Chapter

Prediction of Wave Energy Potential in India: A Fuzzy-ANN Approach

Soumya Ghosh and Mrinmoy Majumder

Abstract

The conversion efficiency of wave energy converters is not only unsatisfactory but also expensive, which is why the popularity of wave energy as an alternative to conventional energy sources is subjacent. This means that besides wave height and period, there are many other factors which influence the amount of "utilizable" wave energy potential. The present study attempts to identify these important factors and predict power potential as a function of these factors. Accordingly, a polynomial neural network was utilized, and fuzzy logic was applied to identify the most important factors. According to the results, wave height was found to have the maximum importance followed by wave period, water depth, and salinity. In total, 12 different neural network models were developed to predict the same output, among which the model with all of the 4 inputs was found to have optimal performance.

Keywords: wave energy, power potential, fuzzy logic, artificial neural network

1. Introduction

Wave energy is considered as one of the most promising marine renewable resources, with global worldwide wave power estimated at around 2 TW [1]. Several renewable energy-generating sources such as wave power, tides, and current which are associated with marine have always been misunderstood though it has strong predictability and other physical properties [2]. Wave energy presents a number of advantages with respect to other CO_2-free energy sources—high-power density, a relatively high utilization factor, and last, but not the least, low environmental and visual impact [3]. Wave energy resource assessments fall into two categories. Renewable energy is continually available, but due to the complexity of conversion and storage procedures and uncertainty in their availability, such sources of energy have till now been used with caution [4]. Most of the drawbacks were found to vary with location. Some of the advantages are high-energy density [5] and good predictability as well as reduced negative environmental impacts on beaches [6], the marine ecosystems [7], and the wave climate [8]. If we consider the energy consumption, then India ranks four just after the United States, China, and Russia. Electricity consumption in India is expected to rise to around 2280 BkWh by 2021–2022 and to around 4500 BkWh by 2031–2032 [9]. Various methods have been used to estimate wave power potential, but most of them are subjective and linear and cannot be adapted to various situations. In the present study, a new method for estimating wave power potential is proposed; it is an objective, cognitive, and unbiased method which estimates the wave energy potential of a location considering the most important nonlinearity.

1.1 Objective

The objective of my study was multi-criteria decision-making (MCDM) methods like fuzzy logic decision-making (FLDM), and cognitive methods like group method of data handling (GMDH) were utilized which incorporate both objectivity and adaptability in the predictive method. As far as the authors know, fuzzy-based MCDM cascaded with GMDH has not previously been used to estimate wave power potential.

1.2 Future aspect

Cognitive study of site variety for wave energy power plant was infrequently attempted, and that is why the authors of the present study tried to propose a novel methodology in selection of most favorable sites for wave energy generation by MCDM and ANN technologies. Finally, the consideration of another multi-criteria decision-making method instead of fuzzy for evaluating the decision alternatives and the comparison of the results with the ones of the present study could represent a subject for future research.

2. Methodology

The new method comprises two steps:

I. Application of MCDM, i.e., FLDM, to find the weight of importance

II. Application of GMDH to provide a predictive infrastructure for making the method resource independent

Sections 2.1 and 2.2 discuss the strengths, weaknesses, and applicability of the method in this study.

2.1 Fuzzy logic

Fuzzy set theory was first introduced as the mathematical programming of the primary works [10]. Fuzzy logic resembles human analysis in its use of inaccurate information to create decisions. Many such problems can be formulated as the minimization of functionals defined over a class of admissible domains. Nondeterministic condition deceits both design variables and allowable limits. A stochastic problem can be transformed into its deterministic form by using expected value and the chance-constrained programming technique. Thus, fuzzy mathematical formulation could be a substitution of this [11]. The advantage of fuzzy logic lies in the depiction of importance for similarly important factors by fuzzy scale, and disadvantages are only found in the qualitative variables which can be used. Fuzzy logic could be applied to such problems as determining a suitable location for a biogas plant, geothermal potential, and the control design of power management [12].

2.2 Group method of data handling (GMDH)

The self-adaptive heuristic ANN based method is one of the learning machine approaches based on the polynomial theory of complex systems, designed by Ivakhnenko (1971). Generally, the first-order (linear) Kolmogorov-Gabor polynomial including n nodes can be used as transfer function [13]:

$$Y = f(x_1, x_2, \ldots, x_n) = a_0 + a_1 x_1 + a_2 x_2 + \ldots + a_n x_n \tag{1}$$

where Y is the middle candidate solution, x is a given initial solutions, and a is the vector of coefficients or weights. New middle candidate solutions can be obtained according to the inputs of the current layer and the transfer function.

Self-organizing models of optimal convolution is constructed by inductive algorithm which was supervised by original GMDH. It is totally based on the input-output relationships of a given dataset, without the need for user interference. The GMDH network is known as a self-organized approach that solves various complex problems in nonlinear systems [14].

The main advantage of the GMDH model is in building analytical functions within feed-forward networks based on quadratic polynomials whose weighting coefficients are obtained using the regression method [15].

3. Methodology

The methods were used to estimate the rank of importance of the parameters based on the study objective shown in **Figure 1**. The procedures to estimate the wave power potential involve the application of the MCDM method to estimate the priority value of the parameters and GMDH to reveal the relationship between the input and output parameters.

The MCDM methodology deduces the importance of the parameters based on their citation frequency, expert inputs, and availability of data. All three methods were used to estimate the rank of importance of the parameters based on the study objective and on criteria like efficiency and cost. The detailed hierarchy of MCDM methodologies is shown in **Figure 2**. The model uses fuzzy logic to determine

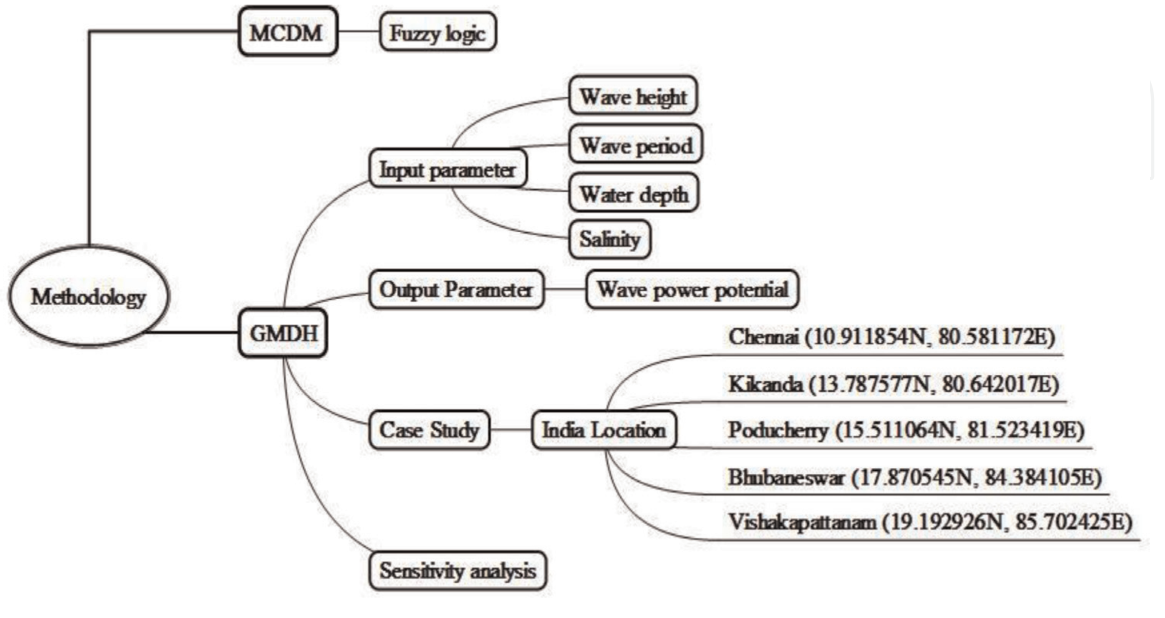

Figure 1.
Schematic diagram of present investigation.

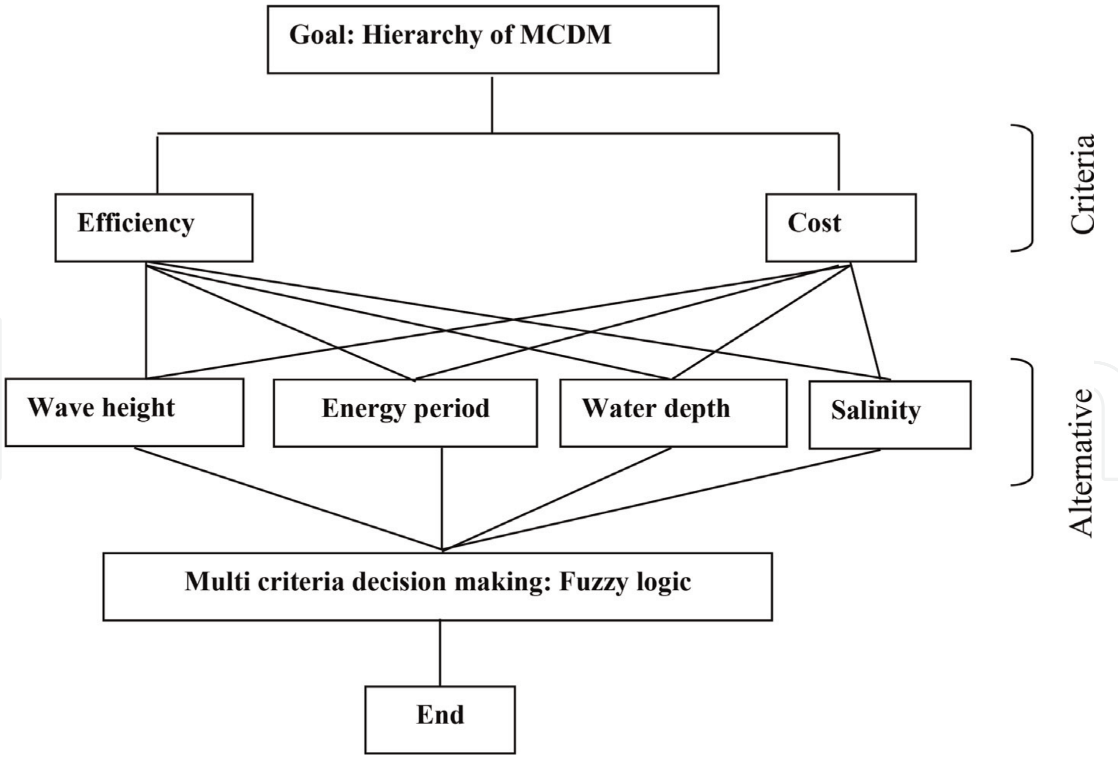

Figure 2.
Figure showing the hierarchy of the MCDM methodologies.

weights of importance as derived from the rank of importance and the aggregation method.

The model uses fuzzy logic to determine weights of importance as derived from the rank of importance and the aggregation method.

3.1 Case study

Figure 3 presents the geographical locations of five points (locations 1–5), which are used to define the wave energy potential of different locations. The data of wave

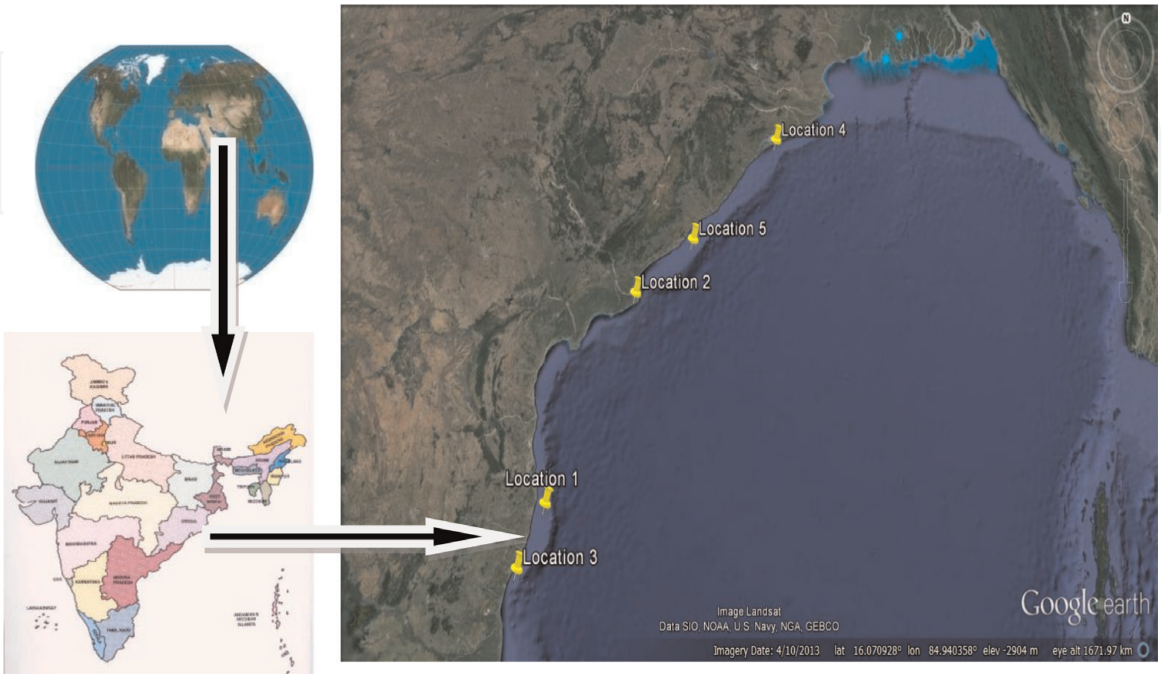

Figure 3.
Locations of the study area.

Parameters	Indian scenario				
	Location 1: Chennai (10.911854, 80.581172E)	**Location 2: Kikanda (13.787577, 80.642017E)**	**Location 3: Puducherry (15.511064 N, 81.523419E)**	**Location 4: Bhubaneswar (17.870545 N, 84.384105E)**	**Location 5: Visakhapatnam (19.192926 N, 85.702425E)**
Wave height (m)	3.5	2.6	3.1	2.4	1.6
Wave period (s)	6.2	7.4	6.5	8.2	8.4
Water depth (m)	3000	2500	700	1400	2200
Salinity (psu)	34.7	33.5	35.6	32.8	33.2

Table 1.
Magnitude of the parameter with respect to the selected location.

height, wind speed, and water depth for the five locations were collected from the National Data Buoy Center. The most recent reanalysis dataset was produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) [16]. The five locations in the Bay of Bengal (BoB) are used to estimate the wave power potential in an Indian scenario. The wave height (H_s) and wave period (T_e) are obtained from the spectral moment as shown in Eqs. (2) and (3):

Significant of wave height (H_s)

$$H_s = 4\sqrt{m_0} \tag{2}$$

$$\text{Energy period (Te)} = \frac{m_{-1}}{m_0} \tag{3}$$

More details about locations 1–5 are provided in **Table 1**, where the corresponding water depth and the geographical coordinates are indicated for each of the five selected locations.

3.2 Development of the cognitive method

In total, 12 GMDH-based models were developed with the same 4 inputs and 1 output as wave power potential. The numbers of inputs were varied from three to five where transformation of input and output data was conducted by the use of tangent and cube root functions. The top three parameters were identified with the help of the fuzzy logic MCDM method. According to the EPI, 3 models which were found to be better than the 12 models developed for the present study were selected for further validation.

The performance of all 12 models was analyzed by aean absolute error (MAE) [17] and correlation (R) [18]. The former metrics are known to be inversely proportional to model accuracy, whereas the other metrics are directly proportional to model performance. The performance of the model during the checking (c) or testing phase is a more important indicator of model reliability than the performance of the model in the training (t) phase [19]. Performance of the three selected models was tested for reliability with the help of root-mean-square error (RMSE), mean relative error (MRE), correlation (R), and percent bias (PBIAS) between the predicted and observed data. The equivalent performance index (EPI) was prepared to represent the performance of the models (see Eq. (4)).

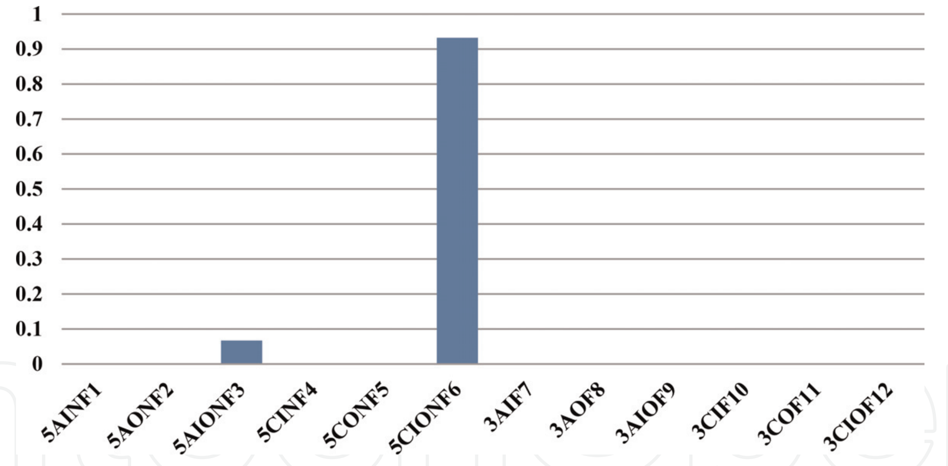

Figure 4.
The 12 models developed for prediction of suitable site selection.

$$\text{EPI} = \frac{\text{R}}{\text{MAE} + \text{MRE} + \text{RMSE} + \text{PBIAS}} \tag{4}$$

The names of the models considered in the study are given in **Figure 4**. The nomenclature was prepared by placing the number of inputs as the first letter followed by the initial letter of the training algorithm, the data transformation function, and lastly the model number.

3.3 Sensitivity analysis

The sensitivity of the better model among the models considered in the study was also tested to verify whether the importance of the input parameters are imbibe into the model result.

4. Results and discussion

Figure 5 shows the score and the rank of the criteria based on the fuzzy logic method. Literature surveys and wave heights were found to be the most important criterion and alternative, respectively, whereas data availability and salinity were identified as the least important criterion and alternative, respectively. According to the results from the MCDM, it can be observed that the wave height (0.4084) and salinity (0.3897) have the highest and lowest importance, respectively, with respect to location selection for wave power plants in **Figure 5**. The performance analysis of the 12 models prepared for prediction is depicted in **Figure 4**.

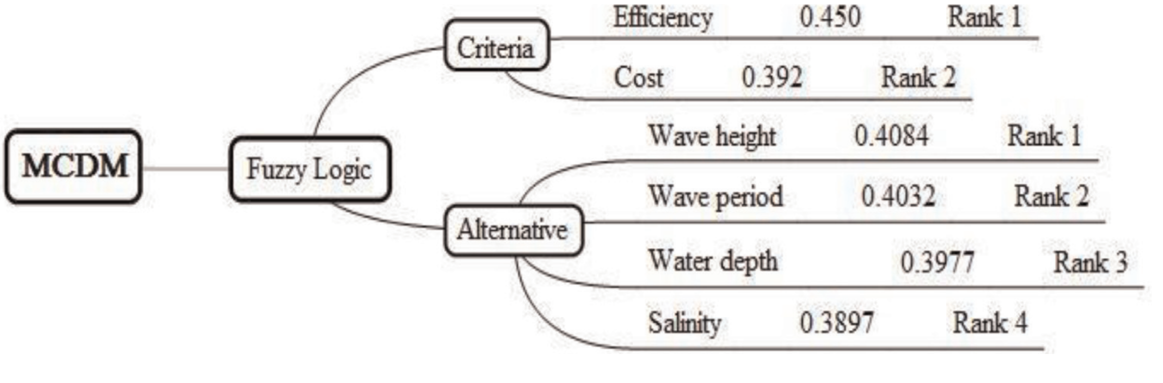

Figure 5.
Fuzzy logic results.

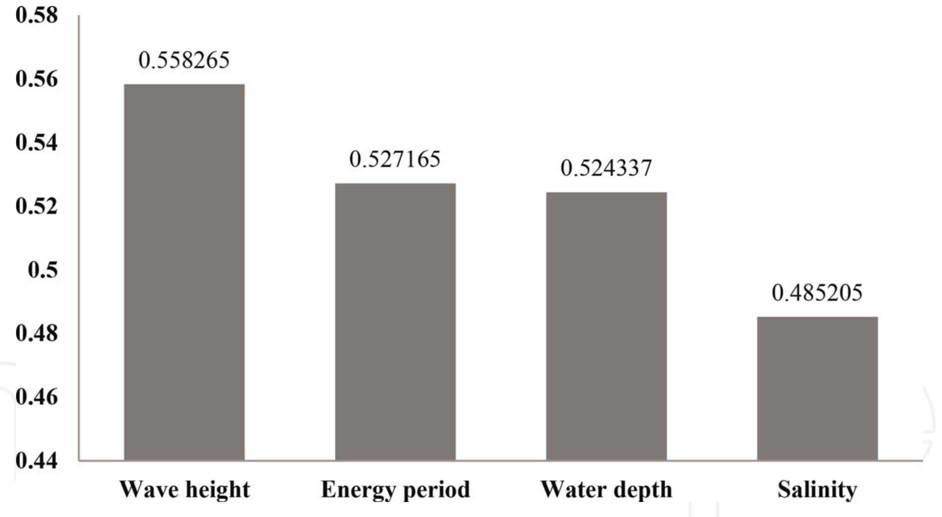

Figure 6.
Figure showing the sensitivity analysis of input variable.

The result of the sensitivity analysis is shown in **Figure 6**, and case study results are shown in **Table 2**.

Figure 7 shows the comparison of predicted and observed output during the training and testing. The performance analysis of the 12 models revealed that the developed model no. "5CIONF6" was the most consistent model among all the models in the study. The most important models were trained with GMDH, the input and output was transformed by the cube root function, and all five variables were used as input.

Location	Wave height	Energy period	Water depth	Salinity	Indicator	Rank
Location 1: Chennai	0.26515	0.16893	0.30612	0.20435	0.01177	1
Location 2: Kikanda	0.19696	0.20163	0.25510	0.19729	0.00724	3
Location 3: Puducherry	0.23484	0.17711	0.07142	0.20965	0.00975	2
Location 4: Bhubaneswar	0.18181	0.22343	0.14285	0.19316	0.00780	4
Location 5: Visakhapatnam	0.12121	0.22888	0.22448	0.19552	0.00261	5

Table 2.
The performance analysis of the locations for wave energy power potential in the case study area.

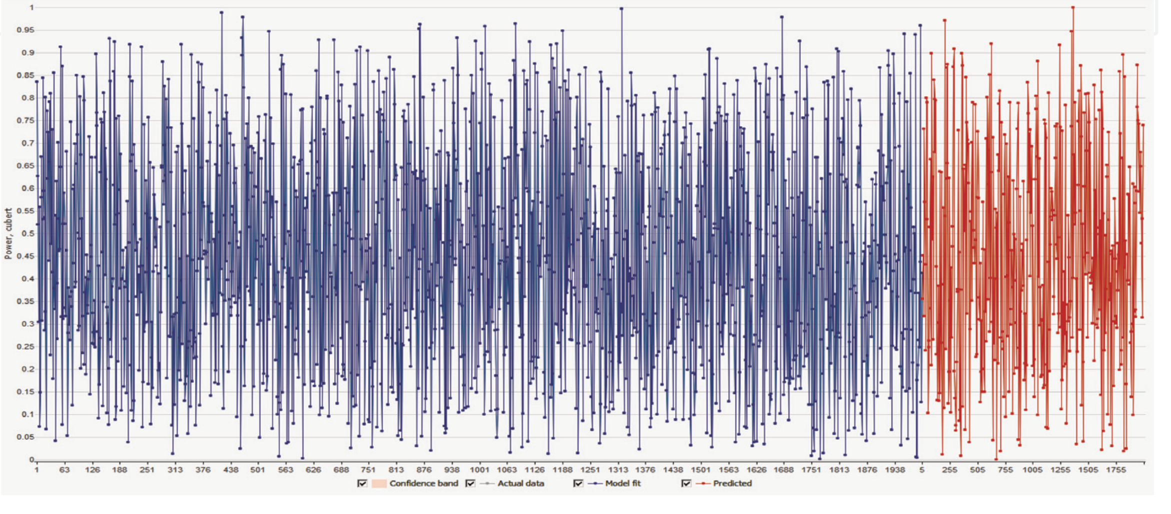

Figure 7.
The comparison of actual and predicted value of the index both with training and testing data.

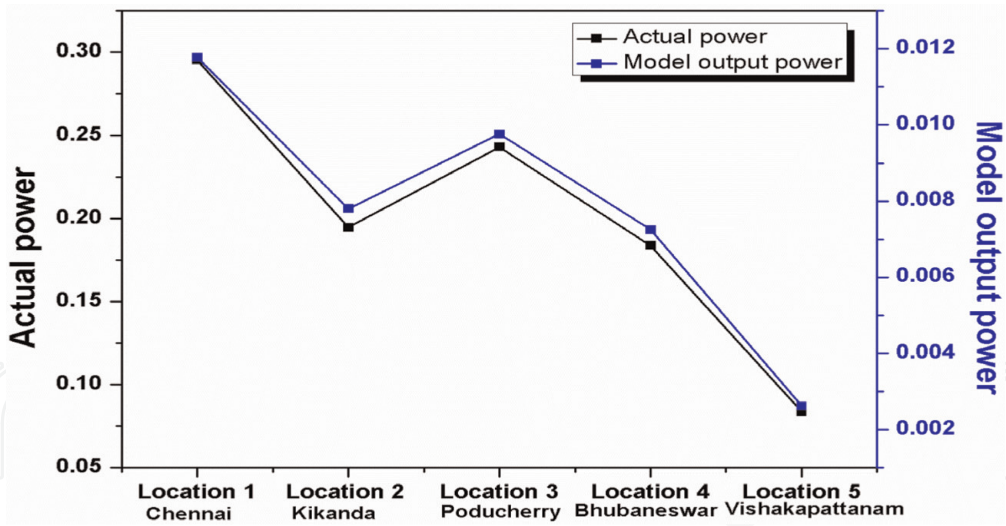

Figure 8.
Location-based model output indicator vs. actual power potential.

Figure 6 depicts that the sensitivity analysis of the model in wave height is maximum and least important of salinity. **Figure 8** depicts the prediction of power potential in form locations of the eastern coastline of India, as predicted in the selected model output with combined the actual power of wave power equation. This model was satisfactory in our objective.

4.1 Study area

In the investigation, the quality of five locations for installation of wave stations was determined by the new methodology. Location 1 (Chennai) has greater practicality than four alternative locations for utilization of wave energy potential. The wave power potential per meter of wave crest of the five locations was also calculated as recommended by [20] in Eq. (5).

$$P = \frac{\rho g^2}{64\pi} H_{mo}^2 T_e \approx \left(0.5 \frac{kw}{m^3 s}\right) H_{mo}^2 T_e \tag{5}$$

where P is the wave power per unit crest length (kw/m), ρ is the sea water density (kg/m^3), g is the gravitational acceleration (m/s^2), Hs is the significant wave height (m), and Te is the energy period (s).

For the Indian scenario, the power potentials of five locations were found to be 12385.224 (kw), 8157.452 (kw), 10186.215 (kw), 7702.158 (kw), and 3506.674 (kw). The model output values, locations 1–5, were found to be equal to 0.011777, 0.007245 0.009758, 0.007801, and 0.002619, respectively. The power potential and the model value were found to be consistent with each other. According to the graph, the model output power and locations are based on the normalized value of power potential shown in **Figure 8**. The values were 0.295324188, 0.194513469, 0.242889081, 0.183657038, and 0.083616223, by locations 1–5, respectively.

5. Conclusion

The present study attempts to predict the wave energy potential of different coastal regions with the help of the four most relevant factors. The study utilized fuzzy MCDM and GMDH models to develop a framework to predict the wave energy potential. In total, four factors were identified as the most important in regard to the calculation of wave energy potential, as found from the literature survey. In total, 12 different models were developed by varying the inputs within these 4 factors and power potential as output. The data representing various scenarios was generated and used to train the models. The arc tangent function was used in six cases to transfer the data of either input or output or both. Performance metrics like RMSE, MAE, PBIAS, and R were used to find the equivalent performance of the models. The model with all the factors as input was found to be most efficient among all the other 11 models. The accuracy of the model was found to be above 99.99%. The power potential of five different locations on the Indian coastal belt was used as a case study. The model output and the result from the power potential equation were compared and found to be coherent with each other, although magnitude of the results is well apart.

Nomenclature

ANN	artificial neural network
MCDM	multi-criteria decision-making
FLDM	fuzzy logic decision-making method
GMDH	group method of data handling
NSE	Nash-Sutcliffe model efficiency coefficient
PBIAS	percent bias
RSR	RMSE-observation standard deviation ratio
R	correlation
PI	performance index

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