Reactive Control Wave Energy Converter with Emulator to withstand irregular Wave Conditions with Artificial Neural Network

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Abstract— **Energy is one of the most dominant requirements in a global scale. Today's global energy demand is significantly fulfilled by the fossil fuels such as coal and oil. The fossil fuel has restricted supply in the future and also plays the vital cause in the global warming. These restrictions direct the scientist and researchers to explore the sustainable and eco-friendly energy resources available in the world. Among the various energy resources, the energy from ocean attracts the researchers today. Thousands of wave energy converters (WECs) are developed and patented to harvest the wave energy. Particularly, a country like India, has a long coastal region contained an immense potential in the ocean energy resources. But the intensity of the energy in the Indian seas is less when compared to the Pacific and other regions in the world. The low energy intensity level combined with economic factors, leads to a barrier for funding agencies to provide funding in the ocean energy research. The efficiency is much increased when a suitable control is incorporated in the energy converter. To attain this an effective control technique this paper presented a technique known as the reactive integrated with the ANN control is implemented. The developed ANN is compared with the results of the statistical method such as linear regression analysis. The energy harvesting efficiency is increased by achieving resonance by adopting reactive control when the non-buoyant type WEC is subject to both the regular and irregular waves. When compared to other devices where the average energy conversion efficiency is found to be between 20%-40%, the proposed energy converter has a significant energy harvesting efficiency of about 58%.Keywords— Wave Energy Converter (WEC), Artificial Neural Networks (ANNs), reactive control, Multistart optimization.**

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I. Introduction

Energy is one of the most dominant requirements in the global scale. Today's global energy demand is significantly fulfilled by the fossil fuels such as coal and oil [1]. The fossil fuel, have restricted supply in the future and play the vital cause in the global warming. Further, every year abundant amount of carbon dioxide is released to the environment which contributes to the greenhouse effect [2]. Among the renewable energy sources, the ocean energy plays a vast contribution. Since nearly 70% of the earth is covered with ocean, there is an ample opportunity to extract the energy from it. Ocean energy is available in two forms, one is thermal energy due to the heating of the earth's surface by the sun and the deep cold water [3]. This temperature difference is utilized to run the thermodynamic cycle to produce power. The other form of energy is mechanical energy which is available in the form of tides, waves and ocean current. The waves are formed from the wind, which is blown due to the rotation of earth and uneven heating of the earth's surface by the sun. The tides and currents are formed due to the gravitational pull between the moon and the earth. Suitable mechanisms are instigated in order to extract the energy from these resources [4]. Effective utilization and sustainability of any ocean energy harvester depend upon its adaptability in the irregular seasonal environment, situation capability in maximum energy extraction and finally fulfilling the economic barriers. Thousands of patterns have been reported to harvest the energy from ocean and among those technologies, the Wave Energy Converters (WEC) plays the predominant role in electricity generation from the ocean waves [5].
Generally wind is the flow of large amounts of air from high pressure to the low pressure area as shown in figure 1. The formation of wind begins with the sun's radiation. The earth's surface heated differently because of the presence of clouds, mountains, valleys and water bodies, etc. The air in the high heated area gets rise and creates low pressure whereas, the area which is low heated creates high pressure [6]. Hence, the air flows from high pressure area to the low pressure area which causes the wind formation. The ocean waves are formed when this wind flow strikes the ocean surface and the waves which are produced can travel for a large distance before reaching the land. Wind waves vary in size from small ripples and to the maximum of over 100 ft (30 m) high. The development of ocean wave happens due to the

variation in the shear stress and the fluctuations of the turbulent air flow on the water surface [7].

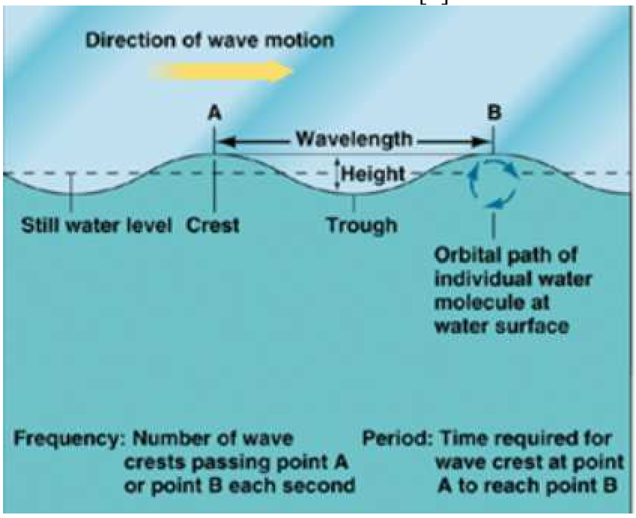

Fig 1: Flow of Ocean Wave

The ocean wave system subjected to vast range of challenges since the ocean wave energy is highly nonlinear, the power output from the wave energy converter is highly fluctuating [8]. In offshore locations, wave direction is highly inconstant, and thus wave energy converters have to align themselves with the help of moorings, or be symmetrical, in order to capture the energy of the wave [9]. The fabrication and installation cost of the wave energy converter is higher when compared to any other renewable energy devices. The ocean environment is highly complicated to any wave energy converters due to the corrosive nature of the ocean and the marine growth [10]. The common classification based on operating principle is dividing the wave energy converters into Oscillating Water Column (OWC), Over topping Devices (OTD) and Wave Activated Bodies (WAB), based on the way they work. It is clear that a robust wave harvester is in great demand which suits to the Indian coastline to fulfill the energy demand of the country [11]. Considering this, a novel concept to harvest the energy from the ocean waves was proposed and fabricated in a small. The electricity from this energy converter is successfully generated in the lab environment with the help of the small wave flume and the results are published previously [12].

This paper concentrated on the construction of the ANN-based non-buoyant structure for ocean wave energy harvesting. The emulator is designed with an oscillator to withstand the non-uniform pecan wave. The developed structure is mathematically examined for performance in terms of both simulation and hardware scenarios. Finally, the developed model is implemented in the ANN network for the computation of the performance of the designed emulator. The paper structure comprises of the related works in section 2. The structural design and mathematical formulation are presented in section 3. The simulation results and analysis are presented in section 4 and the overall conclusion of the designed structure is presented in section 5.

II. Related Works

In [13] proposed an onshore WEC is known as Searaser which harnesses the almost constant power. It is simple in structure which requires less installation and maintenance cost and power fluctuation is minimized. The Searaser itself does not generate electricity, but hoists the water (increasing its potential energy) by an amalgamation of buoyancy and gravity forces. The power generation takes place above the water, on the shore and hence the corrosion is minimized. Seasun power system provides high stability and simple structure to mount the WEC on the sea bed. Submerged plate [14] is moored but not rigidly fixed. It is prevented from sea bed earthquakes and is efficient in damping. The stability of the WEC is a very important criteria to be considered in the design stage. Spar has high structural stability and capable of preventing the energy conversion devices from ocean environment. It also prevents the wave energy harvester from displacement during buoy movement.

ANNs are used in various renewable energy sectors such as solar, wind and ocean. In these sectors, ANN is implemented to predict the wind speed and direction, air humidity and temperature and solar radiations. For example, various neural network models are proposed to predict the wind speed in [15]. The best suited network model with minimum error is obtained among the models tested such as Multilayer Perceptron (MLP), multilayer adaptive linear neuron (Madaline), Back Propagation Neural Network (BPN), and Probabilistic Neural Network (PNN). Generally, the selection of a neuron is made randomly but, in above mentioned work, to select the optimal hidden neurons for the proposed network model nearly 102 criteria are trained and validated. The protocol for finding for optimal hidden neuron is also presented.

In [16] developed a neural network model for predicting the output of a wind power plant. The PNN model was implemented for preprocessing the data which are to be utilized for training. Then few selected turbine data's were identified as input source for the model. Finally, complex valued Recurrent Neural Network (CRNN) model is found with high accuracy. Apart from prediction of wind speed and the power output from the wind power plant, the other parameters such as wind direction, fluctuations, season of a particular area, wind turbine positions are crucial for effective power production. An ANN model with feed forward neural network architecture and back propagation algorithm for effective prediction.

In [17] proposed four neural networks, namely, multilayered perceptron, recurrent, radial basis function and bagged network for solar power generation forecasting ahead of 24 hour for a 24kW photovoltaic system. ANN also has a wide application in the field of ocean research, such as tsunami prediction [18]. The ANN is evaluated for their performance in the prediction of water level during the tsunami. This is achieved by training the ANN with different tsunami conditions. ANN was designed and developed in [19] for the prediction of wave parameters such as the wave height and period. The findings were compared with the results of the Young's model and this has proved the suitability of ANN for the prediction of short term wave parameters. ANN also has its application in the control of WECs. An algorithm was developed in [20] for the reactive control of the point absorbers. The ANN predicts the wave height, wave period and power takeoff damping and hence the developed ANN is found to be effective in maximizing the energy absorption. A combination of numerical and neural network model was proposed in [21] to predict the ocean wave. The numerical model resembles the physical concept and ANN is incorporated to improve the performance of the model. The results are best for short-term wave prediction and the ANN is suitable for simplifying the complex phenomenon as well as predicting the accurate wave parameters.

In this work the ANN is implemented for the efficiency enhancement of the WEC, this is achieved by predicting the displacement of the non-buoyant body for the corresponding incoming wave and tuning the electrical load accordingly to obtain the optimal damping and achieving the maximum energy extraction

III. Oscillating Arm in the Emulator

The concept of the proposed model can be understood in the Figure 2. The setup is essentially comprised of the suspended arm with the steel oscillating frame with the non-buoyant body suspended in the metal rope between one another end with the counterweight. Additionally, the pivots arm are oscillating based on the center coupled with the shift rotatable pivoted table. The shaft rotatable comprises the gearbox that is unidirectional, a step-up gearbox and a generator.

Non-linear Auto Regressive network with Exogenous inputs (NARX). NARX is a highly sophisticated technique which is an advanced version of time series based neural networks. NARX is a multilayered network model with a feedback network (Figure 4.1). This highly sophisticated model is used to learn and predict the behavior of complex nonlinear systems. This technique is used to model the nonlinear relationship among the variables with respect to time. In this model, the target variable does not depend only on the past value of variables, but also it depends on the past values of the target value itself. Multi layered structure and parallel processing ability makes NARX a suitable model for learning from a large number of non-linear data even in the presence of noise. As mentioned earlier the target values of NARX model depends on the past value of both input data and target variables. The target value „y‟ at any specific time „t‟ can be predicted from input value „x‟ and target value „y‟ for „n‟ historic period until time „t‟ as shown in Equation (1)

y(t)=f{y(t-1)…….y(t-n),x(t),x(t-1)….x(t-n)}
(1)

The model of the ANN architecture comprises of a different number of layers where each layer contains neurons. Generally, based on the input and output parameters the neurons in the input and output are considered. Similarly, this work comprises of the parameters as height of the wave in cm (Wh) and wave time period (Wt) and hence the neurons count in the input is identified as the two.

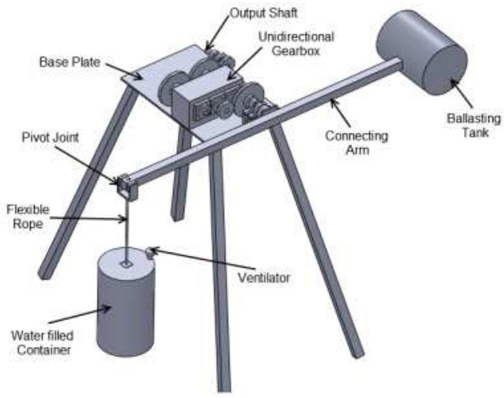

Fig 2: Experimental Setup

The simulation setup for the defined NARX model is tabulated as follows in table 1.

Table 1: Experimental Setup

Structural Parameters	Network Parameters
Network	Non-linear auto regressive network with exogenous inputs (NARX)
Transfer function	Sigmoid transfer function
Learning Algorithm	Levenberg - Marquardt algorithm
Error function	Mean Square Error (MSE)

The output parameter involved in the estimation of the heave displacement with the non-buoyant container in cm (Jc) for the neuron in the input layer as one. To estimate the performance characteristics of the developed model ith data in the oceanic wave is denoted as ei with the ANN actual output of ai.

3.1 Mathematical Formulation

With the coupled generator motor mathematical model is developed and connected to the generator. As with the motor the output is defined as the Kirchoff‟s voltage law and rotational equation as,

$$Va = (Lm + Rm) + E_{bemf} \quad (2)$$

Here, VaIs the motor armature voltage, $Ebemf$Is the backemf of the motor, Im Is the motor armature current, Rm Is the armature resistance of the motor and Lm Is the armature inductance of the motor. Similarly, the governing equation for the generator is defined in equation (3)

$$Eg = Ig(RL + Rg + Lg) \quad (3)$$

The equation for the generator is similar to that of the motor in which parameters are indicated with subscript g, except Ewhich is known as an induced emf of the generator and RLIs the resistive load. Now, the torque of the motor can be derived as in equation (4),

$$Pm = EbemfIm \quad (4)$$

Here, Pm is the mechanical power of the motor. The mechanical power Pm is related to the electromagnetic torque $Tmas$, represented in equation (5)

$$Pm = Tm\omega \quad (5)$$

$\omega$is an angular speed in rad/sec

Now, equating equations (4) and (5) equation (6) is obtained

$$EbemfIm = Tm\omega \quad (6)$$

Further, it can be simplified as in equation (7)

$$Tm = KmIm \quad (7)$$

Here, the torque constant and voltage constant is considered to be equal and denoted as motor constant Km. Similarly for the generator, the corresponding torque equation and induced emf is represented in equation (8) and (9),

$$Tg = KgIg \quad (8)$$

and

$$Eg = Kg\omega \quad (9)$$

Let‟s consider the resistive lamp as the load connected to a DC generator output terminals. At steady state conditions, equation (9) can be rewritten as in equation (10),

$$Eg = Ig(RL) \quad (10)$$

Using equations (9) and (10) the current flowing through the load can be obtained as in equation (11),

$$kg\omega = Ig(RL) \quad (11)$$

Now, the power intake of the resistance load PLIs given as in equation (12),

$$PL=kg^2\omega 2/Rl \quad (12)$$

Where, Kg^2 is the generator constant and the above equation gives the relation between the resistance values of the system to that of the system angular speed and further, the optimal resistive load can be obtained from the corresponding angular speed of the system.

IV. SIMULATION ANALYSIS

The simulation model is developed from the Matlab SimPower Systems library. As shown in Figure 3, the simulation system contains of PMDC motor and PMDC generator which are coupled together. Further, it also consists of MOSFET Switch, DC source, Resistor in RCL block, capacitor in RCL block, PID Controller, Repeat sequence, Gain, PWM generator, power gui, Bus selector, Scope, Display, Manual Switch, Voltage measurement, Current measurement, Product, 2nd order filter. After connecting the components the parameters are to be tuned for obtaining the similar results of the hardware setup. The parameters are given in Table 2.

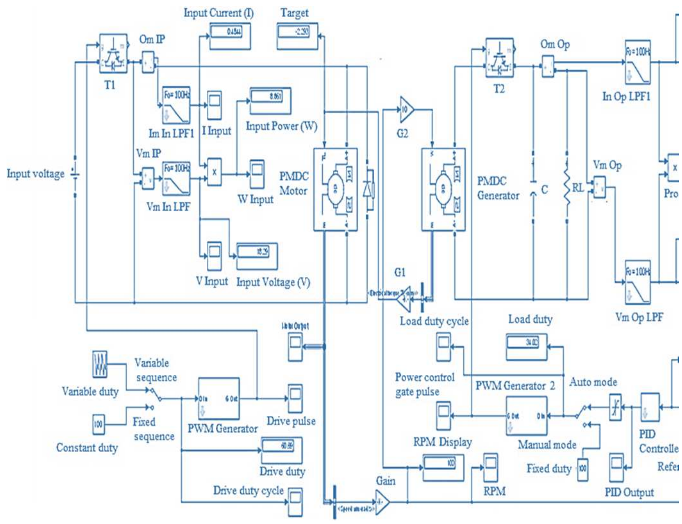

Fig 3: Parameters of DC motor-generator couple

Table 2: Hardware Measurement

The simulation motor speed is achieved same as that of the real motor by providing an appropriate power to the drive motor. The input voltage, the input current and the corresponding duty cycle are shown in the Figures 4,5 and 6 respectively. These parameters are tuned in such a way so that the simulation speed is made to match with the real motor.

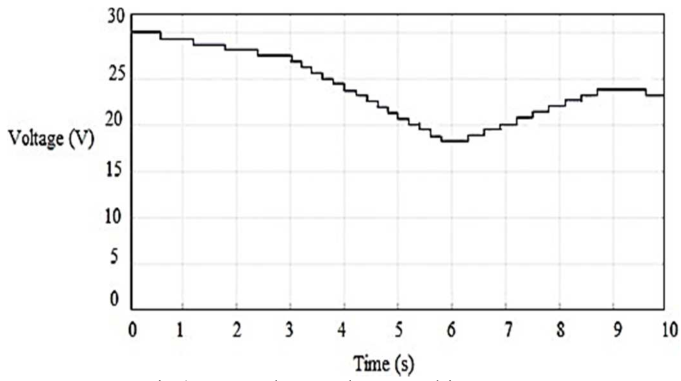

Fig 4: Input voltage to the motor drive

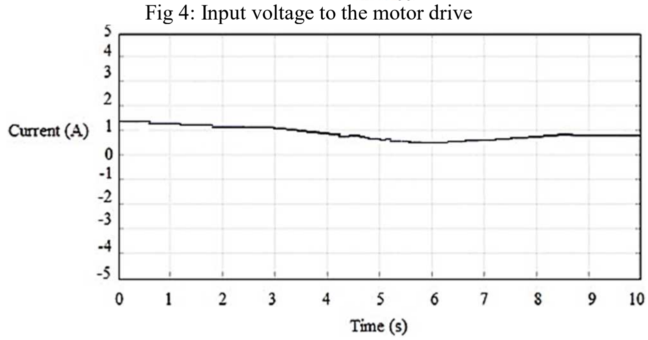

Fig 5: Input current to the motor drive

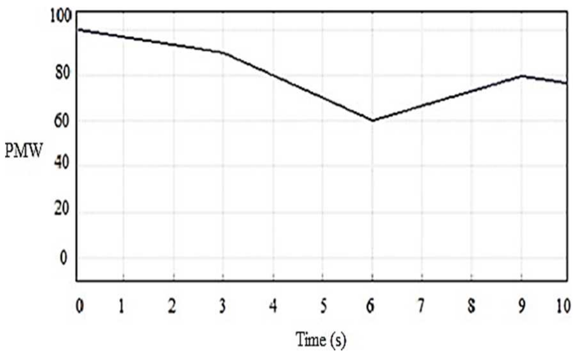

Fig 6: PWM to the motor drive

The simulated motor mimics the rotation of the real motor by providing appropriate pulse width modulation and it also considers the mechanical losses occurred in the real hardware setup. In the simulator the speed of the generator is maintained constant as shown in the Figure 7 such that the quality of the power generated is high. The Figures 8,9 and 10 respectively show the voltage, current and power which varies according to the variation in the load. The load is adjusted to maintain the generator speed constant to maintain the quality of the energy production.

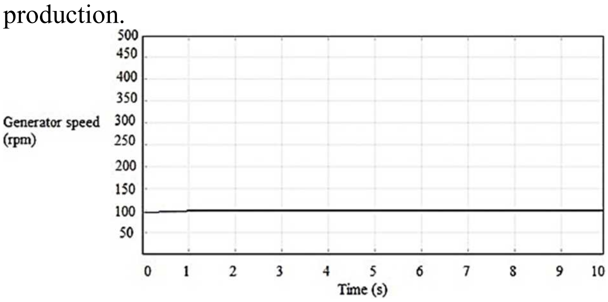

Fig 7: Generator speed (rpm)

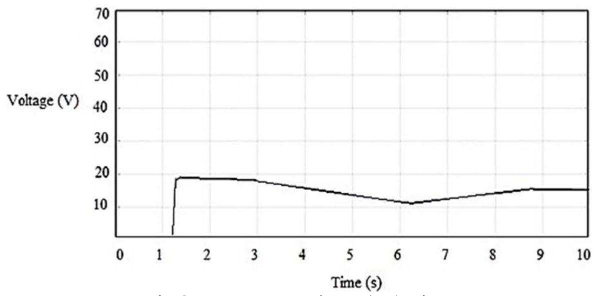

Fig 8: Generator Voltage (Vs) Time

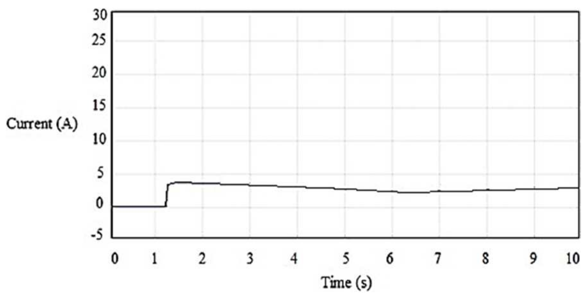

Fig 9: Generator current (Vs) Time

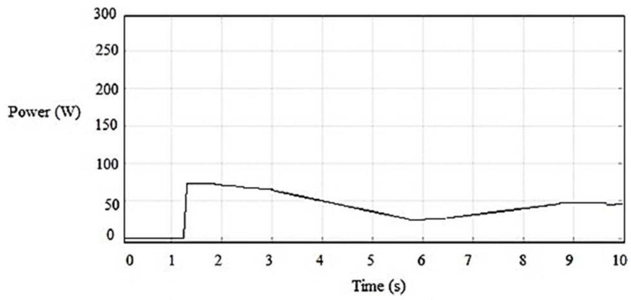

Fig 10: Generator power (Vs) Time

Simulation is carried out where the simulated motor receives the appropriate drive signal as pulsated width modulation by including the mechanical losses occurred in the real WEC. Further, it drives the motor, in turn the motor is coupled to the generator for power production. In order to maintain the quality of power production the speed of the generator shaft has to be maintained constant and this is achieved by providing the optimal load to the generator.

V. FINDINGS

Reactive control of the energy converter is performed for the regular waves in the emulator. As explained in the previous chapter, the emulator has the ability to produce the same static and dynamic characteristics of a real WEC. Any range of waves can be fed to this emulator, and the system converts the wave profile into a corresponding duty cycle which vary between 0% to 100%. The data (wave profile) can be uploaded in the form of Microsoft excel format. As soon as the data is uploaded, the peak value of all the amplitudes of the wave profile is considered and the corresponding duty cycle is generated.

This generated duty cycle is fed to the motor. The control of the emulator for the given wave profile can be done in two modes, one is the auto mode and the other is in manual mode. The auto mode is in the form of closed loop system and the manual mode is in the form of open loop system. In the closed loop system, the parameters such as the sample rate, duty gain are kept constant and the motor rotates as per the duty cycle which is further coupled to the generator. The generator has to be rotated at constant speed and optimal load for quality power production. Finding out the constant speed and optimal load is possible in the emulator. This can be achieved by varying the ranges of the generator set speed and providing the corresponding optimal load. Comparing the results, the optimal set speed and the load damping to the generator can be identified. In the manual mode the parameters such as the sample rate, duty gain can be adjusted as per the requirement and this is done to modify the wave data's which are not responding during the auto mode or for testing the wave profile for a different range of parameters. The emulator is subjected to different regular waves and the reactive control for all the conditions is achieved. The emulator is subjected to two conditions, one is the regular wave which has the fixed time period and amplitude and the other one is the irregular wave which varies in the time period and amplitude. Initially, during the regular wave conditions, the regular wave data is fed to the emulator and the corresponding optimal electrical load is provided by the technique reactive loading control to enhance the generator power production. During irregular wave condition, the Artificial Neural Network (ANN) is developed and implemented to predict the optimal electrical loading control.

VI. Conclusion

This work particularly contributes to the efficiency enhancement of non-buoyant WEC achieved through employing reactive control technique. The control system was developed by considering the practical challenge encountered during implementing the WEC in the real ocean environment. The nature of the sea environment plays the major role in affecting the mechanism and the control system of WEC and thus considering this issue, the WEC is developed in such a way that only the non-buoyant container is made to be in contact with the wave and the remaining parts are outside the incident wave, similarly the propose control system is only about tuning the load condition of the WEC based on the incident wave and thus there is no much complexity in the control system and this favours towards simplest form of mechanism in terms of complexity and cost. Despite, the waves being highly irregular in nature, the continuous power generation is possible when the WEC is subject to active control of the dynamics. The controlling means in terms of both the amplitude and phase matching which leads to the optimal energy extraction. This active tuning of the dynamics of the system leads to the resonance where the natural frequency of the device close to the frequency of the incident wave. The level of tuning the WEC can vary from tunning the dynamics of the system to a particular sea state to wave – by-wave adoption. It is convenient to tune the dynamics of WEC in regular wave, but it is intricate in nature to tune the dynamics of the WEC according to the incident wave when the wave is irregular. Thus, ANN paves the way for optimal energy extraction. The network used to develop the ANN model and other related parameters plays a dominant role in the performance. A multi layered time series based neural networks NARX is highly sophisticated model to learn and predict the behavior of complex nonlinear systems. Multi layered structure and parallel processing ability makes NARX a suitable model for learning from a large number of non-linear data even in the presence of noise. In ANN apart from the input and output layer, the hidden layer plays a vital role in the prediction accuracy. In this work, network with one and two hidden layers is producing promising results with good accuracy and increasing the hidden layer more than two leads to complexity in network and long execution time. Similarly, the number of neurons in the network also plays a dominant role and hence a range of neurons varying from two to thirty is implemented and tested. The MSE and correlation co-efficient are the two factors based on which the performance of the network is evaluated. Among the proposed network the ANN with architecture 2-10-10-1 is performing well with least MSE. This network is most suitable for prediction for the irregular wave conditions. Further, when ANN is compared with the statistical method such as linear regression analysis, the results of the latter is inappropriate due to the possible occurrence of multicollinearity. Hence ANN is considered as a suitable technique for the proposed work.

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