSTM, TCN	SWH forecasting	0.05/ - /4%,	[48]
GANs	Spatial wave height forecasting	0.24 m, / - / 13.4%	[49]

In Table 1 we can see a summary of the outcomes from several DL models that were used to forecast wave energy. Using a mix of different neural network architectures, such as CNNs, LSTMs, and GRUs, might lead to more accurate and efficient forecasts. More and more research is showing that DL can help with ocean wave energy predictions, and advancements in adjacent fields will almost surely result in even better results soon. S. Supervised Learning Regression Various regression methods may be used to predict continuous wave energy from wave parameters. These include linear, polynomial, autoregressive (AR), autoregressive with exogenous (ARX), and support vector regression (SVR). With simpler datasets, these models are solid foundations to build upon [11]. Ensemble methods that employ regression are common; one such method is Random Forest Regression, which involves joining many regression trees to improve prediction accuracy. Ensemble Models (E) As a means to enhance the precision of forecasts, ensemble methods combine a number of ML models, often known as base learners[11][19]. When many models are used together, the results are often better than when using a single model on the same data. There has been encouraging progress in predicting future wave energy levels using ensemble learning approaches like XGBoost and Random Forest (RF). These models integrate the forecasts of many base learners to handle data noise and decrease variability [11]. They are useful in avoiding the problems of bias and overfitting that may occur when relying on a single model. For example, RF has been used with physical models to forecast power production in wave farms, which improves accuracy for complex wave conditions [27]. The prediction of an RF model may be shown as follows:

$$P = \sum_{i=1}^{N} T_i(x) \qquad (4)$$

where x is the input data, N is the total number of trees, and Ti is the i-th decision tree. By merging XGBoost with the SWAN wave model, another study shown that ensemble learning might be beneficial in hybrid systems, leading to better operational wave forecasts. One ensemble approach that has been used for SWH forecasting is the combination of neural networks, regression models, and decision trees[27, 30]. The expected outcome is

$$P_i = \sum_{k=1}^{K} T_k(x_i) \qquad (5)$$

for each feature vector (such as wave height, wave duration, wind speed, etc.), K is the number of trees, Tk is the k-th regression tree, and Pi is the prediction for the i-th occurrence. Attained a 90% accuracy rate when evaluated on coastal wave data using a hybrid RF XGBoost model [27]. Wavelet Transforms for Signal Processing (F) You may use a Wavelet Transform, such a Continuous Wavelet Transform (CWT), Discrete Wavelet Transform (DWT), or Wavelet Packet Decomposition (WPD), to separate the time-frequency components of wave energy signals. If you have data on wave energy, this may help you spot patterns, trends, and periodicities[11, 19]. Incorporating the gathered attributes into regression or DL models might lead to a more precise forecast of wave energy. The Mixed Methods Section (G) Hybrid methods combine numerical wave models with ML techniques to use the assets of both data-driven and physics-based approaches. These models are useful in situations when more traditional models fail to accurately forecast wave behavior, such as during a storm. One hybrid approach to storm-related SWH forecasting uses ML algorithms in conjunction with the Coastal Engineering Manual (CEM); this strategy achieves a 20% improvement over traditional models [11]. One more example: neural networks may be fed wavelet coefficients using Wavelet Neural Networks (WNNs).

METHODOLOGY

The paper ended with an evaluation of the performance, application, and potential future research directions of ML techniques related to wave energy forecasting. The systematic journal paper selection approach began with automatic article selection using Scopus database keyword searches and continued with human review and shortlisting of publications relating to wave energy and SWH forecasting. Accuracy, input parameters, datasets, and forecasting models were the next criteria used to evaluate the selected research.

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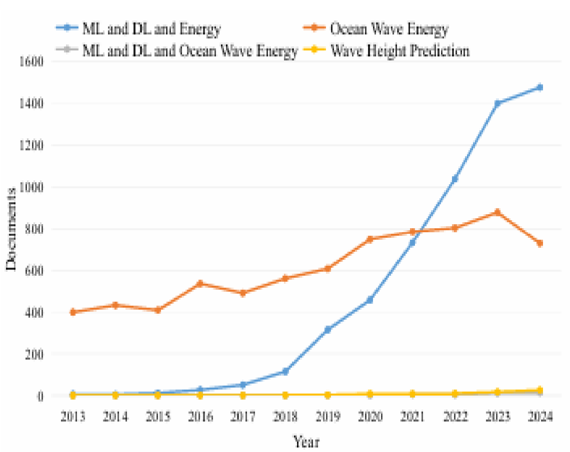

Fig. 1. Journal Papers on ML and DL Applications in Wave Energy

Ocean wave energy and related energy systems have been included in more academic works recently, with a focus on ML and DL methodologies (Figure 1). Articles discussing energy that make reference to ML and DL have been on the increase since 2013, with a sharp spike starting around 2017. This upward trend shows that optimizing wave energy systems using ML and DL is a hot topic and is making great strides. However, as these technologies progressed, the number of journal publications specifically discussing ocean wave energy (shown in orange) remained relatively constant but gained momentum. Section A: A Survey of ML Models several learning techniques make up ML. Some of these approaches include supervised learning, which trains models using labeled data; ensemble methods, which combine several models to increase accuracy; and signal processing methods, which use tools like Wavelet Transforms for preprocessing or feature extraction. Recent advances in machine learning have steadily used deep learning, ensemble models, and hybrid techniques to enhance the precision of SWH predictions. Figure 2 categorizes different ML methods and highlights their use into hybrid models; this is especially helpful for wave energy.

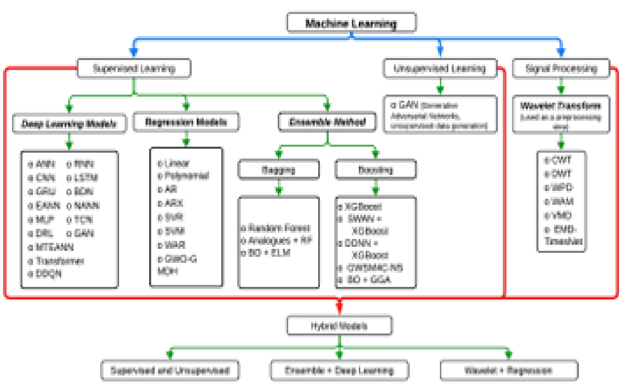

fig. 2. Hierarchical Structure of Machine Learning Techniques for Wave Energy Forecasting

A growing number of WH forecasts are improving their accuracy with the use of deep learning, ensemble models, and hybrid techniques. Incorporating these ML approaches—which are categorized in Fig. 2—into hybrid models proved to be quite beneficial for wave energy prediction. You can get a rundown of all the ML models that have been used for wave energy prediction and forecasting tasks globally in Table II. It has a wide variety of vehicles, from the more traditional to the more advanced hybrid types and beyond. These models were used to forecast energy flow, surface wave height (SWH), and excitation forces for wave energy converters (WECs). Energy flow estimates, SWH forecasting, and phase-resolved wave predictions were among the many forecasting tasks addressed by the models. Some of these models were also used to estimate total organic carbon (TOC) or were combined with physical models such as SWAN. The forecasting responsibilities of different regions are shown in the table. In addition, certain models were enhanced by including additional techniques; for instance, peak wave period forecasting was done using XGBoost and LSTM, and wave excitation force forecasting in WEC systems was done using ARX, illustrating the use of hybrid approaches to enhance performance.

TABLE II. MACHINE LEARNING MODELS AND THEIR APPLICATIONS IN OCEAN WAVE FORECASTING AND ENERGY PREDICTION ACROSS GLOBAL LOCATIONS

Model Type Used	Application	Location	Ref
ICEEMDAN-ELM	SWH forecasting	Queensland, Australia	[19]

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ANNs	SWH prediction using satellite SAR images	Liverpool Bay, Irish Sea, and Southern North Sea (UK)	[20]
RF	Spatial wave data prediction	South West UK (Cornwall)	[31]
H2O-AutoML (AutoML Framework)	SWH forecasting	Nine NOAA buoys in various geographical locations (U.S.)	[32]
LSTM, RNN, GRU, SVM, KNN, PCR	Comparison with baseline models	Nine NOAA buoys in various geographical locations (U.S.)	[32]
BNN	Phase-resolved, real-time wave prediction with quantified uncertainty	COAST Lab, University of Plymouth, UK Same location	[22]
NN (Neural Network)	Comparison with deterministic NN-based wave prediction	COAST Lab, University of Plymouth, UK Same location	[22]
MTEANN	Short-term SWH and energy flux prediction	South West Coast and Gulf of Alaska, USA	[23]
LSTM	SWH prediction	Southwestern Atlantic Ocean (7 buoy)	[21]
Local Cascade Ensemble RF XGBoost	TOC prediction in source rocks	South China Sea, L Depression	[33]
LSTM	Wave energy forecasting	Gulf of Lion, Gulf of Mexico	[34]
CNN	Feature extraction wave forecasting	DNN used for Coast of Central America	[34]
RNN	Wave forecasting and prediction	Gulf of Mexico and North Atlantic	[34]
Seq2Seq (Sequence-to-Sequence)	Wave height and energy prediction	Gulf of Mexico, Korean region, UK region	[34]
NANN	SWH prediction	North Sea, 30 locations	[24]
Composite ANN	Prediction of wave spectra and integral wave parameters	Chesapeake Bay Bridge-Tunnel, USA	[14]
BDNN	SWH forecasting	Lianyungang and Xiaomaidao China	[16]
Dual-Branch Network (DBNet)	Phase-resolved, real-time 3D wave forecasting	WaveHub test site, offshore from Hayle, UK	[35]
GRU, LSTM, MLP, CNN	Phase-resolved, real-time 3D wave forecasting	WaveHub test site, offshore from Hayle, UK	[35]
Prophet + LSTM	Effective wave height prediction	NDBC Stations USA	[25]
PatchTST (Time-Series Transformer)	Long-term SWH prediction	Bering Sea, North Atlantic, Southern Indian Ocean, and Southern Pacific Ocean	[26]
Prophet	Wind speed and wave height forecasting	Pacific Ocean, northwest of California	[36]
SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous variables)	Wind speed and wave height forecasting	Pacific Ocean, northwest of California	[36]
ARX	Wave excitation force prediction for arrays of WECs	Shandong, China (Modeled simulation for directional waves)	[37]
SVR	Wave excitation force prediction	Shandong, China (Modeled simulation for directional waves)	[37]

Pyramid Neural Network (PNN)	SWH prediction for renewable energy farms	North Sea, various renewable energy farms including Nordsee-Ost, Meerwind, Gode, Amrumbank	[38]
Ensemble Learning Model	Wave height prediction	North Sea, various renewable energy farms including Nordsee-Ost, Meerwind, Gode, Amrumbank	[38]
H2O-AutoML	SWH Forecasting	Nine NOAA buoy locations (U.S.)	[61]
Seq2Seq, LSTM, RNN, GRU, KNN, SVM, PCR	Baseline model comparison	Same locations	[61]
Clustering Analysis	Temporal clustering for buoy stations	NOAA buoys (U.S.)	[32]
ARX Model	Wave Excitation Force Prediction	Shandong, China	[15]
AR Model	Short-term Prediction of Wave Excitation	Shandong, China	[15]
VAR Model	Multivariate Prediction for WEC Arrays	Shandong, China	[15]
DDQN	Control strategy for WECs	Cornwall, United Kingdom	[39]
XGBoost and LSTM	Predicting SWH and peak wave period	Lake Erie, Great Lakes, USA	[40]
Hybrid model combining VMD,RCMFE, and E-GRU	Multistep-ahead prediction of significant wave SWH	Atlantic Ocean, using data from buoy stations 41,025, 44,065, and 42,058	[43]
Hybrid Intelligent Models	Weekly mean SWH prediction	Various marine stations, China	[42]
CNN	SWH forecasting	South China Sea	[46]
GWO-GMDH	Monthly Mean SWH Prediction	Atlantic	[47]
ANN, LSTM, TCN	SWH forecasting	Offshore China (Various locations)	[48]
GANs	Spatial wave height forecasting	West Pacific (15°-40°N, 105°-130°E)	[49]

Assessment and Performance Metrics The effectiveness of ML models in wave energy forecasting is assessed using a number of significant metrics. We often utilize these performance indicators in regression, forecasting, and classification: A metric that may be used to assess the spread of prediction errors is the Root Mean Square Error (RMSE)[19][16].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=0}^{N}(y_i - \hat{y}_i)^2} \qquad (6)$$

By calculating the absolute difference between the actual and anticipated values, the Mean Absolute Error (MAE) may be used to measure the average size of the mistakes, regardless of their direction [19, 16].

$$MAE = \frac{1}{N}\sum_{i=0}^{N}|y_i - \hat{y}_i| \qquad (7)$$

A Determination Coefficient/Correlation Coefficient Equation (R^2) Values closer to 1 imply a better fit, and the data is better fit when the model explains more of the variance in the response variable [19][20][25]. R2 shows the proportion of variance that can be explained by the model, as opposed to error measures like RMSE and MAE. Still,

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$$R^2 = 1 - \frac{\sum_{i=0}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=0}^{N}(y_i - \bar{y})^2} \qquad (8)$$

Mean Absolute Percentage Difference (MAPE): This statistic measures the percentage difference between predicted and actual values, providing an explanation in percentage terms rather than hard figures [21] [32].

$$MAPE = \frac{100}{N}\sum_{i=0}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \qquad (9)$$

RESULTS AND DISCUSSION

Performance Comparison by Model Type

We evaluated ML models using real-world datasets with an eye toward both the short and long term. In Figure 3, we can see the results of MAPE's evaluation of several deep learning models for significant wave height prediction using the aforementioned academic articles. A number of models' relative performances are shown in the bar chart. As the MAPE number drops, the model becomes more accurate. At the top of the chart, you can see that hybrid models like Deep Learning LSTM and Prophet + LSTM + Transformer are the most effective, with MAPE values below 5%. These models excel at handling sequential data, which is useful for time-series forecasting tasks like predicting wave height. An additional kind of effective model is a hybrid model that combines approaches such as Extended GRU (E-GRU), Variational Mode Decomposition (VMD), and ML algorithms.Both Convolutional Neural Networks (CNNs) and Temporal Convolutional Networks (TCNs) are capable of capturing the spatial and temporal relationships seen in wave data. As we go down the screen, we can see that LSTM + RF, GAN-based image-to-image translation models, and XGBoost all have somewhat bigger MAPE values, but they still show excellent performance.

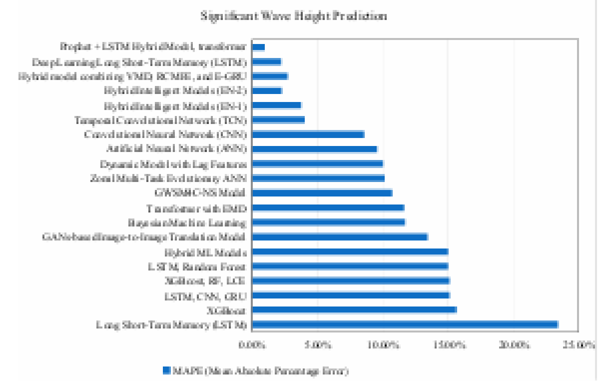

Fig. 3. DL Models and Their Performance in Wave Energy Forecasting

Spread of Data for ML Models Incorporating 44 ML models from 22 papers, the analysis demonstrated a wide range of approaches to forecasting wave energy from ocean wave dynamics. Among the several machine learning-based approaches to wave energy forecasting, 18 models used deep learning, 10 used regression, 13 used ensemble methods, and 3 used wavelet-based approaches (Figure 4). For the purpose of comparing models across datasets of varying magnitudes in wave energy forecasting, these papers choose to employ MAPE for performance evaluation due to its scale-independent nature and its clear interpretation. You may find a full inventory of the models that were used for wave energy projections in Table III of the model research distribution. Recent advances in machine learning have shown that hybrid approaches, ensemble models, and deep learning are being used more often to enhance the precision of SWH predictions. When it came to predicting SWH and peak wave timings in Lake Erie, USA, the XGBoost and LSTM models performed better than older models like WW3, with MAPE values ranging from 8.3% to 13.4% and significantly decreased computing time. Additionally, a CNN model's 12-hour SWH forecasts in the South China Sea had an RMSE of 0.083 m.

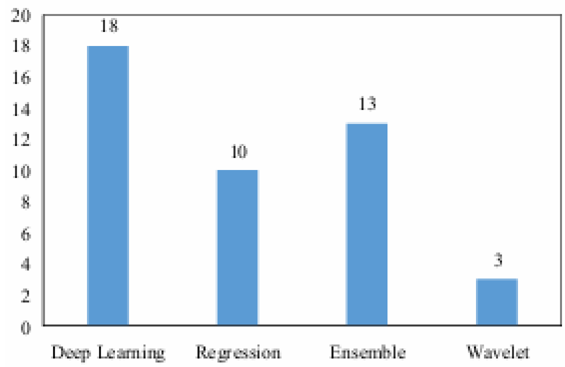

Fig. 4. Distribution of Research Focus in Machine Learning Techniques for Wave Energy

TABLE III. SPECIFIC MODELS USED FOR WAVE ENERGY

Model Type	Specific Models
Deep Learning	DRL, DDQN, DDNN + XGBoost, LSTM (4), NN, Multilayer Perceptron, EANN, WANN, MTEANN, E-GRU, GAN, EMD-TimesNet, ANN, TCN, CNN
Regression	AR, ARX, WAR, Linear Regression, SVR, SVM (2), GWO-GMDH, Empirical Equations, GMDH
Ensemble Learning	RF (3), Analogues + RF, BO + GGA, BO + ELM, Analogues, SWAN + XGBoost, DDNN + XGBoost, Hybrid Intelligent Models (EN-1, EN-2), GWSM4C-NS Model, GWO-GMDH
Wavelet	WAM, EMD-TimesNet, VMD

Specifically, the Double Deep Q Network (DDQN) was used to improve WEC control utilizing Deep Reinforcement Learning (DRL) [39]. Another study used

XGBoost and Convolutional Dense Neural Networks (CDNN) to forecast electricity output from wave farms [41]. For offshore short-term SWH prediction, ANN, LSTM, and TCN performed well, with RMSE values of under 0.05 for 2-hour predictions. A reflection of the trend toward mixing ML techniques like RF with ensemble methods, hybrid intelligence models (EN-2) are gaining popularity to increase accuracy and efficiency for challenging wave height prediction problems [42]. Thirteen models improved their prediction accuracy and decreased bias by using ensemble techniques like XGBoost and RF. Integrating physics-based models with RF improved the accuracy of energy output projections for wave farms [19]. This enabled more accurate forecasting, especially in the face of complex wave conditions. Hybrid models that include both XGBoost and the SWAN wave model have the potential to improve operational wave forecasts, according to further research [27]. In terms of monthly mean wave height prediction at three Atlantic sites, the GMDH model demonstrated good predictive accuracy, outperforming solo GMDH models with training RMSE values of 0.202 and testing RMSE values of 0.175. Wave heights in the Atlantic Ocean at different buoy locations were predicted in a separate study using a hybrid model including VMD, RCMFE, and E-GRU. With R^2 values ranging from 0.9726 to 0.9826 and RMSE values lying between 0.0984 and 0.0816, this combined strategy is one of the most accurate models for multistep-ahead forecasting [43].

We used a mix of Bayesian Optimization (BO), a Grouping Genetic Algorithm (GGA), and an Extreme Learning Machine (ELM) to predict SWH and wave energy flow. This shows how optimization techniques, in conjunction with ML, have the potential to boost model accuracy [44]. Several models included ML techniques including Support Vector Machines (SVM), Neural Networks (NN), and Long Short-Term Memory (LSTM) with the main goal of power forecasting. Incorporating the very variable wave data, these models performed well when it came to managing future power predictions. A combination of SWH and energy flow predictions was made possible with the introduction of MTEANN [23]. a group of buoys, which improves the predictions Finally, hybrid models, such as EMD-TimesNet (Empirical Mode Decomposition) for weekly SWH prediction and GANs-based image-to-image translation models for spatial wave height forecasting, demonstrate the potential of hybrid methodologies. The accuracy of the GANs-based model in converting wind data into wave height forecasts is shown by its RMSE of 0.44 m, which is particularly noteworthy for spatial predictions [45].

CONCLUSION AND FUTURE DIRECTION

With the use of machine learning, wave energy forecasting has become much more efficient and accurate. Hybrid models, which combine machine learning with more traditional methods of prediction, are the subject of an increasing amount of research. Wave data's unique properties make LSTM networks and CNNs, two deep learning models, well-suited to different prediction horizons. These models, when combined with ensemble and hybrid methodologies, have shown promising results in predicting the height, energy flow, and duration of waves. The integration of wave power into power systems and the enhancement of energy collecting will have more significance as ML advances. More accurate and reliable future forecasts are possible with hybrid models since they combine multiple approaches and take use of the best parts of each. This work highlights the increasing importance of machine learning, and hybrid models in particular, for wave energy forecasting. For both present and future research, wave height predictions derived from physical models and ensemble methods are invaluable due to their high efficiency and accuracy. Researchers may significantly improve the precision of future predictions by using real-time data with other environmental factors like wave direction and tidal currents. In order to effectively handle complex and severe wave scenarios, it is essential to create hybrid models that integrate physical and data-driven approaches. Integrating machine learning into real-time WEC systems is one approach to optimizing the use of ocean waves for energy extraction. Advanced models, such as GANs and transformers, together with real-time data processing, will determine the future of wave energy forecasting. Combining machine learning with BO and GA in hybrid models has the potential to significantly increase prediction accuracy. Modern alternatives to older models for processing sequential data, such as transformers and TCNs, offer more promise than LSTM and GRU.

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