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Optimal Energy Extraction of Non-Buoyant Type Wave Energy Converter Using Grey Relation Analysis

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Abstract. The wave energy converters involved in ocean wave energy harvesting are subjected to various natural calamities and thus obtaining the optimal energy extraction is a challenging task. It is normally noted that the energy extraction is maximum when the frequency of the ocean waves matches the natural frequency of the device. The natural frequency of the converter can be modified by tuning its dynamics, but it is intricate to performin the ocean environment, so an alternative method should be adopted. In thiswork, the optimal electrical damping is performed to modify the frequency of the system to match the natural frequency of the incident wave. The grey relation analysis is carried out to find out the optimal damping value. Further,the obtained results are subjected to experimental verification and it is observed that the energy extraction is significantly improved. This approachis less complex and effective when compared with the other methods.

Keywords: *Wave energy, Ocean wave, Natural frequency, Grey Relation Analysis, Electrical damping.*

1 Introduction

Energy demand raises globally due to a sigificant surge in population growth and development in the industrial and transport sector. Currently, energy generated from non-renewable resources such as coal takes the majority of portion in fulfilling theenergy demand. This leads to a carbon footprint and global warming which forces the researchers to divert their attentation to renewable energy. The researchers proposed different wave energy converter (WEC) techniques to extract energy fromthe ocean waves [1-2]. Each and every converter have their own success and failure. The WECs are generally classified as oscillating water columns (OWC), overtopping devices (OTD) and wave-activated bodies (WAB) as shown in Fig. 1.

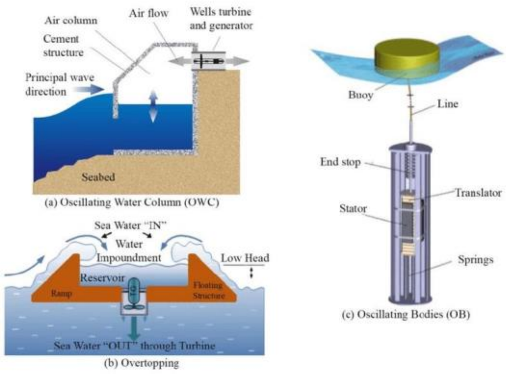


Figure 1 Types of WEC [3]

Among the WEC's the wave-activated type WEC's are the most predominant [4– 7]. Among the various types of wave-activated type WECs, point absorber-type WEC plays a successful and diverse role. In these types of WEC's the dimension is much smaller when compared to the length of the wave and the WEC's are normally implemented in the offshore environment. Normally, the point absorber buoy is constrained to heave motion and the point absorber is the only part in the WEC which is in contact with the ocean waves and other parts are placed in non-contact with the waves, this can avoid maintenance issues due to the salinity and other factors. In this proposed work, a non-buoyant type of WEC which is a point absorber is implemented for the research investigation. The proposed non-buoyanttype energy converter consists of an oscillating arm suspended with a non-buoyant body at one end and a counterweight at the other end. When the incident wave approaches the container the device gets unbalanced due to the variation in the container's effective mass. This leads to the oscillation in the WEC, the produced oscillation is sent to the unidirectional gearbox which is further integrated with thegenerator to produce electrical power. The productivity of the point absorber WEC's is much improved when the approaching wave frequency is in matches thenatural frequency of the WEC. The frequency matching can be achieved by tuning the dynamics of the system but it is intricate in the ocean environment and thus an alternative method is adopted. It is noted that the current produced in the generator indirectly affects the absorber in the opposite direction with the force conflicting with the direction of motion of the generator. Hence a controlling technique is known as reactive control which is an effective method to achieve frequency matching where the natural frequency of the device coincides with the incident wave. In this method, the frequency is fine-tuned by optimal electrical damping. Suitable electrical damping is provided with respect to the incoming wave conditions and thus attaining resonance where the energy extraction is maximum. Obtaining the optimal electrical load for the incoming wave is a crucial task and there are different methodologies are available in machine learning and artificial intelligence such as Artificial Neural Network (ANN), Random Forest (RF) etc., topredict the load condition for the incoming incident wave based on the previous conditions. In a work the ANN is implemented to find out the response of the buoyfor various parameters is predicted and the values are experimentally validated [8]. In another work the power generation analysis of the WEC is performed in the Computational Neural Network (CNN) instead of ANN and the conditioning monitoring is done for fault diagnosis in the system [9]. But, these methodologies required complicated algorithm to complete the task and thus an alternative methodknown as grey relation analysis (GRA) is investigated in this work. In GRA obtaining the optimal parameter is much more simpller when compared to the othermethods and also the computational time is drastically reduced.

2 Grey Relation Analysis

Generally, to solve the complexity of decision problems, traditional methods such as linear programming [10] or regression analysis [11] are normally preferred. Butin the real case scenario decision has to be made from the more complicated situations with partial information, and unstable and irregular data. To makedecisions under this kind of uncertain circumstances a sophisticated technique suchas GRA is essential. GRA was developed in the year 1982 by Deng [12-13] and isimplemented for decesion making from partial information such as partially knownand partially unknown. The well-known information is considered white and the unknown information is considered black thus the partially known information is considered as grey. The grey system analysis evolved from the grey system theory and is implemented to complex problems subjected to complex data. GRA is applied in different sectors such as logistics, economic analysis, medicine, agriculture and optimization processes. Apart from this, the GRA has a wide contribution to renewable energy research. In one of the research works [14] GRA is applied in therenewable energy systems (RESs) to valuate the various parameters. The GRA is also used in the selection of suitable renewable methods for energy production [15]. The technique is used in the optimization of small scaled boilers which are used inthe combustion process of various biomass fuels [16]. The selection of complex power production planning is performed using GRA and the authors argued that theGRA along with the multi-objective grey linear programming is an effective tool for optimizing of complex systems [17]. In another work, the GRA is used to analyse the amount of energy consumption, emission and growth patterns from insufficient data [18].

3 Grey Relatıon Analysıs Modellıng

Normally the GRA analysis involves five major steps [19-22] as shown in fig. 2. The first stage is the data pre-processing where the data is pre-processed to the required measure of quantities. The next is normalizing where the data is normalisedto gray numbers range between 0 and 1, based on the equations which are given below. For performing the normalization two different categories are followed: the higher the better and the smaller the better. Then the stages such as deviation sequence and grey relation coefficient are implemented and finally, the grey relationgrade is awarded to the parameters as per the priority.

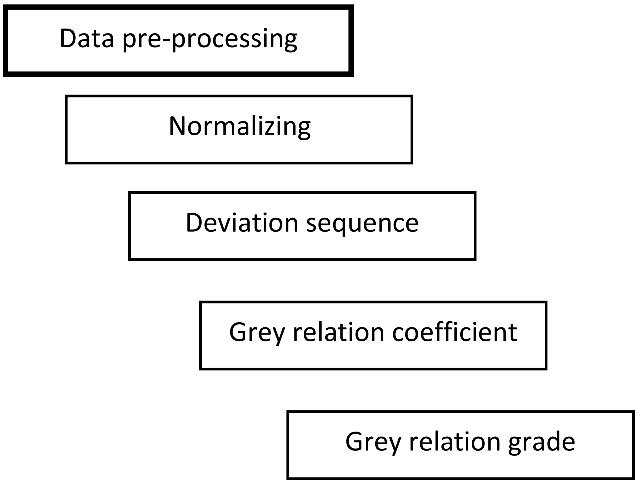


Figure 2 Steps in GRA

If the normalization equation for the projected data is of the form “Higher-the- better”, then the actual data can be normalized as

$$x_i^*(k) = \frac{x_i^0(k) - min x_i^0(k)}{\max x_i^0 - min x_i^0(k)} \qquad (1)$$

If the normalization equation for the projected data is of the form “Smaller-the-better”, then the actual data can be normalized as

$$x_i^*(k) = \frac{max x_i^0(k) - x_i^0(k)}{\max x_i^0(k) - min x_i^0(k)} \qquad (2)$$

where $x_i^0(k)$ is the actual data order, $x_i^*(k)$ the order of sequence after the data processing, max $x_i^0(k)$ the largest value of $x_i^0(k)$, and min $x_i^0(k)$ imply the smallest value of $x_i^0(k)$

The deviation sequence of the reference sequence is given by

$$\Delta_{0i}(k) = \left\| x_i^0(k) - x_i^*(k) \right\| \qquad (3)$$

$$(x+a)^n = \sum_{k=0}^{n} \binom{n}{k} x^k a^{n-k} \qquad (4)$$

is distinguishir ζ or identification coefficient

$\zeta \in [0, 1]. \ \zeta = 0.5$ (5)

Grey relation coefficient is calculated to give an association between the model and actual normalized experimental results. Thus, the grey relation coefficient can be derived as,

$$\zeta_i(k) = \frac{\Delta min + \zeta \Delta max}{\Delta 0i(k) + \zeta \Delta max} \qquad (6)$$

where Δ_{oi}(k) is the deviation sequence of the reference data

After finding the grey relational coefficient, generally the average value of the greyrelational coefficient is considered as the grey relational grade. It is defined as

$$\gamma = \frac{1}{n}\sum_{k=1}^{n} \omega_k(k)\, \xi_i(k) \qquad (7)$$

Where γ_i is the grey relation grade, $\omega_k(k)$ is the weight coefficient which can bean equal value to all the parameters or can be obtained from the grey relation coefficient.

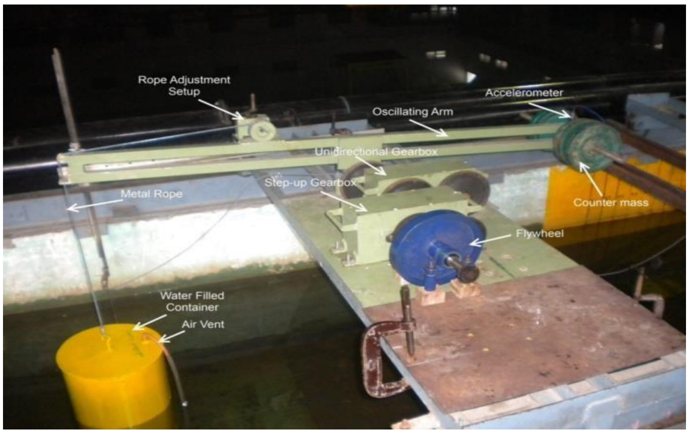
4 Experımental Investıgatıon

The experimental investigation is performed in the lab-scaled experimental setup. The wave parameters such as the wave height, the time period and the WEC parameters such as speed, torque and electrical loading are considered. The experimentation is performed by varying the wave height and the time period. Further, the obtained data are recorded and subjected to GRA and the optimal combination is identified. Table 1 shows the incident wave values such as H(cm), T(s) and corresponding WEC parameters such as speed (rpm) and torque (Nm) which are subjected to GRA analysis.

Table 1 Different wave and WEC parameters

H (cm)	T (S)	Speed (rpm)	Torque (Nm)
10	2	97	0.358
20	2.2	280	1.032
25	2.4	369	1.36
30	2.6	303	1.117

Figure 1 Experimental setup



The ranking is given to the different incident wave conditions and the corresponding WEC's response from the GRA technique. It is obtained that the wave condition with 25cm, 2.4s, 369rpm and 1.36 Nm awarded rank 1 followed by 30cm-2.6s-303 rpm-1.117 Nm, 20cm-2.2s-280 rpm-1.032 Nm, 10cm-2s-97 rpm-0.358 Nm. The GRA result is experimentally validated by bringing the wave in the wave flume to a value of wave height 25cm and time period 2.4s and it is noted that the ranked 1 combination gives the output power of 52.21 W. The experimentally validated results are given in table 2.

Table 2 Experimental Validation

H (cm)	T (S)	Speed (rpm)	Torque(Nm)	Power(W)
10	2	97	0.358	3.61
20	2.2	280	1.032	30.06
25	2.4	369	1.360	52.21
30	2.6	303	1.117	35.20

Conclusion

The non-buoyant WEC is among the most efficient WECs to harvest wave energy efficiently. To further enhance the energy extraction, from the incident waves, a control technique known as reactive control is implemented where the frequency of the WEC is in phase with the frequency of the incident wave by tuning the electrical load. To obtain the optimal load conditions GRA method is implemented and the best combinational parameters are obtained from the investigation and the obtainedresults are experimentally validated.

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