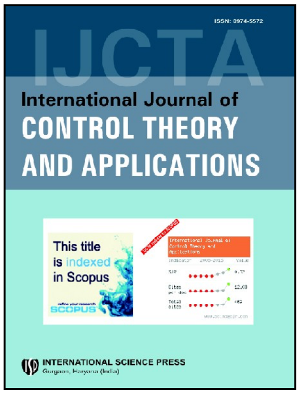

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Application of Non-Parametric and Cognitive Modelling for Development of Location Selection Indicator for Wave Energy Converters

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Abstract: With the rising population level, there is an increase in demand for energy all over the world. In order to overcome demand deficits, the use of energy from the renewable resource, particularly in the form of wave power has become more prevalent in recent years. Ocean wave power, therefore, provides an important solution to the problem of potential energy deficit. This study aims to provide some insight into the manner in which parameters can be deployed in order to maximize gains both in terms of economic cost as well as the minimization of environmental damage. Specifically, it utilizes the Analytical Hierarchy process along with its more generalized form the Analytical Network Process to identify optimal locations for power units using data from case studies of European and Australian coastlines. The MCDM methods combined with optimization techniques are used to determine the domain for searching for the ideal priority value of the parameters implicit when considering where to establish a hydroelectric power generator. This approach has a distinctive advantage as it allows for the consideration of both technical as well as the financial implication of the parameters in the selection of a location for wave power generation.

Keywords: Wave energy, site selection, Analytical Network Process (ANP), Analytical Hierarchy process (AHP), optimization techniques (OT).

I. INTRODUCTION

The demand for energy supply has increased compared to the previous decade due to the economic development and growing population that has been observed in the recent years. As a result, scarcity of energy is observed in many parts of the world. This present situation has enforced the search for an alternative which can substitute the conventional fuel resources [1]. As a response wave energy has shown significant potential to meet supply deficits with relatively fewer environmental costs compared to other non-conventional energy sources [2]. Indeed, the scope of this energy source has been exemplified by the total global theoretical wave energy potential that is estimated to be 32,000TWh/yr (115 EJ/yr) [3], approximately twice the global electricity supply in 2008 (16,800 TWh/yr or 54 EJ/yr). The assessments of the ocean wave energy resource has been done at global [3–5], as well as regional local scales [6-8] for selected sites more recently.

Although there is a large potential to supply demand with wave energy, due to the irregularity in wave patterns, survivability, complexity in energy conversion as well as due to diffraction and reflection, the cost of electricity generation via wave energy generation is still relatively expensive [9] and has at maximum achieved an efficiency rate of 90% [10]. In addition disturbances to wildlife in the form of floral and faunal as well as the navigability of oceans, and visual and noise pollution caused by the floating converters are some further costs to be considered [11, 12].

Most of the obstacles for which the conversion of wave energy becomes non-optimal depend on location; however data supporting this hypothesis is sparse owing to the unreliability and expensive nature of data collection systems in the field. Owing to this uncertainty with respect to optimal practices in wave power generation, this present investigation proposes a new method to determine the ideal location at which the conversion efficiency of a wave energy converter (WEC) will be maximized. In this aspects, Analytical Hierarchy Process (AHP) and Analytic network process (ANP) Multi-criteria decision-making methods (MCDM) along with Genetic Algorithm (GA) technique were utilized.

II. METHODS ADOPTED

The present study involves the application of ranking methods in the form of Maximin, Minimax and Average Ranking methods to rank parameters selected from the literature survey. MCDM methods, such as Analytical Hierarchy Process (AHP) and Analytical Network Process (ANP) were used to find the priority value of each of the parameters. The maximum and minimum magnitude of weights from the different weights proposed by the MCDM methods were used as the upper and lower limit of the search space for the priority value at which the utilization potential will be maximum.

Optimization methods such as Genetic Algorithms (GA) was used to maximize the objective yielding the ideal priority values for which the conversion potential will be maximum and for which the parameter that is most influential in maximizing the potential can be also identified.

2.1. Ranking Method

2.1.1. Maximin

The Maximin method ranks the input variable based on the higher limit of their influence on the output. The maximin method looks for the maximum of the minimum value [13]. The minimum of the maximum value obtains the highest rank, whereas the minimum of the minimum value is taken as the lowest rank of all of the data available. The maximum approach is used to evaluate the relative efficiency of decision-making units (DMUs) with respect to multiple outputs and a single exact input with common weights [14].

2.1.2. Minimax

The Minimax method ranks the input variables based on lower limit of their influence on the output. Minimax is a decision rule used in decision theory for minimizing the possible loss for maximum loss scenarios. This method looks for the minimum of the maximum and ranks it the [13]. Many manufacturing sectors use this method for decision making [15], while Minimax is also used in optimal Inference from Partial Rankings [16].

2.1.3. Average Ranking Method

This is a simple ranking method applying by Friedman's M statistics. It has been used to develop the Fuzzy Weighted Average for Ranking Alternatives [17] and in attempts to optimize energy consumption in Iran by ranking priorities [18]. In the present investigation, this method was used to rank the variables based on the average influence of each parameter on the output.

2.2. Multi-Criteria Decision Making Method

2.2.1. Analytical Hierarchy Process (AHP)

The Analytical Hierarchy Process (AHP) is a multicriteria decision-making method (MCDM) introduced by Thomas L. Saaty in1980, it is based on the relative priorities assigned to each criterion's role in achieving the objective.

Whenever a goal for a decision can be clearly stated, a set of relevant criteria can be determined and a set of alternatives can be described using these criteria; AHP is an appropriate tool for these problems. In this method, the problem is broken down into its consistent elements with the best alternative usually being selected by making comparisons between alternatives with respect to each attribute.

2.2.2. Analytical Network Process (ANP)

The ANP is a more generalized form of the analytic hierarchy process (AHP) also developed by Thomas L. Saaty (1980) and has been used in multi-criteria decision making (MCDM) to calculate priorities. This method consists of two parts. Firstly, is generates a control hierarchy of criteria and sub-criteria that control the feedback network. The second part consists of the networks of influence that contain the factors of the problem and the logical groupings of these factors into clusters. The ANP, unlike the AHP, allows for the interactions and influences among the various components of the decision problem to be considered, which makes it a better choice [19].

2.3. Optimization Technique (OT)

2.3.1. Genetic Algorithms (GA)

GA is an example of a nature-based OT first proposed by Holland [20] and further developed by Goldberg [20]. In effect, GA systems simulate the survival of the fittest among individuals over consecutive generations to solve a problem. Each generation consists of a population of character strings that are analogous to the chromosomes that we see in our DNA. Each individual represents a point in a search space and a possible solution. The individuals in the population are then made to go through a process of evolution.

A genetic algorithm gives multiple solutions of a given problem. As the execution of this method is not dependent on the error surface, it can solve multi-dimensional, non-differential, non-continuous, and even non-parametrical problems. In the past, genetic algorithms have been used to develop a robust, systematic method of optimizing the collector shape to improve energy extraction [21]. GA is applied in the allocation of energy conservation and renewable energy facilities in a campus [22] and in the design of a shunt active filter with a multilevel inverter [23].

III. DETAILED METHODOLOGY

In the present study, the most important parameter for the identification of the optimal location for wave energy production was identified by the application of two MCDM and GA optimization techniques. The objective function was proposed in such a manner that, at a certain priority value and magnitude of the parameters, the utilization potential will be maximized. The MCDM methods comprises the following three steps:

But before the MCDM method can be initialized the parameters which responsible for the selection of optimal location was to be selected and ranked as per their absolute importance of the study objective.

3.1. Selection of Criteria

Name of the Criteria	*Description*	*Example*
1. Citation Frequency in the Related Literature (CF) (To consider the views of other researchers)	Various studies were surveyed to seek out citations of all of the parameters in connected studies. If the range of studies that mentioned the parameter is c and the total number of literature surveyed is C, then the score, the Survey of the literature (SL), is calculated by Eqn.1 SL= (c/C)……………….. (1) The commonly used equation for calculating the power potential, as proposed by Pontes *et al.* (1995) and Tucker and Pitt (2001), is given in Eqn. 2 $P_w = \frac{\rho g^2}{64\pi} T_e H_s^2$ (2)	In total 30 studies on wave energy, including wave energy potential, converter selection, and converter design, were reviewed. Within the 30 works, each considered significant wave height as the most important parameter. Therefore, the SL for significant wave height is (30/30) = 1 (100%) according to equation 1.The SL of the other six parameters was also calculated in a similar manner.
2. Efficiency Potential (EP) (To include the technical influence)	Where P_w = average wave power : H_s^2 = significant wave height; T_e = peak period; ρ = density of water; and g = accelarationdue to gravity As H_s squared is directly proportional to Pw, the efficiency potential or location with a high magnitude wave height will have a higher level of conversion efficiency. The relative score was calculated by Eqn.3 $RS = \left(\frac{R}{Max\,R}\right) - 1$............(3) where R = 1, 2, ..., 7; Max (R) = 7.	The parameters that are directly proportional to the Wave Power Potential were considered to be conducive, and the factors that are decreasingly proportional to the power potential were taken as deductive for the conversion efficiency of wave power plants. The equation of the power potential (Eqn.2) was used in this regard to estimating the score of the alternatives with respect to the efficiency potential. The equation of power potential states that PW (power production) is directly proportional with T_e (time to peak) and H_s^2 (significant wave height). Again, H_s is also dependent on wave amplitude, wind speed, duration, and fetch. Te is again a function of ocean depth
3. Cost Potential (CP) (To include the economic influence)	The cost potential of parameters depends on the proportionality of the parameter to the mooring cost.The score of the parameters for the cost potential was calculated by Eqn. 4, here if ΔC is the difference in cost for two different locations and ΔHs is the change in the wave height, then the cost potential of wave height can be represented by equation no.4 $C = \frac{\Delta C}{\Delta H} - - - - - (4)$ The general equation for the estimation of the cost potential for the parameter is depicted in Eqn. 5 $\frac{\Delta C}{\Delta P} - - - - - (4)$ Where ΔP is the change in the magnitude of the parameter with respect to locations.	Now, the higher the value of C, the lower the rank of the alternatives. That is why if the C of the Significant wave height is more than the C of the wind speed, then the significant wave height will have a lower rank than wind speed.

3.2. Ranking Methods

Table 2
The selected sub-criteria for the present study

Name of the Sub- Criteria	*Description*	*Example*
Average Ranking Method	In this method, the data set is ordered the algorithms according to the measured error rates and assign rank accordingly. Let r_j^i be the rank of algorithm j on dataset i, then the average rank for each algorithm, $\bar{r}_j = {(\Sigma_i r_j^i)}/{n}$, where, n is the number of data set. The final ranking is obtained by ordering the average ranks and assigning the ranks to the algorithms accordingly.	Rank of the each parameter for the three different criteria as citation frequency, efficiency potential and cost potential, were used as r_j^i in this study. 1, 2, and 5 are the rank of the significant wave height according to the Citation frequency, Efficiency potential and cost potential. Therefore, $\bar{r}_j$ = (1+2+5)/3= 2.7 for significant wave height. In this manner, for all the parameters were calculated and the final ranking was obtained by ordering the ranks to the parameters accordingly.
Minimax	This method looks for the minimum of the maximum and ranks it the highest. Here, a1, a2, a3….an are the maximum values of any parameter. Therefore, the Min (Max) for that parameter(P), PMin(max) = min $(a_1, a_2, \ldots \ldots \ldots \ldots \ldots a_n)$ The final ranking is obtained by ordering the $P_{Min(max)}$ value for all the parameters.	In this study 1, 0.8 and 0.63 are the normalized maximum values of significant wave height according to the Citation frequency, Efficiency potential and cost potential. Therefore, $P_{Min(max)}$ = 0.63 for significant wave height. Likewise, all for all the parameters were calculated and rank accordingly.
Maximin	The maximin method looks for the maximum of the minimum value. The minimum of the maximum value obtains the highest rank, whereas the minimum of the minimum value is taken as the lowest rank of all of the data available. Let, A1, A2, A3….An are the minimum values of any parameter. $P_{Max(min)} = \max (A_1, A_2, \ldots \ldots \ldots \ldots A_n)$ The final ranking is obtained by ordering the $P_{Max(min)}$ value for all the parameters.	0.0, 0.2, 0.37 are the normalized minimum values of significant wave height according to the Citation frequency, Efficiency potential and cost potential.Therefore, 0.37 for significant wave height. Likewise, all for all the parameters were calculated and rank accordingly.

3.3. Selection of Alternatives

Table 3 shows the alternatives selected for the present investigation. Their relationship with the objective function was also depicted in the same manner.

4.3. Aggregation Method

The first step of the aggregation method was to rank the parameter with respect to the Maximin, Minimax, and Average ranking methods. In the second step, the weights of importance or ranges of weights of the parameters were estimated with the AHP and ANP MCDM methods. In the last step, with the determined priority values of all the parameters , Optimization methods such as Genetic Algorithms (GA) was used to maximize the objective yielding the ideal priority values for which the conversion potential will be maximum and for which the parameter that is most influential in maximizing the potential can be also identified.

Table 3
The alternatives selected for the present study

Alternative	*Description*	*Proportionality with power potential*	*Citation Rank*
Significant Wave height(Hs)	Power production is directly proportional to the square of the significant wave height.	$P \propto H_s^2$	1
Wave amplitude (a)	Power is directly proportional to the amplitude. The greater the amplitude of a wave then the more energy it is carrying.	$P \propto 4\,H_s^2$	1
Peak Period (Te)	Power is directly proportional to the Peak Period.	$P \propto T_e$	1
Wind Duration(WD)	Power is directly proportional to the Peak Period. The greater the wind blow there is a more chance to the generation of the wave.	$H_s \propto WD$	4
Depth of the Ocean(OD)	Wave period is directly proportional to the ocean depth. This means that the depth of the ocean influences the power potential.	$T_e \propto OD$	5
Fetch(F)	With the highest fetch, there is an increase in wave energy power.	$H_s \propto F$	5

IV. STUDY AREA

Three locations in the European and Australian coastal region were utilized for this study namely the Biscay Marine Energy Platform (bimep) in Spain, Port Kembla in Australia, and Cornwall's St. Ives Bay in the United Kingdom. The averages of their key parameters are depicted in Table 4.

Table 4
Magnitudes of the top five important parameters at the selected location

Parameters	*Bimep, Spain (43.28º N, 2.51ºW)*	*Port Kembla (34.27ºE 15.54ºS)*	*Wave Hub (50.36° N 5.67° W)*
Significant Wave height (m)	11.45	6.6	14.4
Wave amplitude (m)	5.725	3.3	7.2
Peak Period (sec)	15.4	10	14.1
Wind Duration (hour)	5	2	5
Wind Velocity (m/sec)	47	50	33.2
Power Potential (KW) per meter of wave crest (Calculated using wave power potential equation) [24]	88.12	33.00	101.52

V. RESULTS AND DISCUSSION

The result from the ranking methods is depicted in Fig. 1 and the priority value of the parameters based on the results from the MCDM methods are shown in Fig. 2. According to the ranking method fetch, wind speed and depth was found to be highest compared to other parameters. But according to the MCDM method the significant wave height was found to be the highest compared to other parameters. The maximum and minimum priority value were selected from the results of MCDM.

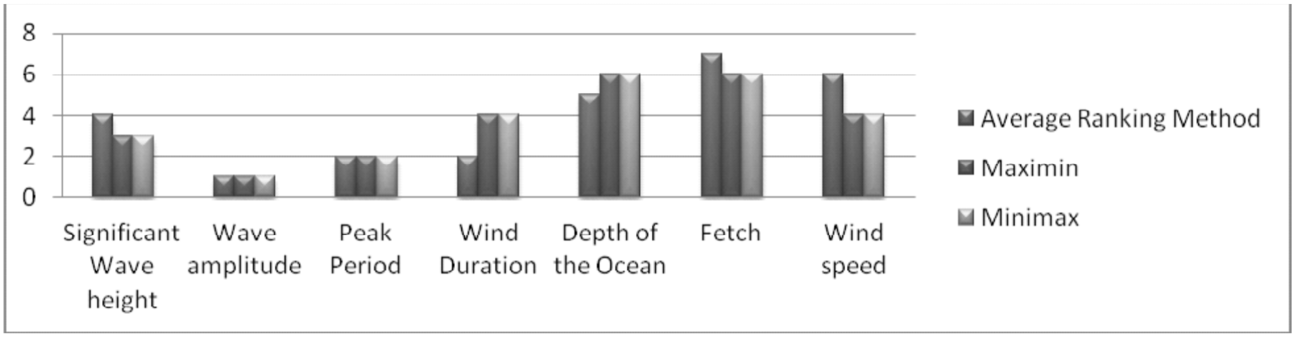

Figure 1: Parameters ranking with respect to the ranking method

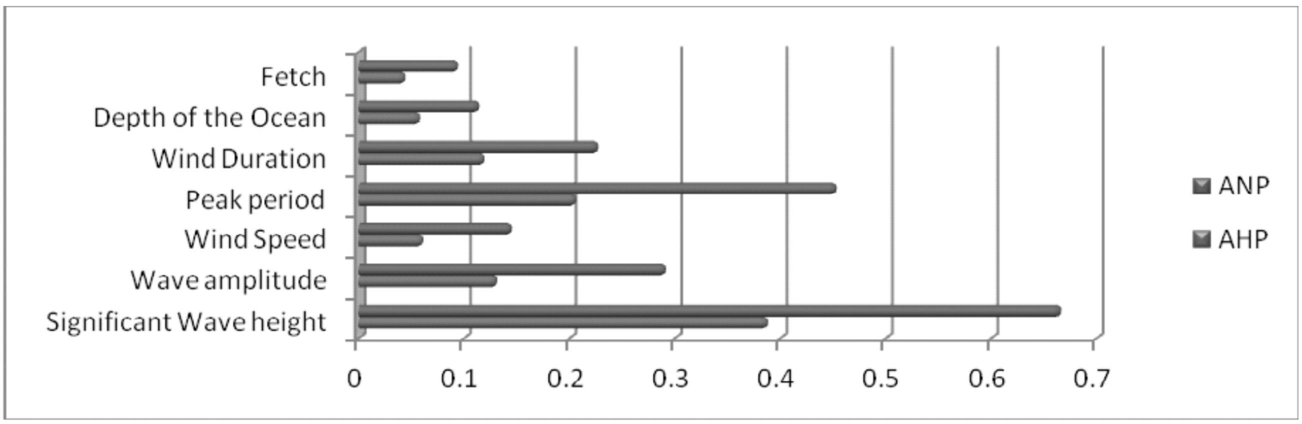

Figure 2: The relative Weights or priority values of each parameter according to the AHP and ANP MCDM methods

The maximum and minimum priority values of each of the parameters are depicted in Fig. 4. According to the results (Fig. 4), the significant wave height and fetch are the most important and least important parameters, respectively.

5.1. Determination of the objective function for optimization

Eqn. 6 depicts the objective functions developed to represent the utilization potential of wave energy, once the domain of the priority values and the range of the selected locations and their magnitudes were identified. The GA technique was applied to maximize the objective equation (Eqn 6).

$$\begin{aligned} F(x) = ((W_{1max} - W_{1min}) \times \text{Rand}(0, 1)) \times (V_{1min} + (V_{1max} - V_{1min}) \times \text{Rand}(0, 1)) \\ + (W_{2max} - W_{2min}) \times \text{Rand}(0, 1)) \times (V_{2min} + (V_{2max} - V_{2min}) \times \text{Rand}(0, 1)) \\ + (W_{3max} - W_{3min}) \times \text{Rand}(0, 1)) \times (V_{3min} + (V_{3max} - V_{3min}) \times \text{Rand}(0, 1)) \\ + (W_{4max} - W_{4min}) \times \text{Rand}(0, 1)) \times (V_{4min} + (V_{4max} - V_{4min}) \times \text{Rand}(0, 1)) \\ + (W_{5max} - W_{5min}) \times \text{Rand}(0, 1)) \times ((V_{5min} \times (V_{5max} - V_{5min}) \times \text{Rand}(0, 1)) \\ + \end{aligned}$$

Where, V_1 = wave amplitude, V_2=Significant Wave height, V_4=Wind Speed, and V_5=wind duration, and W_1 = weight values of the wave amplitude, W_2=weight values of the Significant Wave height, W_3= weight values of the Wind Speed, W_4=weight values of the peak period, and W_5=weight values of the wind duration.

Table 5 shows the maximum and minimum value of each of the parameters estimated by the AHP and ANP MCDM for the locations considered, and Table 6 shows the variables, constraints, population size as well as function evaluations and values of the maximum objective function according to the population size of the three different algorithms.

Table 5
Minimum and Maximum values of the parameters of the locations considered

Parameters	*Maximum Value*	*Minimum value*
Significant Wave height (m)	14.4	6.60
Wave amplitude (m)	7.20	3.30
Peak Period (sec)	15.4	10.0
Wind Duration (hour)	5.00	2.00
Wind Velocity (m/sec)	50.0	6.00

Table 6
Programming Techniques used

Variables	*Weights (Wn)*	*Parameter (Vn)*
Constraints	Minimum and maximum values of weights predicted by two MCDM	Maximum and minimum magnitude of each of the parameter from the three locations
Programming Techniques		GA
Population size		25-200
No. of the function evaluation		200000
Value of Objective Function (Maximum)	0.767 (where maximum value is 1 and minimum value is 0), for population size 100	
Convergent point		12

Table 7
The magnitude and priority value of the parameters for which Eqn. 6 becomes the maximum

Parameters	*Priority value*
Significant Wave height	0.481
Wave amplitude	0.249
Wind Speed	0.072
Peak period	0.056
Wind Duration	0.032

Table 6 shows that the maximum objective function value that was found by the GA technique at a population size of 100, and Table 7 shows the corresponding optimal values of each of the parameters and the weights. The maximum weight value was found to be 0.481, which depicts Significant Wave height is the most important parameter for the wave energy production potential. It implies that if the values of the parameters are as per their importance then an optimal output can be found from the location.

It can be depicted from the table 4 that, the power potential is more where the value of Significant Wave height is maximum among the other's location. Among the three locations Bimep, Spain, Port Kembla, and Wave Hub, Wave Hub was found to be the most suitable location for wave energy potential.

VI. CONCLUSION

The present investigation has tried to identify the optimal location with respect to wave energy. The said investigation has been made by the application of AHP and ANP MCDM with the help of GA Optimization Technique. The study shows that Significant Wave height to be the most significant factor in identifying optimal locations for wave power generation plants. A case study was also performed using this developed method to identify the most suitable location for wave power generation in the European and Australian coasts.

Although the model can be an important tool with which engineers can easily identify the suitable locations for wave energy, this method has some limitations. Only the Locational parameters were selected in the present study. The importance of the variables was estimated by the two MCDM methods and one optimization technique but may change if other MCDM methods are used. This shows that the model is dependent on the type of methods utilized to find the priority value of the parameters. These drawbacks can be mitigated if some uniform policies are adopted regarding the selection of parameters, method, criteria and alternative while the indicator is implemented in a decision support stem.

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