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Wave Energy Converter Cone-Cylinder Buoy Dimension Optimization using Backpropagation Neural Network and Genetic Algorithm Method

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Abstract

Wave energy converter (WEC) technology is currently being explored as one of most promising renewable energy sources. Heaving point absorber is the most used type of WEC because it has a shape that easily adapts to wave conditions. The unreliability in extreme weather and dependence on buoy size caused WEC technology to be underutilized. Research to utilize shape changes is needed to reduce WEC dependence on buoy size. The purpose of this research is to design a WEC buoy showing maximum power absorbed with the minimum value of volume and comparing it with the existing buoy shape such as the basic cone-cylinder and bullet shape. The research begins by determining the variant of dimensions for the cone-cylinder buoy head cylinder height with the value of 0.40, 0.55, 0.70, 0.85, 1.00, and 1.15 in meters and cone concavity diameter with the value of 3.20, 3.90, 4.60, 5.30, 6.00, 6.70, 7.40, and 8.10 in meters. The Simulation process will use Ansys AQWA software with heaving motion values as output to calculate the absorbed power. The optimization process uses the Backpropagation Neural Network (BPNN) method followed by the Genetic Algorithm (GA) on MATLAB software. The optimized parameters will be simulated to validate the prediction of GA. For the buoy volume BPNN training, the best setting is 2 hidden layers, 5 nodes, Log-Sigmoid activation function, 70% training ratio, 15% validating ratio, and 15% testing ratio with 4.59E-09 mean squared error (MSE). For the buoy power absorbed BPNN training, the best setting is using 4 hidden layers, 5 nodes, Tan-Sigmoid activation function, 70% training ratio, 15% validating ratio, and 15% testing ratio with 5.95E-25 MSE. For GA the best setting is generating 500 chromosomes with using weight 0.5. The result of GA is 1150 mm of cylinder height and 7146.10 mm of cone concavity diameter, simulation shows 12.8503 m3 of volume and 3379.00 Watt of power absorbed.

Keywords: Buoy Optimization, Power Output, Renewable Energy, Wave Energy Converter.

1. Introduction

The need for energy has increased rapidly. Based on data taken by the Our World in Data Organization, there was an increase of 20,802 terawatt-hours in energy consumption from 2012 to 2022 [1]. To meet this increasing demand, Wave Energy Converter (WEC) technology is currently being explored as one of the most promising renewable energy sources. Among the various WEC categories, the heaving point absorber is commonly utilized due to its low manufacturing cost, and it does not depend on a certain wave direction.

Despite its potential, the heaving point absorber technology faces limitations in commercial application due to its unreliability in extreme weather and a heavy dependence on the size of the buoy as the energy capturing medium, resulting in a short operational lifespan and financial losses [2]. Consequently, WEC technology remains poorly implemented, making it difficult to attract investment from the private sector. Therefore, it is necessary to explore how geometric modifications can minimize a buoy's size while maintaining high efficiency in power absorption to decrease the heaving point absorber type WEC dependence on the buoy's size.

The potential for geometric modification in WEC buoys has been demonstrated in several studies, such as the differences in optimal power output between concave wedge and cone-cylinder shapes [3] alongside research employing multi-objective optimization techniques to determine the geometric configurations of multi-axis WECs [4]. Other studies, such as the optimization of boat-shaped buoys by Lin et al. [5], showed prominent potential in utilizing artificial intelligence (AI) technology to find an optimal shape.

This research focuses on designing an optimized-

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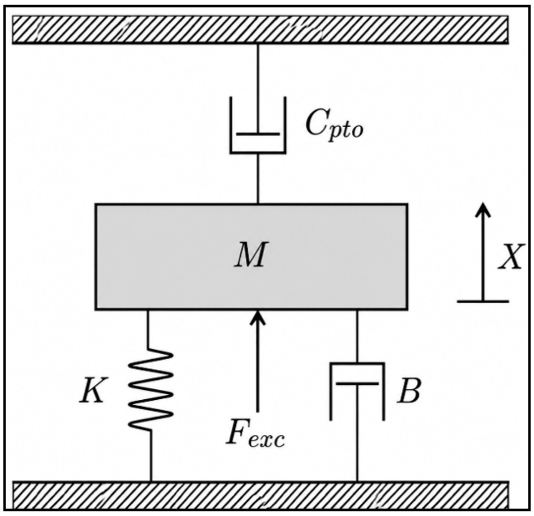


Figure 1. Buoy as a mass-spring-damper system.

cone-cylinder buoy to achieve maximum power with minimum size which will be represented with volume by giving variety of cylinder height (ranging from 0.40 to 1.15 m) and cone concavity diameter (ranging from 3.20 to 8.10 m). By utilizing Ansys AQWA for hydrodynamic simulations and a hybrid Backpropagation Neural Network (BPNN) and Genetic Algorithm (GA) approach, this study seeks the optimal cylinder height and cone concavity diameter of a cone-cylinder shaped buoy and the influence of this type of geometry modification on hydrodynamic performance of a buoy.

2. Experimental/theoretical method

2.1. Wave energy converter

A wave energy converter, or commonly abbreviated as WEC, is a device that captures wave energy in the sea and converts it into electricity. This technology, which is still developing, presents an opportunity to obtain renewable energy with incredibly low emissions. Based on their operating principles, WECs can be divided into three types, namely oscillating water column (OWC), heaving point absorbers, and overtopping systems. This study focuses on the heaving point absorber type of WEC. A heaving point absorber works by capturing movement driven by buoyancy forces with a buoy as the main medium and then converting this movement into energy using a system called a power take off or PTO.

2.2. Device mathematical model

Figure 1 above is a figure showing the WEC buoy represented as a mass-spring-damper system affected by the excitation force of the wave.

Considering the hydrodynamic force which include excitation force, radiation force, and hydrostatic force, the equation of motion become Equation 1 below [3].

$$M\ddot{Z} + (B + C_{PTO})\dot{Z} + (\rho g S)Z = f_{exc} \tag{1}$$

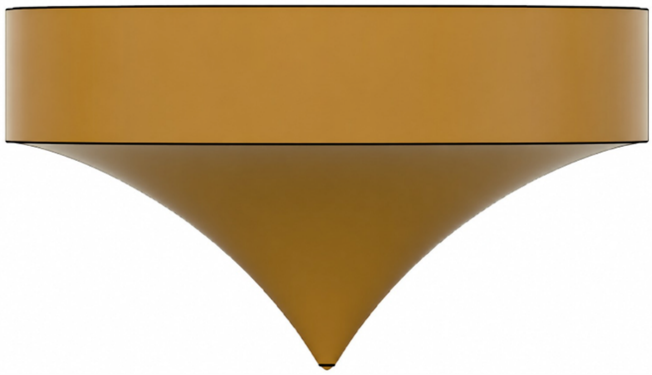


Figure 2. Simulated buoy model side view.

Where B is the radiation damping, C_{PTO} is the PTO damping, ρ is the seawater density, g is the gravitational acceleration, S is the cross-sectional area, f_{exc} is the excitation force, and Z is the heave displacement of the buoy.

2.3. Power absorption calculation

The WEC's power absorption (P_{abs}) can be calculated using the PTO damping, heave displacement, and the system natural frequency (ω_{sys}) through Equation (2) [6].

$$P_{abs} = \frac{1}{2} C_{PTO} {\omega_{sys}}^2 \hat{z}^2 \tag{2}$$

To achieve the highest number of wave energy absorption, the system natural frequency must be the same as the wave frequency (ω_w), and the value of PTO damping value must be the same as radiation damping [3]. Using the hydrostatic force and the buoy's mass, the PTO damping can be obtained.

2.4. Artificial neural network

Artificial Neural Network or commonly abbreviated as ANN is a form of data processing system design that resembles the workings of the biological nervous system in humans [7]. The main purpose of ANN is to find functions from data containing input and target values, which are generally difficult for humans to understand. There are three types of layers contained in ANN, namely the input layer, hidden layer, and output layer. The input layer is the part that contains the initial data or input data. The hidden layer is the part located between the input and output layers that contains the place where processing occurs. The output layer is the part that contains the results of the processed initial data.

2.5. Initial data determination

In this stage, the author will need to collect and determine data on the research object and factors that will be included in this research. For reference buoy shapes, this research will use a cone-cylinder buoy with a diameter of 3.50 m and a total height of 2.00 m; the material will be polyethylene with a density of 960 kg/m^3. The wave condition used in this research is a regular wave with a

Table 1. Mesh settings used in Ansys AQWA/Hydrodynamic Simulation.

Mesh Settings	
Physics Preference	Hydrodynamics
Element Size (m)	0.30 – 0.45
Mesh Type	Triangle
Face Sizing Element Size (m)	0.15 – 0.25
Capture Curvature	Yes
Curvature Normal Angle	10° – 40°

Table 2. Simulation validation condition from reference paper (Olukayode, 2019)

Validation Simulation Condition	
Buoy Model	Cone-Cylinder
Model Dimension (m)	Diameter 3.5 m, Height 2 m
Buoy Material Density	990 kg/m^3
Sea Depth	30 m
	Wave Height 0.4 m, Wave Period 8 s
Wave Condition1	Wave Height 0.8 m, Wave Period 10 s
	Wave Height 1.2 m, Wave Period 12 s

Table 3. Simulation validation result comparison with data from reference paper (Olukayode, 2019)

Validation Simulation Result			
Wave Condition	Reference Data (m)	Simulation Result (m)	Error
1	0.1836	0.1837	5.45 E-4
2	0.3520	0.3690	4.83 E-2
3	0.5577	0.5790	3.82 E-2

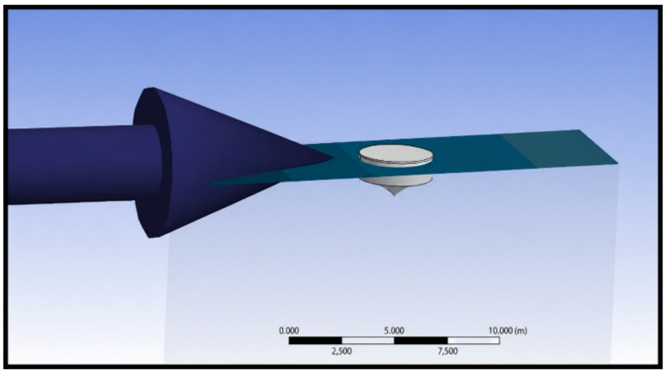


Figure 3. Hydrodynamic simulation of buoy using Ansys AQWA/Hydrodynamic.

1.30 m wave height and a 10-second period, obtained from buoyweather.com at the coordinate -8.7°S / 115.2°E, or specifically the area near Sanur Port, Bali, Indonesia.

The input parameters of this research are the cylinder height ranging from 0.40 m to 1.15 m and the cone concavity diameter ranging from 3.20 m to 8.10 m, while the output parameters are buoy volume in cubic meters and power absorbed in watts. Figure 2 shows an example of the simulated buoy model.

Table 4. Wave settings used in Ansys AQWA/Hydrodynamic Simulation.

Wave Settings	
Water Depth	1000 m (Deep)
Wave Type	Airy Wave Theory
Mesh Type	Triangle
Wave Amplitude	0.65
Wave Period	10

2.6. Hydrodynamic simulation

Buoy motion under the effect of the wave will be simulated using Ansys AQWA / Hydrodynamic on Ansys Workbench under an education license. Several inputs, such as the water surface level, buoy mass, buoy center of gravity, buoy radius of gyration, generator damping, wave type, and wave condition, will be defined. The output of the simulation is the value of buoy displacement in heave motion. Figure 3 shows the simulation process in Ansys AQWA.

Before performing the simulation, some input must be filled. Mesh and wave settings inputs that are used in the simulation are listed in Table 1.

Before performing the simulation for this research, a comparison was done using data from previous research

Table 5. Parameter/settings used in BPNN process for this research.

Parameter	Description
Number of Input and Output	2
Number of Hidden Layer	2 - 5 layers
Number of Neuron in each Hidden Layer	3, 5, 7 nodes
Stopping Criteria	Max epoch, Validation Number, MSE value, Gradient, Momentum term.
Activation Function	Tansig, Logsig, Purelin
Training Function	Levenberg – Marquardt
Data for Training	60 - 90 %
Data for Testing	5 – 20 %
Data for Validating	5 – 20 %

to validate the simulation method. By attempting to replicate the wave conditions from the research of Olukayode et al., the following results were obtained (Table 3).
After validating the simulation method using previous research data, the same method will be used to obtain data in this research using the wave settings (Table 4).

Other inputs such as the water surface level, object mass, center of gravity, radius of gyration, and generator damping are also considered.

2.7. Power absorbed calculation

Using the heave displacement from the simulation, the buoy power absorption can be calculated with Equation 3.

$$P_{abs} = \frac{1}{2} C_{PTO} {\omega_{sys}}^2 \hat{z}^2 \tag{3}$$

Where, C is the power take off / generator damping coefficient value (kg/s), ω is the angular speed of the wave, and is the amplitude of the buoy displacement in the heave movement. In this research, the value of the generator damping coefficient is the same as the buoy radiation damping coefficient [6, 8].

2.8. Backpropagation neural network

Backpropagation Neural Network is a form of supervised learning algorithm that works to change the weight values in hidden layer neurons. BPNN is commonly used in multilayer perceptron, where this method functions to minimize error values and make prediction results more accurate. The way BPNN works is to calculate the error value that occurs against the target value and then iteratively change the weight value at each layer until the error value is acceptable. In its implementation, the BPNN method needs to carry out forward propagation first to obtain the error value; therefore, it can be seen that BPNN has a backward working direction, as its name suggests [9, 10]. Before running the BPNN program, the input data will need to be normalized to have the same minimum and maximum values as shown in Equation 4.

$$\frac{x - 3200}{8100 - 3200} = \frac{x_{norm} - 400}{1150 - 400} \tag{4}$$

Where x is the base input value and x_{norm} is the normalized value that will be used in the BPNN algorithm. The settings used in this research are presented in Table 5.

2.9. Genetic algorithm

After going through the backpropagation neural network (BPNN) process, the rel7ationship between input values and output values, which in this case are cylinder height and cone concavity diameter dimensions as inputs with buoy volume and power absorbed as outputs, is now obtained in the form of a net or objective function. These two objective functions will be combined into a function that will determine the fitness value from input values that will be generated in the genetic algorithm (GA) process. In the GA process, a determined number of chromosomes or input values will be generated and will go through several processes such as elimination, crossover, and mutation to find input values that have the best fitness value [11]. In the elimination stage, all generated chromosomes will first enter the fitness value calculation to obtain their fitness values, which then will be used to sort the chromosomes from the best to the worst and then to determine which input values to eliminate and keep. In the crossover stage, the program will try to breed a pair of input values or trade genes in the hope of obtaining better input values. Lastly, the mutation stage is where parts of the genes in a chromosome will be changed randomly to find a better gene that may not be included in the first generation of chromosomes. The process will be repeated until the determined number of generations or iterations is achieved. The equation used as the fitness function is written in Equation 5.

$$fitnessvalue = w_1(10f_1) - (1 - w_1)(0.1f_2) \tag{5}$$

Where f_1 is the buoy volume, f_2 is the buoy absorbed power, and w_1 is the weight of f_1. The value of f_1 is positive and the value of f_2 is negative, because the genetic algorithm used is programmed to find the lowest fitness function value. Therefore, to search for the lowest value of buoy volume and the highest value of buoy absorbed power, the buoy absorbed power needs to be given a neg-

Table 6. Better Parameter Setting BPNN Model Training.

BPNN Training Model	Hidden Layer	Nodes	Activation Function	MSE
Buoy Volume	2	3	Logsig	4.59 E-09
Buoy Power Absorbed	4	5	Tansig	5.95 E-25

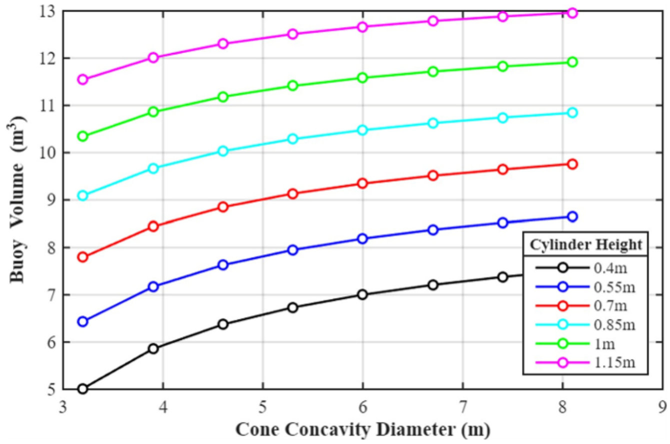


Figure 4. Buoy volume compared with cone concavity diameter chart.

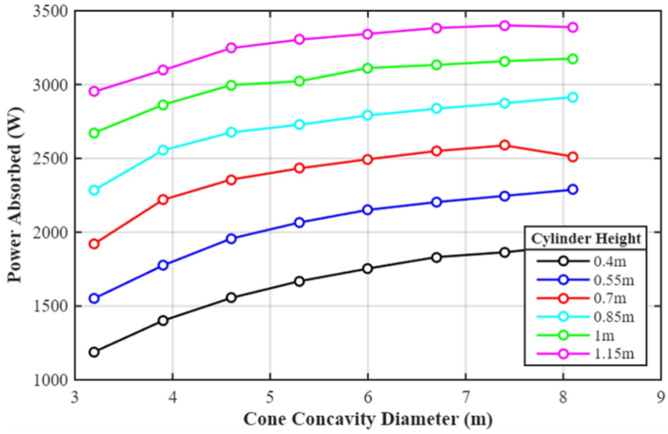


Figure 5. Buoy power absorbed compared with cone concavity diameter chart.

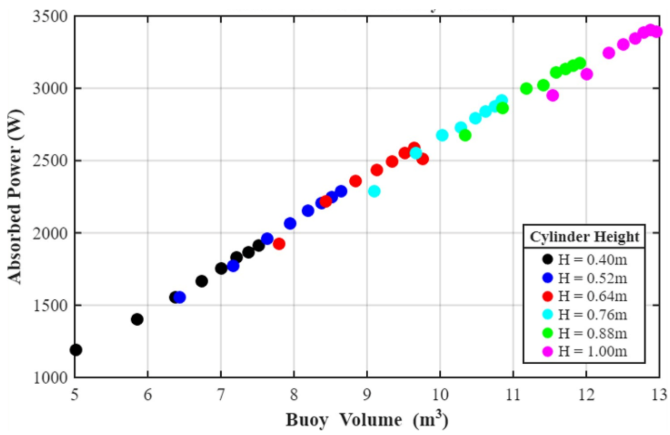


Figure 6. Buoy power absorbed compared with cone concavity diameter chart.

ative value. The multiplication of f_2 with 0.1 and f_1 with 10 is due to the difference in the ranges of values between buoy volume and absorbed power, the buoy volume value is around 5 to 15, while the buoy absorbed value is around 1000 to 3500.

Settings used in the genetic algorithm optimization process are the number of chromosomes generated with the values of 100, 300, and 500, while the weight will use values of 0.1, 0.3, 0.5, 0.7, and 0.9.

3. Results and discussion

3.1. Buoy volume result

After creating the 48-buoy model, the buoy volume data can be obtained. Figure 4 is the graph of the buoy volume data. From Figure 4, the bigger the cone concavity diameter value, the bigger the volume of the buoy. This happens due to the bigger concavity that creates a smaller degree of slope, causing smaller cuts on the buoy cross-sectional area. It can also be seen that the buoy cylinder height value has a direct ratio with the volume. This is due to the fact that the greater the height value, the smaller the bottom cone size and the concavity area.

3.2. Power absorbed result

Based on the power absorbed calculation performed using the simulation result and the predetermined data, a graph can be made as shown above in Figure 5. From the Figure 5, the graph of the power absorbed calculation results shows similarities to the volume graph. This happens because the absorbed power is calculated using the heave motion amplitude and damping coefficients, which are affected by the buoy mass, which is calculated using the buoy volume multiplied by the material density of the buoy. With the buoy volume data and the power absorbed data, a comparison can be made as shown in the following Figure 6.

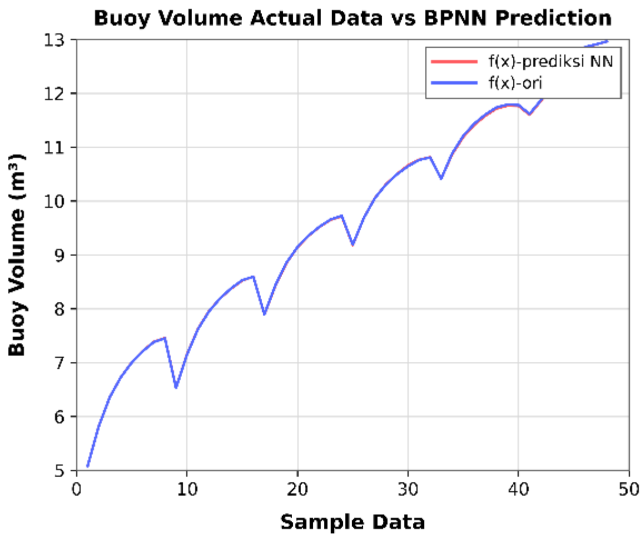
From the Figure 6, it can be seen that along with the increase in volume, the power absorbed also tends to increase. However, several points show that even with a higher volume, power absorbed can still be lower, for example, data number 47, which has the highest power absorbed with a value of 3400.00 Watt and a volume of 12.883 m^3, compared with data number 48, which has the highest volume value. It can also be seen that there are several inconsistencies between volume and power for the same cylinder height value, such as data number 22 with

Table 7. BPNN-GA Buoy Volume Prediction Validation.

Chromosomes	Weight	Optimization Results	Simulation Results	Error
500	0.1	12.8813	12.8812	7.76E-06
300	0.3	12.8847	12.8848	7.76E-06
500	0.5	12.8314	12.8503	1.47E-03
500	0.7	11.4537	11.4442	8.29E-04
300	0.9	5.1066	5.09877	1.53E-03

Table 8. BPNN-GA Buoy Power Absorbed Prediction Validation.

Chromosomes	Weight	Optimization Results	Simulation Results	Error
500	0.1	3393.10	3373.15	5.88E-03
300	0.3	3396.50	3370.61	7.62E-03
500	0.5	3384.50	3379.00	1.62E-03
500	0.7	3081.30	3029.16	1.69E-02
300	0.9	1225.00	1203.46	1.76E-02



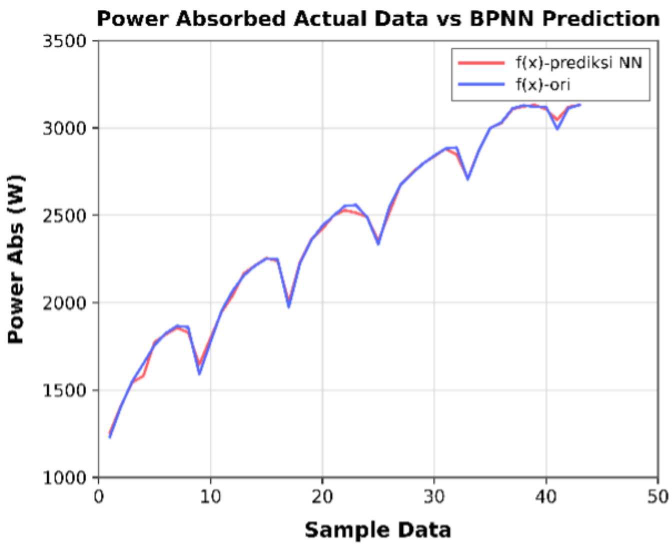


Figure 7. BPNN Prediction compared with actual data.

a power absorbed of 2587.00 Watt showing better performance than data number 23, which has a higher volume value. This shows that the highest power absorbed is generated not by the highest volume, but by the model data below it. This may be caused by an excessively high damping coefficient causing a lack of heaving motion, therefore resulting in lower power absorbed.

3.3. Backpropagation neural network result

Table 6 shows variations in backpropagation neural network parameters such as the number of hiddenlayers, number of nodes, and activation function, which are found to have lower mean square error values for the buoy volume and power absorbed training models. Graphs showing comparison between BPNN prediction with the actual data can be seen in the Figure 7.

3.4. Genetic Algorithm and Optimization Result

From the result of the GA, the effect of weights is shown in the predicted volume and power absorbed values, with the highest weight meaning the algorithm will be more focused on finding the lowest volume and the lowest weight meaning the algorithm will be more focused on finding the best power absorbed. Another thing that can be seen is that the fitness value of the 500 chromosomes tends to be better than that of the 100 and 300 chromosomes, as shown by the fact that 3 out of the 5 best fitness values come from using 500 chromosomes. This is caused by the fact that the more chromosomes generated by the algorithm, the better the chance of finding the best parameter. For weights 0.1, 0.5, and 0.7, the best fitness value can be found using 500 chromosomes, while for weights 0.3 and 0.9, the best fitness value can be found-

Table 9. Performance Comparison between Optimized Buoy and Basic Reference Cone-Cylinder Buoy.

Comparison Factor	Optimized Buoy	Basic Cone-Cylinder	Changes	
Buoy Volume (m^3)	12.8503	12.8282	0.17%	Increased
Buoy Power Absorbed (W)	3379.00	3322.42	1.70%	Increased

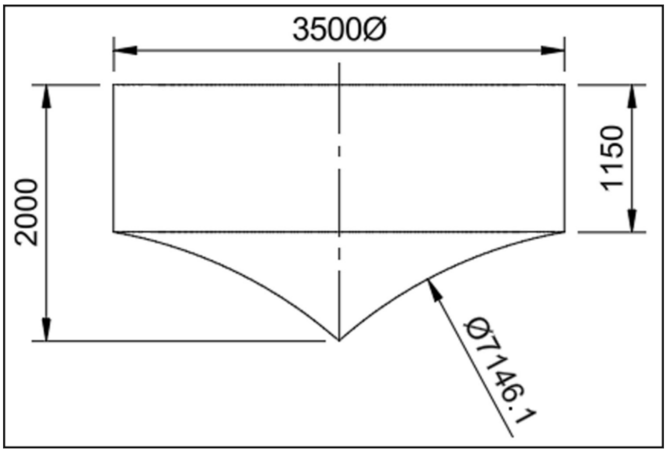


Figure 8. Optimal cylinder height and cone concavity diameter dimension of the cone-cylinder buoy (unit in millimeter).

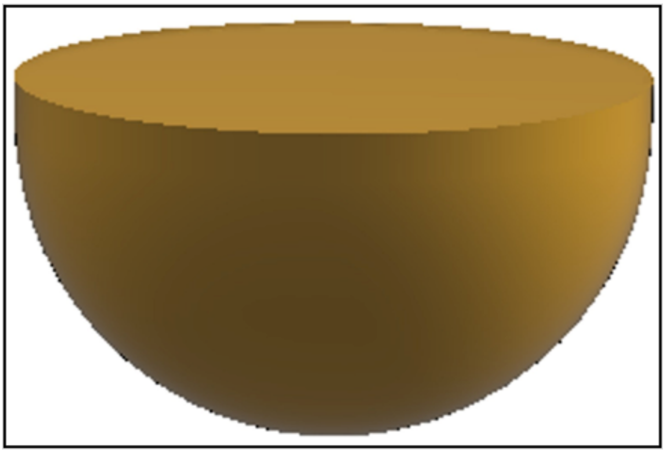


Figure 10. Bullet shaped buoy.

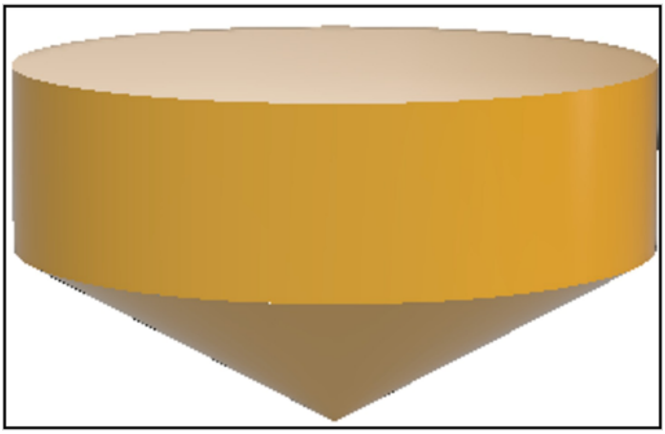


Figure 9. Basic reference cone-cylinder buoy.

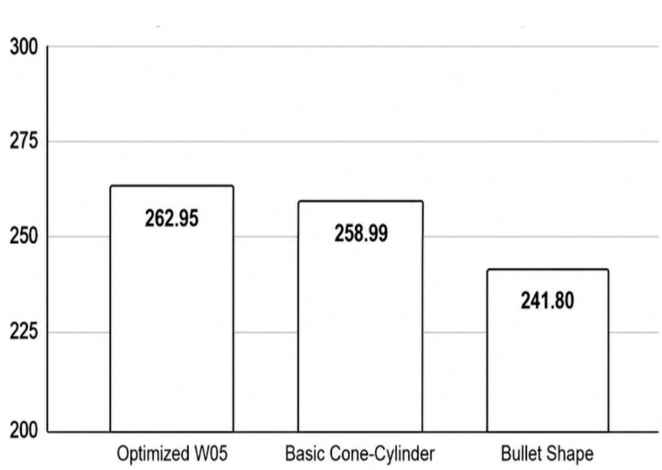


Figure 11. Power to Volume Ratio Comparison Graph.

using 300 chromosomes. From the 15 results, only the best fitness value for each weight will be used for comparison. This means that weight 0.1, 0.5, and 0.7 will use the result from 500 chromosomes, while weights 0.3 and 0.9 will use the result from 300 chromosomes. The five possible optimal dimensions are once again simulated to validate the prediction of the BPNN-GA. Table 7 and 8 show the results of the validation.

From the comparison shown in the Table 6 and 7, the optimization results have small errors due to the imperfectobjective function from the backpropagation neural network process. But overall, the errors are below 5%, which means that the results are acceptable. The optimal dimensions for the cone-cylinder buoy from this optimization are the ones with a weight of 0.5, consisting of 1150 mm of cylinder height and 7146.1 mm of body concavity diameter, resulting in a volume of 12.8503 m3 and a power absorption of 3379 Watt. This is shown in Figure 8 above.

3.5. Comparison with Existing Buoy Shape

To show the improved performance of the optimized buoy, it will be compared with two existing wave energy converter buoy shapes, which are the basic reference cone-cylinder buoy and the bullet-shaped buoy [12]. Figures 9 and 10 above show the two shapes that will be compared with the optimized buoy.

The comparison between the optimized buoy and the basic reference cone-cylinder buoy can be seen in Table 9 above.

As the Table 9 shows the comparison between the optimized buoy and the basic cone-cylinder shape, the optimized buoy manages to increase power absorption by 1.70%, although this was accompanied by a 0.17% increase in buoy volume. The percentage gain in power absorbed is ten times greater than the increase in volume, which could cause the genetic algorithm to identify this specific geometry as the most balanced solution. This result also demonstrates that the geometry modification performed in this research was not fully capable of removing the dependency of WEC power absorption on buoy volume.

Other comparisons have also been made between the optimized buoy and the two existing shapes based on the power-to-volume ratio. Figure 11 above shows a comparison graph of the power-to-volume ratio between the optimized buoy and the two other shapes.

As shown in the Figure 11, the highest value of the power-to-volume ratio belongs to the optimized W05 shape with a value of 262.95 W/m^3. While the lowest value belongs to the bullet shape with a value of 241.80 W/m^3. This shows good results of the optimization, where the optimized cone-cylinder shape has a better power-to-volume ratio compared with the other two common shapes.

4. Conclusions

From this research on the optimization of wave energy converter cone-cylinder buoy dimensions, there are several conclusions that can be obtained. The conclusions are presented below:

1. For the buoy volume BPNN, after testing a total of 36 settings, the better setting was using 2 hidden layers, 5 nodes, a Log-Sigmoid activation function, a 70% training ratio, a 15% validating ratio, and a 15% testing ratio, resulting in an 4.59E-09 MSE, while for the power absorbed BPNN, the better setting was using 4 hidden layers, 5 nodes, a Tan-Sigmoid activation function, a 70% training ratio, a 15% validating ratio, and a 15% testing ratio, resulting in an MSE of 5.95E-25. These results, verified by the 15% validation and testing split, confirm the high precision of the BPNN in mapping the hydrodynamic response. For the genetic algorithm, the better chromosome number was 500 chromosomes when compared to 300 chromosomes and 100 chromosomes; this was shown where 3 out of 5 optimization results showed that using 500 chromosomes have better possibilities of finding better fitness values compared to only using 300 and 100 chromosomes. Other than the chromosome number, it is shown that the weight number 0.5 was the better weight number.
2. The optimization result for the optimal buoy dimension is 1150 mm of head cylinder height and 7146.10 mm of body concavity diameter, showing a 12.8314 m^3 of predicted volume and a 3384.50 Watt of predicted power absorbed, which have errors when compared to the simulation results of 0.15% for the volume, which resulted in 12.8503 m^3, and 0.16% for the power absorbed, which resulted in 3379.00 Watt.
3. On the comparison of the optimized buoy with the basic cone-cylinder shape and the bullet-shaped buoy, the optimized cone-cylinder is able to increase the power absorbed by 1.70% for the basic cone-cylinder shape with only a 0.17% increase in volume. When compared to the bullet-shaped buoy, the optimized cone-cylinder can increase the power absorbed by 2.53% and decrease the buoy volume by 5.72%. While the optimization did not result in a lower absolute volume compared to the basic cone-cylinder, it successfully identified the optimal shape in terms of the power-to-volume ratio. The optimized cone-cylinder shape also shows better results in the power-to-volume ratio with a value of 262.95 W/m^3.

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