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# Artificial Intelligence in Wave Height and Energy Prediction: A Comprehensive Review

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**ABSTRACT**: Wave energy is a renewable energy source that exhibits a huge potential for sustainable growth. The design and deployment of wave energy converters at a given location require the prediction of the amount of available wave energy flux. This and other wave parameters can be estimated by means of Computational Intelligence techniques (Neural, Fuzzy, and Evolutionary Computation). Prediction of wave height is one of the most important issues in coastal engineering and for coastal structures. Over the past few years, advancements in the prediction of significant wave height using soft computing techniques have been developed drastically. Apart from traditional prediction of significant wave height, soft computing technique has explored a new way for prediction of significant wave height. This research work explains studies carried out in prediction of significant wave height using different soft computing techniques. This paper reviews those used in wave energy applications, both in the resource estimation and in the design and control of wave energy converters.

**KEYWORDS**: Artificial intelligence techniques, Wave energy, Renewable energy, Wave energy converters, Environmental impact.

## I. INTRODUCTION

Sustainable and renewable energy is becoming increasingly important due to the expected exhaustion in current energyresources and the reduction of environment pollution.Sun provides more than 99.99% of energy and earth contributes about 0.01% [1]. Fossil fuels are a form of antediluvian eon solar energy. All sources of energies, except geothermal and nuclear, are ultimately powered by the sun [2]. Earth radiates heat and its thermal energy come from radioactive decay (80%) and planetary accretion (20%) [3]. Oceans encompass over 70% of the earth's mass. Ocean tides are caused by earth's gravitational interaction with the moon (68%) and sun (32%). Ocean waves are caused by friction of winds with the water surface. Oceans are a great form of renewable energy which is stored in the form of thermal energy (heat), kinetic energy (tides and waves), chemical energy (chemicals) and biological energies (biomass). Tidal current or wave generators harvest kinetic energies, and osmotic power plants and thermo-electric generators reap salinity and thermal gradients [3].Wave power density distribution all over the earth is shown in figure 1.

Wave energy transfer provides a convenient and natural concentration of wind energy within the waves.Wave energy generation refers to the energy ofocean surface waves and the utilization of that energy to generateelectricity. The energy within a wave is dependent on the followingfactors; wind speed, duration of the wind blowing, the distanceof open water that the wind has blown over (fetch), andwater depth [1]. Wave power could be determined by wave height, wavelength, and water density. This mathematically could be described as in [4]:

$$P = \frac{\rho g}{64\pi} H^2 T \approx \frac{1}{2} H^2 T \; kW/m$$

Where, P is the wave energy flux per unit wave crest length (kW/m);q the mass density of the water (kg/m$^3$); g the gravitational gravity(m/s$^2$); H the wave height (m) and T is the wave time cycle (s).For example: for a 1.6 m wave and 10 s period, the power producedis approximately 12.8 kW/m.

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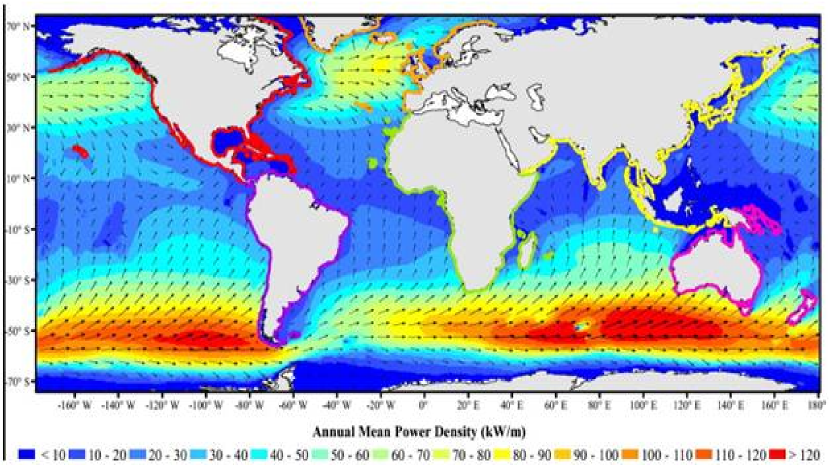


**Figure 1: Annual Mean Power Density over Earth**

Worldwide tidal power generation sites explored include4,200 MW Pent land Firth (UK) [5-6] 818 to 1,320 MW Incheon and Red Tides Sihawa Bay (South Korea) [7], Kislaya Guba (Belgium) [8], 6500 MW Turnagain (USA, 2,800 MW Walcott Inlet (Australia), 5338 MW Cobequid (Canada), 7000 MW Khambat Gulf (India) and Johnstone Strait [9] and Minas Passage Bay of Fundy (Canada) [10-11].

Some estuaries and channels, like Hudson Strait (Canada), are reported to be reminiscent of half-wave resonant oscillations [12]. Old tidal current power stations such as 3.2 MW Jiangxia Tidal Power Station (China), 20 MW Annapolis Royal Generating Station (Canada), 240 MW Rance Tidal Power Station (France) and 250 MW Sihwa Lake power Station (South Korea) have relatively low to moderate power generation capacities, but recently planned large tidal power stations such as2,200 MW Dalupiri Blue Energy Project (Philippines), 3640 MW Tugurskaya Tidal Power Station (Russia), 8640 MW Seven Barrage (UK) and12,000 MW Mezenskaya Tidal Power Station (Russia) are large power stations.India intends to construct a 50 MW tidal power station in the Gulf of Kutch and there is unconfirmed news of 87,100 MW Penzhinskaya Tidal Power Station in Penzhin Bay Russia [13].

There are hundreds of types of marine current turbines. The British government has started an ambitious target of 200–300 MW ocean energy by 2020. Denmark started a €3 million project for wave energy in 2012 under national initiative to produce 35% of electricity from renewable energy by 2020. As of 2012 Europe produced 246.20 MW compared to 259.20 MW by Asia. Global ocean energy production was 527.70 MW by the end of 2012 which is likely increase many times by 2020 due to multiple wave energy projects worldwide. Ireland has an estimated potential of 29 GW ocean energy [14].

## II. TYPES OF WAVE ENERGY CONVERTER

The developmentof wave energy generation (WEG) has been taking place forabout 35 years. In most devices developed or considered so far, thefinal product is electrical energy to be supplied to a grid.In practice, three main methods of energy storage have beenadopted in WEG. An effective WEG way is storage as potentialenergy in a water reservoir, which is achieved in some overtoppingdevices, like theWave Dragon [15] and the Tapchan [16]. The workingprinciple of these devices is shown in Fig. 2 (a). The overtoppingwave energy converter works in much the same way as a hydroelectric dam [17].

The second WEG method is based on the oscillatingwater column. This WEC type depends on the air column andthe difference in pressure generated by waves as in Fig. 2(b). In thisdevice, the size and rotational speed of the air turbine rotor make itpossible to store a substantial amount of energy as kinetic energy(flywheel effect - the Wells turbine) [18].

The third energy conversionwaywhich is paid more attention to in recent years is floatingbuoywave energy converters as shown in Fig. 2(c). In a large class of these devices, the oscillating (rectilinear orangular) motion of a floating body

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(or the relative motion betweentwo moving bodies) is converted into the flow of a liquid (water oroil) at high-pressure by using hydraulic systems.

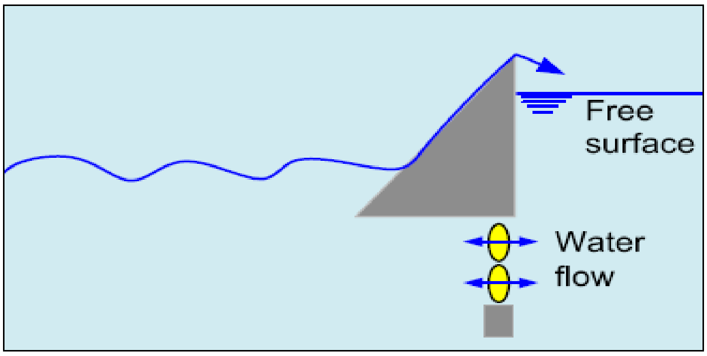


**Figure 2(a): Overtopping WEC**

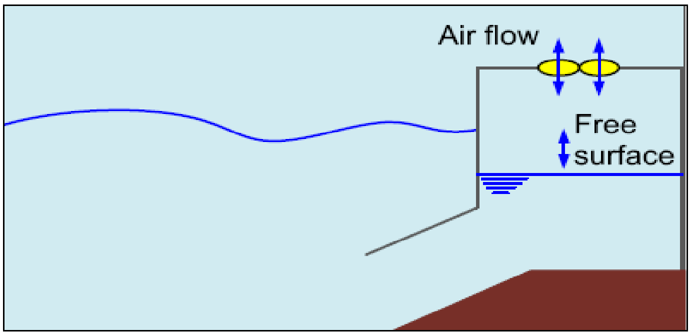


**Figure 2(b): Oscillating water column WEC**

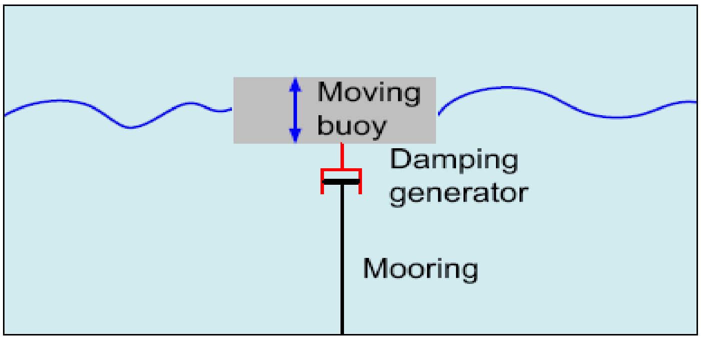


**Figure 2(c): Floating-buoy WEC**

## III. WAVE HEIGHT AND ENERGY PREDICTION

Ocean waves' kinetic energy can be transformed into electricity by means of Wave Energy Converters (WEC), contributing this way to reduce our deep dependence on fossil fuels [19], [20]. This type of marine facilities to obtain energy shows a clear potential for sustainable growth [21]: marine energy resources do not generate CO2 and reduce oil imports, a crucial geo-economical issue.

However, in spite of this potential, the use of marine energy sources is nowadays still minor at global level. In spite of this, wave energy plays a key role for sustainable development in several offshore islands because it provides not only technical and economical benefits (to satisfy the demands of clean electricity) but also without significant

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environmental impact, a key concern in offshore islands, committed to the protection of ecological systems [22]. Some interesting reviews of the most important issues involved in the generation of electricity from oceans (including converters, their related economical aspects, and the potential of a number of ocean regions to be exploited worldwide) can be found in [23], [21]. Ocean waves are usually produced by wind action and are therefore an indirect form of solar energy. Wave energy uses Wave Energy Converters (WECs) to convert ocean energy into electricity [21].

WECs transform the kinetic energy of wind-generated waves into electricity by means of either the vertical oscillation of waves or the linear motion of waves, and exhibit some important advantages when compared to alternatives based on tidal converters, for example. Note however, that not all of the available wave energy resources can be realized as usable power, mainly due to various factors including socio-economics, the severe ocean environment, power conversion losses, and cost. Moreover, ocean waves are difficult to characterize, because its generation and propagation can be modelled as nonlinear processes. The real sea is a superposition of irregular waves trains which differ in period, height and direction. The local behavior of the sea estate can be represented by a spectrum, which specifies how the wave energy is distributed in terms of frequency and direction. As a consequence of this complexity, both the design, deployment, and control of WECs [24], [25] become key topics that require a proper characterization and prediction of waves. Maybe, the most important wave parameters in this regard to characterize waves is the significant wave height (Hs), in which prediction this paper is focused on.

Wave height is one of the most important factors in coastal processes and coastal engineering studies. In case of energy extraction from waves, sediment movements, harbour design and soil erosion, wave height plays a vital role in these. Long- term observed data's are needed for all the practical applications. There are different methods for finding wave heights such as field measurements, theoretical studies and numerical stimulation. But in most of these cases there won't be long-term measurements, so prediction of wave height is essential. Now day's soft computing based models have been used for wave prediction.

Soft computing based methods give results with high accuracy and time taken for training and prediction is very less compared to other traditional methods. This paper explains different studies carried out in prediction of significant wave height using different soft computing techniques such as Support Vector Regression (SVR), Extreme Learning Machine (ELM), Adaptive Neuro-Fuzzy Inference System (ANFIS), Neuro-Wavelet technique, Artificial Neural Network (ANN), Genetic Algorithm (GA) and other models. Every method has its own advantages and disadvantages.

## IV. WAVE PARAMETERS

Themainwaveparameters are:

**Wave Height**

$$H_s = 4(m_0)^{\frac{1}{2}}$$

is theparameterrelatedtothewaveheightthatismostusedinwaveenergyandinthedesignofships and marinestructuresandcoastalprotection.

**Wave Energy Period**

It can be computed by using, among others, the estimator $T_e$ as:

$$T_e = \frac{m_{-1}}{m_o}$$

$T_e$ is an estimate of the average period used in the design of turbines for wave energy conversion.

**Spectral density S(f)**

It is spectralmomentsoforder n can becomputedas:

$$m_n = \int_0^\infty S(f)df$$

The spectralmoments $m_{-1}$, $m_0$, $m_1$, and $m_2$are equated using above equation. Theyprovide information ondifferentstatisticalandphysicalcharacteristicsof waves.Forinstance, $m_0$ is thevarianceofthewaveelevation.

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**Peak Period**
The peak period is defined as:

$$T_p = \frac{1}{f_p}$$

**Goda'sPeakedness Parameter**
It is computed as:

$$Q_p = \frac{2}{m^2}\int_0^{\infty} f.S^2(f)df$$

$Q_p$has the potential to describe the statistical features of consecutive wave heights.
**Longuet–Higgins Spectral Bandwidth**
It is computed as:

$$v = \sqrt{\frac{m_2 * m_o}{m_1^2} - 1}$$

Quantifies thedegreetowhichspectralenergyspreadsoverthefrequencyrange.
**Spectral Width Parameter**

$$S_p = \sqrt{\frac{m_0 m_4 - m_2^2}{m_0 m_4}}$$

## V. RELATED WORK

Regression trees and ANN was used by Mahjoobi and Etemad-Shahidi (2008) [26] for predicting significant wave height. They used wind speed and wind direction as the input parameters and significant wave height as the output parameter. Regression tree was built and evaluated by CART algorithm. Result shows that error of both ANN and Regression tree was almost same, regression tree is a novel approach with tolerable range of error. They argue that the main advantage of regression tree than ANN is that they represent rules.

Kemal (2008) [27] used ANN and regression method for wave forecasting. He used monthly mean wind speeds, air temperature and sea level pressures as input parameters and used seven different combinations of these to get the best result. The result shows that the ANN with all input parameter shows the best result. In these input parameters wind speed has the maximum effect on output wave height.

Özger (2009) [28] used hybrid neuro-fuzzy approach for estimating wave characteristics of ocean.

To overcome the problem of missing data, he shows that the significant wave. Height of one buoy location can be predicted using the data from adjacent buoys using neuro-fuzzy approach. This approach shows a possibility of retrieving missing and also to determine the optimal position of buoys.

Georgioset. al. (2009) [29] has done wind wave modelling through fuzzy interface system (FIS) and developed FIS act as a valuable tool for forecasting wave parameters. The proposed method showed a quick convergence of observed and predicted data.

Ozgeret. al. (2014) [30] used fuzzy inference system for predicting wave parameters. They used Fetch length, duration, wind speed and wave heights as variables for wave height prediction, and used different combinations of these. They compared there results with Jonswap, CEM, Wilson, SPM and found that ANFIS is the best model with less error. They also found that combination of wind speed and duration of wind blowing as input gives better result.

Hashimet. al. (2016) [31] done selection of climatic parameters using enhanced Takagi-Sugeno-based fuzzy which affects wave height forecasting. They used wind speed, wind direction, sea surface temperature and air temperature as input variables and significant wave height as output. The main aim of that study was to identify the most predominant input parameters influencing wave height prediction. They found that wind speed, air temperature, sea surface

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temperature and wind direction has most to least influence in wave height prediction respectively. They also found that the combination of wind speed, air temperature and wind direction are the most influencing set of input parameters.

To improve the wave height prediction they suggest considering air temperature and sea surface temperature. The advantage of ANFIS model is that its adaptability to optimization, computationally efficient, adaptive methods and is faster compared to other control strategies.

Stefanakos (2016) [32] forecasted non stationary wind and wave data using combination of Fuzzy Inference Systems (FIS) and Adaptive Network- based Fuzzy Inference Systems (ANFIS), it will remove non-stationary character of wind wave data before we predict the data. The data is first decomposed by means of the above-mentioned non stationary modelling into a residual and seasonal mean value time series multiplied by a seasonal standard deviation and FIS or ANFIS model is applied. By that method they obtained point wise prediction for specific data points and field-wise prediction for whole field of wave parameters. The results were compared with only FIS and ANFIS and it shows that the combination outperforms than these methods.

The research focused on the application of various soft computing techniques in predicting significant wave height.The predictive efficiency of a machine learning approach depends upon quality and size of the data set available.ANN takes more computational time and finds difficulty in determining the effective structure of the network. Hybrid models give better result than plain model. Wind speed, air temperature, sea surface temperature and wind direction has most to least influence in wave height prediction respectively. Combination of wind speed, air temperature and wind direction are the most influencing set of input parameters. The advantage of ANFIS model is that its adaptability to optimization, computationally efficient, adaptive methods and is faster compared to other control strategies. The advantages of GA is that it can even work with discontinuous data The main drawback of GA is that it requires large computation data support and longer running time Advantage of Extreme learning machine is that it is an extremely fast- training approach with excellent result based on prediction quality. Advantage of SVR algorithm is that it removes calibration necessity and can predict wave height accurately after training.

## VI. CONCLUSION

Ocean energy is clean and renewable in nature,yet has minor environmental reservations. Major ocean energy research activities include wave technologies (45%), tidal stations (23%), economic or policy studies (15%) and environmental concerns (17%). In this paper we have reviewed the use of Computational Intelligence (CI) techniques in the field of wave energy. The benefits of applying CI techniques to wave energy problems reside on their great potential to work with a huge amount of imprecise or missing data. This is just the case of the design, deployment, and even control of wave energy converters (WECs), whose fundamentals have been summarized.

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