frontiers | Frontiers in Energy Research

TYPE Original Research
PUBLISHED 24 October 2022
DOI 10.3389/fenrg.2022.1009987

Check for updates

OPEN ACCESS

EDITED BY
Iskander Tlili,
National School of Engineers of Monastir, Tunisia

REVIEWED BY
Muhammad Shahzad Nazir,
Huaiyin Institute of Technology, China
Olena Rubanenko,
University of West Bohemia, Czechia
Ateeq Ur Rehman,
Government College University, Lahore, Pakistan

*CORRESPONDENCE
Salah Kamel,
skamel@aswu.edu.eg

SPECIALTY SECTION
This article was submitted to Process and Energy Systems Engineering, a section of the journal Frontiers in Energy Research

RECEIVED 04 August 2022
ACCEPTED 05 October 2022
PUBLISHED 24 October 2022

CITATION
Ghosh S, Majumder M, Mohammed OH, Bajaj M, Singh AR and Kamel S (2022), Estimation of failure probability of wave energy farms by group method of data handling: An indian scenario.
Front. Energy Res. 10:1009987.
doi: 10.3389/fenrg.2022.1009987

Estimation of failure probability of wave energy farms by group method of data handling: An indian scenario

Soumya Ghosh[1], Mrinmoy Majumder[2], Omar Hazem Mohammed[3], Mohit Bajaj[4], Arvind R. Singh[5,6] and Salah Kamel[7]*

[1]Department of Electrical Engineering, Mallabhum Institute of Technology, Bankura, West Bengal, India, [2]Department of Civil Engineering. National Institute of Technology, Agartala, Tripura, India, [3]Department of Technical Power Engineering, Technical College, Northern Technical University, Mosul, Iraq, [4]Department of Electrical Engineering, Graphic Era (Deemed to be University), Dehradun, India, [5]Department of Electrical and Electronics Engineering, Koneru Lakshmaiah Education Foundation, Guntur, India, [6]School of Electrical Engineering, Shandong University, Jinan, China, [7]Electrical Engineering Department, Faculty of Engineering, Aswan University, Aswan, Egypt

The failure probability of the wave energy converters is exceptionally high, which again increases the operation cost of the entities. The cause of this high cost lies in the fact that various factors influence the production efficiency of the converters. To solve this problem, multiple converters are utilized in series and parallel formation to produce energy simultaneously. This multiple converter system, known as wave energy farms, also fails to increase efficiency and decrease the cost of operation sufficiently. The reason for this is that not only technical but socio-economic as well as different environmental factors have a significant role in this aspect, which remains undetected or under- or over-detected while calculating the potential wave energy. The present investigation tries to classify the different factors which are most influential in controlling the transfer efficiency of wave energy farms to solve the problem of erroneously detecting significant factors. The authors offer a new indicator for estimating the failure likelihood of wave energy farms in converting ocean wave energy into electricity by combining Multi-Criteria Decision Making and Polynomial Neural Networks with information collected from an unbiased ranking technique.

KEYWORDS

wave energy farm, GMDH, fuzzy, AHP, ANP

1 Introduction

With the current population and economic growth, it is predicted that in the near future, demand for energy will increase considerably by 17 TW (Rotty, 1979). Global climate change, as well as the warnings linked with it, constitute a serious threat to the world's ecosystems. The possibility of reversing this trend relies on lowering CO_2

emissions into the environment. By investing in renewable energies such as wind and solar electricity, international treaties are playing a critical role. However, there is another renewable energy cluster with great potential and a bright future. This is the energy created by waves, which is quickly gaining traction as a viable alternative to reducing the environmental impact of fossil fuel use (Abanades et al., 2014). Wave energy has a number of advantages, including, but not limited to, large energy capacity One of the most concentrated, reliable, and long-lasting energy sources, wave energy is available in many nations but is underutilized (Mackay et al., 2010).

As a result, the utilization of wave renewable energy offers enormous potential for lowering greenhouse gas emissions. More wave energy providers are showcasing their products to draw investors in a competitive manner as a result of the growing marine renewable sector. Information about WEC is frequently confidential. Developers want to place a device in the best possible way, but investors just want to make money. The rivalry also causes WECs on the market to have very dynamic properties. Therefore, research is necessary to improve evaluations of novel WECs and offer recommendations for matching WECs and locales (Choupin et al., 2021). Because the wave energy converter (WEC) produces no gaseous, liquid, or solid emissions, wave power is less environmentally damaging than most other forms of energy generation (Brooke, 2003). Wave farms vary depending on the device type, condition of the ocean, farm size, proximity to shore and grid connection, and device and plant cost estimation of the farm layout.

Wave farms (Guanche et al., 2014) are arrays of wave energy converters that are arranged in either series or parallel connections to cumulatively convert the available potential of wave energy resources. The efficiency of conversion mainly depends on the performance efficiency of the converters (Bódai and Srinil, 2015), the transmission loss incurred in the connecting cables (Sharkey et al., 2013), the park effect (Katsaprakakis and Christakis, 2014; Gatzert and Kosub, 2016), and some other factors which depend on location, such as wind speed, duration of fetch (Carrasco et al., 2012), water quality (Ghosh et al., 2016), tourism potential (Greaves et al., 2016), etc. Due to various crucial characteristics, such as gap resonance, array arrangement, wave nonlinearity, 3-D flow field effect, power take-off (PTO) mechanism, and oblique wave incidence, the hydrodynamic behavior of multi oscillating wave surge converter devices is still not fully known (Cheng et al., 2021).

It is particularly difficult to determine how nonlinear multi-body hydrodynamic interaction would affect the harvested energy of OWSC devices. It is necessary to do systematic research into the additional nonlinear hydrodynamic performance of an array of OWSCs.

1.1 Objective and novelty

The goal of this research is to determine the best arrangement for wave energy farms so that the most quantity of utilizable energy can be transformed. The study's unique contribution is the creation of an indicator that may objectively describe the performance efficiency of wave farms in terms of location, design, and cost. The creation of an instinctual indication was accomplished, and it was used to solve a problem for the first time.

2 Method applied

The present study includes the application of the Multi-criteria decision making (MCDM) and ANN-based GMDH methods. The latter method was used to incorporate adaptability, and MCDM was used to find the priority of the input parameter with respect to the study objective. Sections 2.1, 2.2 depict the strengths, weaknesses, and application of the MCDM and GMDH methods in the related fields.

2.1 Multi-criteria decision making

The MCDM is used to make objective decisions and determine the significance of selected characteristics for the study's specific goal. In this study, MCDMs such as Fuzzy-AHP (Shaw et al., 2012) and ANP (Aragonés-Beltrán et al., 2014) were used to determine the importance of selected characteristics in relation to the investigation's goal.

2.1.1 Fuzzy-AHP

The computation approach developed by Saaty (Saaty, 1980) for the analytical hierarchy process was based on crisp judgment. On the basis of fuzzy set theory and hierarchical structure analysis, many fuzzy AHP approaches have been devised. In the application process, Saaty proposed the significance scale, which uses numbers from 1 to 9 while the decision-maker performs paired comparisons. Most real-life decisions, on the other hand, have unknown outcomes (Chang, 1996).

The weights for evaluative elements are determined using fuzzy AHP, which is based on fuzzy interval arithmetic using fuzzy triangular numbers and confidence indexes, and an interval means method (Buckley, 1985; HMd and Wu, 2011). To enhance decision-making, some academics have combined fuzzy theory with AHP.

2.1.2 Analytical network process

Analytical network process (ANP) is a flexible decision-making strategy that works with both quantitative and qualitative data and qualitative data. Saaty introduced ANP as a novel MCDM technique to solve the real-world concerns of interaction and feedback among criteria and options (Saaty, 2004). ANP is a nonlinear dynamic structure that is based on the Markov Chain notion and is an extension of AHP (Saaty, 1999). We discovered that while dealing with ANP, the

TABLE 1 Table showing advantages, disadvantages, and application of Fuzzy-AHP method.

MCDM method	Advantages	Disadvantages	Application
Fuzzy-AHP	• The reciprocal matrix may be used to model the views of numerous decision-makers • It's simple to adapt to the fuzzy situation, and it ensures a unique reciprocal comparison matrix solution (Chen et al., 2008)	• Even for a simple issue, there is not always a solution to the linear equations, and the computational requirements are enormous	• Using the fuzzy AHP approach to evaluate manufacturing partners in the challenge of integrated manufacturing planning • A fuzzy AHP-based inventory categorization system in a firm that manufactures electrical small household products. The study developed a decision-making system that incorporates fuzzy ideas and real-world inventory data. (Chiu et al., 2006)
Analytical network process	• The advantage of the network structure is both alternatives and criteria are rated based on each other because the criteria are weighted as per their importance with respect to the alternative • It has a nonlinear dynamic structure	• Even specialists find it challenging to establish a suitable network structure, and different topologies provide varied outcomes (Velasquez and Hester, 2013)	• The ANP method was used for an engineering purpose in a diesel engine manufacturing firm (Tan et al., 2007) • Determine the appropriate fuel combination for power generation from a long-term perspective (Köne and Büke, 2007) • In the case of independency and interdependency, it should be applied to the ultimate priorities of suppliers in an automotive manufacturing firm. (Kasirian and Yusuff, 2010)

standard way of normalizing the non-weighted super matrix was not appropriate since, in the actual world, varying degrees of impact exist within clusters of factors/criteria. As a result, the weighted super matrix's weighted assumption of equal weights for each cluster is impractical and has to be modified (Luo et al., 2010). Three matrix analyses are included in the ANP method: the super matrix, the weighted super matrix, and the limit matrix (Yang et al., 2003). Table 1 depicts the advantages, disadvantages, and application of the ANP method.

2.2 Ranking method

Duncan was the first to suggest an economical design for X control charts (Duncan, 1956). By adding statistical restrictions into the economic model, Saniga was the first to propose the economic-statistical design of X bar and R charts (Saniga, 1989). Multiple objectives, including cost function and statistical features, are maximized simultaneously in their method. As a result, the best control chart design is modeled as a Multi-criteria decision making (MCDM) issue (Allen, 2006) (Table 2).

TABLE 2 Table showing the features of the twelve development models.

Model No.	No. of input	No. of output	MCDM adopted	Ranking method	Training algorithm
21AHG1	21	1	AHP	Citation frequency	GMDH
21ANG1	21	1	ANP	Citation frequency	GMDH
21AHANG1	21	1	AHP-ANP	Citation frequency	GMDH
21SAHG1	21	1	AHP	X, R, P	GMDH
21SANG1	21	1	ANP	X, R, P	GMDH
21SAHANG1	21	1	AHP-ANP	X, R, P	GMDH
21FAHG1	21	1	Fuzzy-AHP	Citation frequency	GMDH
21FANG1	21	1	Fuzzy- ANP	Citation frequency	GMDH
21FAHANG1	21	1	Fuzzy- AHP- ANP	Citation frequency	GMDH
21FSAHG1	21	1	Fuzzy-AHP	X, R, P	GMDH
21FSANGM1	21	1	Fuzzy-ANP	X, R, P	GMDH
21FSAHANG1	21	1	Fuzzy-AHP-ANP	X, R, P	GMDH

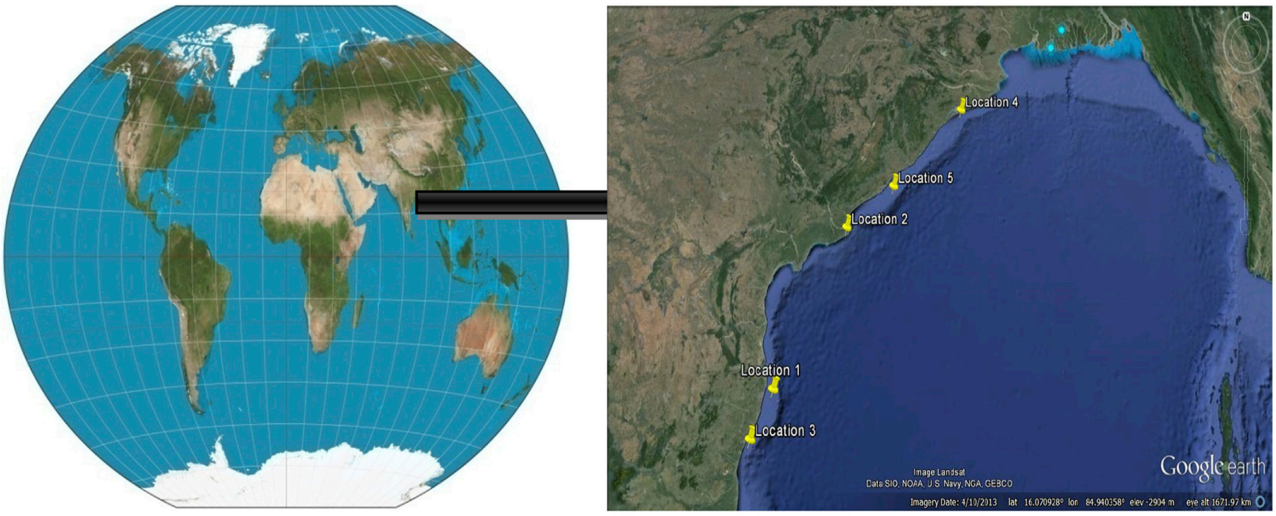

FIGURE 1
Locations of the study area (Noori and Kalin, 2016)

The present investigation also uses some statistical control charts to find the rank of the selected factors in an unbiased and non-preferential way.

The control charts are used to detect system performance outliers. The charts are used in this study to determine the relevance of the index's optimal performance and the associated features of the input parameters without outliers. The separation of the factors in terms of their contribution to optimizing the index performance. The X-bar, R, and P control charts were used separately to rank the variables as per their contribution to the study objective.

2.3 Group method data handling algorithms

Ivakhnenko (Ivakhnenko, 1971) created the Group method data handling algorithms (GMDH) model, which is one of the learning machine models based on the polynomial theory of complex systems. The most important input parameters, the number of layers, the number of neurons in the middle layers, and the network's ideal topology design are all automatically defined by this network. As a result, the GMDH network is a model of active neurons that self-organize. During the training step, the GMDH network's topology is set using a polynomial model that yields the least amount of error between the predicted value and the observed output.

The neuro-fuzzy GMDH network is a highly versatile algorithm that may be integrated with other iterative and evolutionary algorithms with ease (Nariman-Zadeh et al., 2002). The GMDH neural network is a self-organizing, unidirectional structure with many layers made up of neurons with comparable structures.

After selecting the model criterion in line with the modeling and information division's aims, GMDH will automatically confirm the model. If several types of input units are used, this modeling approach will generate multiple types of models. This automated modeling method has been used to create Bayesian networks (Xiao et al., 2009) and Mamdani-type fuzzy models (Lemke and Müller, 2003).

The noise-immunity of GMDH is another attractive feature. We all know that when data contains noise, the greatest danger is over-fitting (Tan et al., 2006), which means that models become too complicated and generalizable. This issue, however, may be overcome in the case of GMDH.

3 Methodology

3.1 Brief description

Following an examination of the literature, the twenty-one most critical factors for the efficiency of a wave energy converter farm design were chosen. These factors are wave height, shipping density, wave period, water depth, distance from the coast, wind speed, salinity, regularity of wave, number of WEC, the distance between WEC, wave incidence direction, array layout, length of cable connecting to shore, buoy diameter, rated power, converter efficiency, unit cost, operating and maintenance costs, capital costs, taxes and rate of energy charge per unit.

The current research took two steps to create an indicator for representing farm performance in terms of the installation site, converter design, and system cost.

The control charts X bar, R, and P were used in the first phase based on their significance to the study goals. The Fuzzy-AHP and ANP MCDM techniques were then used to determine the priority value of each of the parameters. The MCDM technique is divided into three parts, which will be detailed in the next section.

3.2 Application of multi-criteria decision making

The application of MCDM involves three steps, which are described in the next section.

3.2.1 Criteria selection

The criteria were selected based on the study objective. In the present study, the location (L), Design (D), and Cost (C) were selected as the criteria on which the parameters will be compared.

3.2.2 Alternative selection

All the selected parameters were considered as alternatives to the decision-making method. Based on the rank obtained using the control chart method, each of the possibilities is compared to one another.

3.3 Application of aggregation method

After comparing each of the alternatives against each other based on the criteria and with respect to the study aim, the criteria and alternatives were utilized to identify the equal weight of the given parameters.

The criteria were then compared to one another based on the available possibilities, all while keeping the study's purpose in mind. To evaluate the weight of importance for each of the elements, both findings were cross multiplied based on the criteria and in relation to the study's purpose.

The weight vector or priority values of the parameters were used to convey the relevance of the parameters at the end of this strategy, which is directly proportional to the significance of the variables.

Weight Function as the Indicator: The W-value, or Indicator for Performance Evaluation of Wave Energy Converter Array Design, was calculated by Eq. 1

$$W_{value} = \frac{\sum w_n b_n}{\sum w_m b_m} \quad (1)$$

where "w_n" and bn denote the degree of the weight of importance, beneficiary and non-beneficiary variables, respectively, and n and m indicate the number of the beneficiary and non-beneficiary variables.

3.4 Development of the group method data handling model

With twenty-one inputs and one output, the GMDH model was created. The models' datasets were standardized, and 60 percent of the data was utilized for training, while the remaining 40 percent was preserved for testing. A total of twelve models were created using a variety of control charts, MCDMs, and data transformations. Table 1 demonstrates how the models were created in different methods to anticipate the same goals.

Mean Absolute Error (MAE) (Willmott and Matsuura, 2005), Root Mean Square Error (RMSE) (Despotovic et al., 2016), Mean Relative Error (MRE) (Gray et al., 2016), and Correlation(R) (Pascual-González et al., 2016) were used to evaluate the performance of all forty-eight models.

Model accuracy is known to be inversely proportional to the former measures, but model performance is known to be directly proportional to the latter measurements. The model's performance during the checking (c) or testing phase is a better predictor of model dependability than the model's performance during the training (t) phase (Noori and Kalin, 2016).

According to the EI, three models were chosen for additional validation after they were shown to be superior to the forty-eight models produced for this investigation.

Root Mean Square Error (RMSE), Mean Relative Error (MRE), and Percent bias (PBIAS) (Gupta et al., 1999) between predicted and observed data were used to assess the dependability of the selected three models. The Performance Index (PI) was created to represent the models' performance. Equ.2.

$$\left[\mathrm{PI} = \left\{ \frac{\mathrm{R_t}}{\mathrm{MAE_t + MRE_t + RMSE_t + PBIAS_t}} * 0.6 \right\} + \left\{ \frac{\mathrm{R_T}}{\mathrm{MAE_T + MRE_T + RMSE_T + PBIAS_T}} * 0.4 \right\} \right] \quad (2)$$

where t is for testing and T is for the training phase.

Table 1 shows the nomenclature, which starts with the number of inputs, then the first letter of the training process, the data transformation function, and finally, the model number.

3.5 Sensitivity analysis

The most efficient model's sensitivity will always be proportional to the importance of the parameters in the model output. For a model to be trustworthy and efficient in predicting its output with dependability, the sensitivity and significance must be consistent and associated. The model was

TABLE 3 Table showing the rank of the parameter of X bar, R, and P control chart.

Parameters	Rank			The parameters are ranked according to the frequency of citations (number of citations/number of publications surveyed)
	X bar	R Chart	P Chart	
Location aspect				
Wave height	11	13	10	17
Shipping density	14	5	11	5
Wave period	13	17	13	9
Water depth	8	2	17	18
Distance from coast	18	20	15	11
Wind speed	7	14	18	8
Salinity	5	8	5	16
Regular wave (%)	15	6	7	21
Design				
Number of WEC	17	15	8	2
Distance between WEC	4	1	6	7
Wave incidence direction	20	4	21	13
Array layout	3	18	3	15
Length of cable connecting two converters	1	16	1	4
Buoy diameter	2	7	2	6
Rated power	10	10	12	19
Converter efficiency	19	9	19	1
Cost				
Unit cost	21	3	9	20
Operating and Maintenance costs	9	11	4	14
Capital costs	16	12	16	12
Taxes	12	19	20	3
Rate of charge per unit	6	21	14	10

subjected to a sensitivity analysis, and it was discovered to have the highest EI of all the models produced for this study.

3.6 Case study

In Figure 1 represents the geographical locations of five points (location 1 to location 5), which are used to define the wave energy converter efficiency analysis.

Several industries are currently developing and implementing novel technologies in wave energy generation across the world. AquaEnergy Group, Ltd. (AquaEnergy), an ocean wave corporation, describes its categorization growth and optimization efforts in this study. Ocean energies have witnessed a resurgence in attention in recent years, owing to a growing recognition that we will need all types of clean energy to lessen our reliance on fossil fuels.

4 Results and discussion

The weight vector of the parameters was calculated to analyze the X bar, R, P control chart, and citation frequency; the citation frequency refers to the number of citations divided by the number of the literature surveyed, as defined in Table 3. The twelve models were specified as AHP, ANP, AHP-ANP, Statistical method with AHP, Statistical method with ANP, Statistical method with AHP-ANP, Fuzzy AHP, Fuzzy ANP, Fuzzy –AHP, Fuzzy-ANP, Fuzzy-AHP-ANP, Statistical method with Fuzzy-AHP, Statistical method with Fuzzy-ANP and Statistical method with Fuzzy-AHP-ANP in Table 4. The performance of the twelve models in the prediction of wave energy farm performance is depicted in Table 5. Figures 2, 3 depict the comparison of predicted and observed output during the training and testing or predictive phase and the

TABLE 4 Table showing the parameters as determined by various MCDM methods.

Parameter	Method											
	AHP	ANP	AHP-ANP	STAT-AHP	STAT-ANP	STAT-AHP-ANP	Fuzzy-AHP	Fuzzy-ANP	Fuzzy-AHP-ANP	Fuzzy-STAT-AHP	Fuzzy-STAT-ANP	Fuzzy-STAT-AHP-ANP-
Wave height	0.024885	0.021292	0.091205	0.048335	0.091490	0.045554	0.040029	0.048903	0.039714	0.008883	0.049112	0.039407
Shipping density	0.032338	0.042080	0.111114	0.049945	0.101482	0.051438	0.038773	0.049194	0.037587	0.009719	0.048870	0.054746
Wave period	0.032815	0.033518	0.066049	0.044774	0.077201	0.045542	0.041705	0.045725	0.04105	0.008053	0.046067	0.05198
Water depth	0.024461	0.010851	0.197297	0.052647	0.031022	0.051857	0.031636	0.050961	0.031478	0.006651	0.050412	0.035905
Distance from coast	0.075579	0.104201	0.048901	0.037481	0.041714	0.040412	0.06604	0.037825	0.064299	0.005811	0.03794	0.053525
Wind speed	0.016812	0.008698	0.113818	0.046184	0.034116	0.050197	0.04782	0.045851	0.047996	0.00639	0.045827	0.050524
Salinity	0.009393	0.005664	0.268996	0.054396	0.080674	0.050662	0.02897	0.055024	0.028305	0.008946	0.055261	0.037306
Regular wave	0.066567	0.052836	0.10262	0.050979	0.017126	0.042855	0.041572	0.050706	0.039699	0.005475	0.050525	0.023096
Number of WECs	0.064576	0.083191	0.031245	0.045783	0.027685	0.047032	0.046944	0.046116	0.044724	0.005915	0.046165	0.054034
Distance between WEC	0.022312	0.004628	0.048297	0.058122	0.045352	0.057871	0.031471	0.057849	0.030471	0.007882	0.057753	0.050242
Wave incidence direction	0.129103	0.162064	0.025158	0.042508	0.022345	0.046208	0.044695	0.038916	0.045257	0.005468	0.037568	0.045925
Array layout	0.02362	0.003837	0.061875	0.04958	0.018173	0.045724	0.059004	0.052009	0.053925	0.0056	0.052931	0.044306
Length of the cable connecting to shore	0.002947	0.002837	0.178793	0.050295	0.115126	0.050165	0.04917	0.052614	0.043773	0.010295	0.053497	0.057605
Buoy diameter	0.003961	0.00325	0.091831	0.055727	0.024764	0.055423	0.030491	0.056477	0.02857	0.006698	0.056766	0.054754
Rated power	0.018024	0.016988	0.037059	0.048495	0.016083	0.045244	0.044245	0.04895	0.0419	0.005427	0.049127	0.037015
Converter efficiency	0.119335	0.130206	0.028027	0.040284	0.030321	0.046615	0.046661	0.038068	0.046315	0.005744	0.037237	0.058387
Unit cost	0.170989	0.200263	0.270791	0.047488	0.024653	0.042718	0.071167	0.045453	0.07216	0.00564	0.044557	0.034992
O&M cost	0.061227	0.013567	0.260522	0.051528	0.086709	0.048189	0.051002	0.052952	0.048222	0.008955	0.053476	0.04421
Capital cost	0.060504	0.066323	0.125976	0.043173	0.103173	0.046177	0.070251	0.042209	0.067999	0.009195	0.041848	0.054107
Taxes	0.029302	0.026707	0.11842	0.038645	0.007114	0.04495	0.077474	0.038629	0.072529	0.004517	0.038712	0.061021
Rate of energy charge per unit	0.01125	0.006998	0.224291	0.04363	0.003676	0.045169	0.082786	0.045567	0.074024	0.004616	0.046348	0.056911

distribution of residuals derived from the predicted and observed output, respectively.

According to the results of the fuzzy-AHP and ANP strategies, the potency of the wave energy farm was found to be the highest three most vital factors among the twenty-one thought-about parameters.

The study's performance analysis found that Model No. 21ANG1 was the most dependable of all the models studied, followed by Model No. 21FAHG1. Both of the essential models were GMDH-trained, utilized non-linear neuron function, and modified the output. Models three and seven, which were discovered to be the study's second and third most important models, incorporated variable ranking as well as output transformation, and the model was trained with GMDH. All the models that employed all twenty-one input variables were included in the analysis.

The model 21ANG1 was found to be better than the other models in Table 5. According to the results, one model was selected for prediction as performance will depend on the method of variable ranking and may change if the method is changed in Table 5. If the MCDM approach is altered, the performance accuracy of the chosen model may change as well. Thus it was assumed that if the method of MCDM

TABLE 5 Table results of the 12 models developed for prediction of efficiency of wave energy farms.

Model name	No. of input	No. of input	Control chart	MCDM method	Training					Testing					Performance index	Rank
					PBIAS	MRE	MAE	RMSE	Correlation	PBIAS	MSE	MAE	RMSE	Correlation		
21AHG1	21	1	Citation frequency	AHP and GMDH	5.88E-13	3.01E-15	0.009734	0.0129395	0.99729	−0.41852	−0.00202	0.01019	0.013691	0.996396	16.08680507	**04**
21ANG1	21	1	Citation frequency	ANP and GMDH	0.0485223	0.0375392	−2.59147E-15	0.09456E-13	0.980194	0.0527452	0.0405997	−0.001701981	0.089902993	0.968775	18.95901594	**01**
21AHANG1	21	1	Citation frequency	AHP-ANP-GMDH	0.058395	0.046122	2.37532E-15	0.76172E-13	0.993053	0.058549	0.047452	-0.003636977	0.270815175	0.992229	16.85281	**02**
21SAHG1	21	1	X, R, P	STAT-AHP - GMDH	0.082308	0.065057	−4.54997E-15	0.082308	0.98111	0.108371	0.07747	0.005494411	0.108371	0.965873	10.42604	**10**
21SANG1	21	1	X, R, P	STAT-ANP - GMDH	0.213197	0.156989	0.114248	0.24157	0.94751	0.24157	0.176355	0.086742	0.213197	0.942146	4.621591	**12**
21SAHANG1	21	1	X, R, P	STAT-AHP-ANP- GMDH	0.077556	0.061728	1.05985E-14	0.077556	0.980692	0.083027	0.06789	0.009581961	0.083027	0.976466	12.58417	**09**
21FAHG1	21	1	Citation frequency	Fuzzy-AHP-GMDH	0.050294	0.04013	9.8116E-17	0.050294	0.990764	0.071842	0.050668	0.00286622	0.071842	0.983248	16.26858	**03**
21FANG1	21	1	Citation frequency	Fuzzy- ANP-GMDH	0.063017	0.050143	−1.88655E-15	0.063017	0.986361	0.074005	0.056932	0.000500592	0.074005	0.978017	14.31441	**05**
21FAHANG1	21	1	Citation frequency	Fuzzy- AHP-ANP -GMDH	0.183057	0.138718	−5.02931E-16	0.183057	0.885673	0.224924	0.162731	0.031966321	0.224924	0.856691	5.853031	**11**
21FSAHG1	21	1	X, R, P	Fuzzy-STAT-AHP-GMDH	0.071289	0.056897	−1.57263E-15	0.071289	0.983314	0.07706	0.060123	−0.001496169	0.07706	0.979203	13.12914	**07**
21FSANGM1	21	1	X, R, P	Fuzzy-STAT-ANP-GMDH	0.067748	0.055097	−3.04701E-15	0.067748	0.986213	0.084338	0.061257	−0.003342629	0.084338	0.98268	12.73374	**08**
21FSAHANG1	21	1	X, R, P	Fuzzy-STAT-AHP-ANP-GMDH	0.071242	0.057606	1.21611E-15	0.071242	0.988134	0.078869	0.0609	0.006539586	0.078869	0.987113	13.34419	**06**

The bold value is mention the best model of the prediction of efficiency of wave energy farms.

10.3389/fenrg.2022.1009987

TABLE 6 Table showing the performance analysis of five locations.

Serial No	Location	Index value
1	Chennai (10.91185 N, 80.58117 E)	0.21571
2	Kikanda (3.78758 N, 80.64202 E)	0.17164
3	Poducherry (15.51106 N, 81.52342 E)	0.20960
4	Bhubaneswar (17.87055 N, 84.38411 E)	0.21019
5	Vishakapattanam (19.19293 N, 85.70243 E)	0.19284

remains unchanged, the accuracy of the model will be uniform in any system as the model was trained with a normalized data set that is independent of scale problems.

Chennai has the highest probability of failure among the sites, according to the conclusions of the case study research. In addition, criterion and alternative selection has a significant impact on the model findings in Table 6.

The importance of the variables was considered based on normal conditions; it depicts no information regarding the process to optimal performance efficiency of the converter. However, the importance variable by estimated MCDM depends on the information retrieved from the literature survey of a certain number of reports.

Figure 3 shows the comparison of predicted and output data, as estimated by the selected model. The distribution of residual value is depicted in Figure 2.

4.1 Objective equations

Using twenty-one input and one output parameter, the wave energy farm designs of five sites were estimated. The network was trained using the GMDH technique and Supplementary Equation S54 in Supplementary Annexure S1 shows the number of hidden layers and the value of the weight vector for each input.

$$Y1 = -0.10507 - N707{*}N2{*}0.103405 + N707^2{*}0.0782601 + N2{*}1.08516 + N2^2{*}0.0159021$$

where $Y1$ = model output and $N2$ and $N707$ are the sub-model output as given in Supplementary Annexure S1.

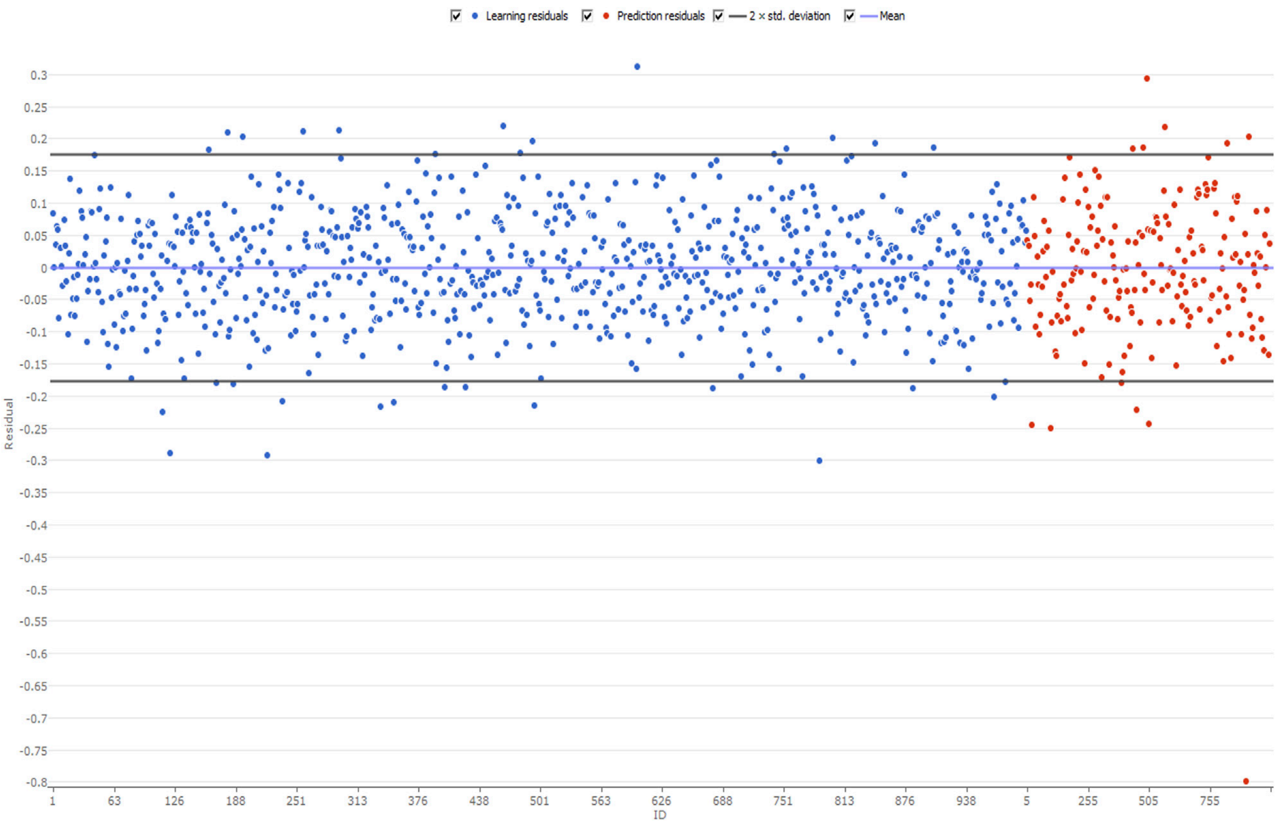

FIGURE 2
Figure showing the distribution of residual value for the model #21ANG1.

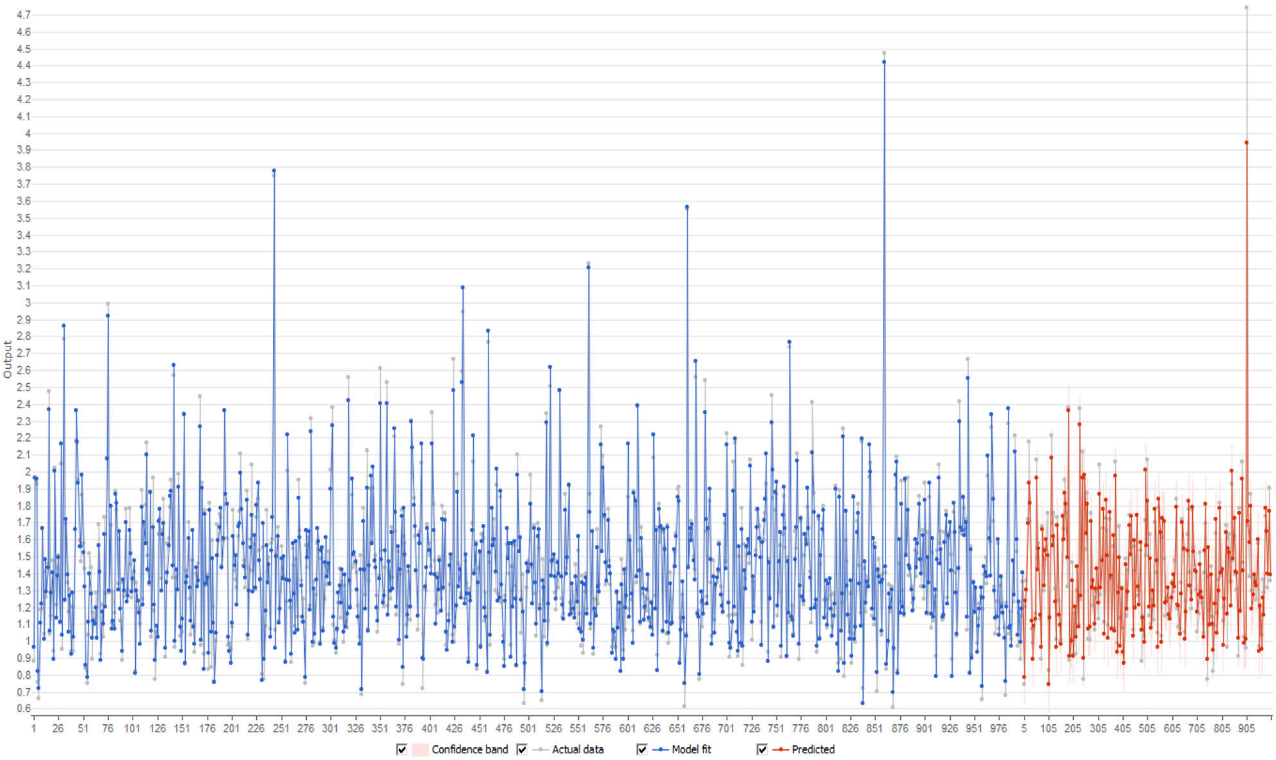

FIGURE 3
Figure showing the distribution of residuals derived from observed and predicted output for #21ANG1.

4.2 Multiple linear regression model

The objective equation of model was developed by

$$Y = b0 + b1{*}x + b2{*}x + b3{*}x + b4{*}x + b5{*}x + b6{*}x.$$

In the current analysis, it was discovered that the GMDH trained model had acceptable performance metrics. To establish a relationship between the dependent and independent variables, a multiple linear regression was run on the dataset. The PI test for the MLRM model is not as significant as 0.122945. Correlation was calculated to be 0.992075, indicating that the developed model suited the dataset well. The MLRM model performed better at predicting in Table 7 than the regression model, which was determined by the MSE, which was obtained for both cases and was 0.03498 for the regression model and 0.0367 for the GHDH model. To validate the model, the created GHDH and regression model were both given the test dataset. The regression model was created utilizing the entire dataset, which included the test data points, but the MLRM model was never exposed to the test dataset during training. The GMDH method required to include data points that were near to the minimum and maximum values of the dependent variable when creating the test dataset.

4.3 Sensitivity analysis

Each number in the sensitivity analysis represents the difference between the expected result and the level of uncertainty associated with a single input variable. It was observed that with a change in each of the input variables (i.e., wave height, shipping density, wave period, water depth,

TABLE 7 Performance index of multiple linear regression model.

Mean square error (MSE)	NSE (NE)	PBIAS (B)	RSR (SR)	Correlation (R)	Performance index (PI)
0.03498	0.097307	0.012012	3.288013	0.992075	0.122945

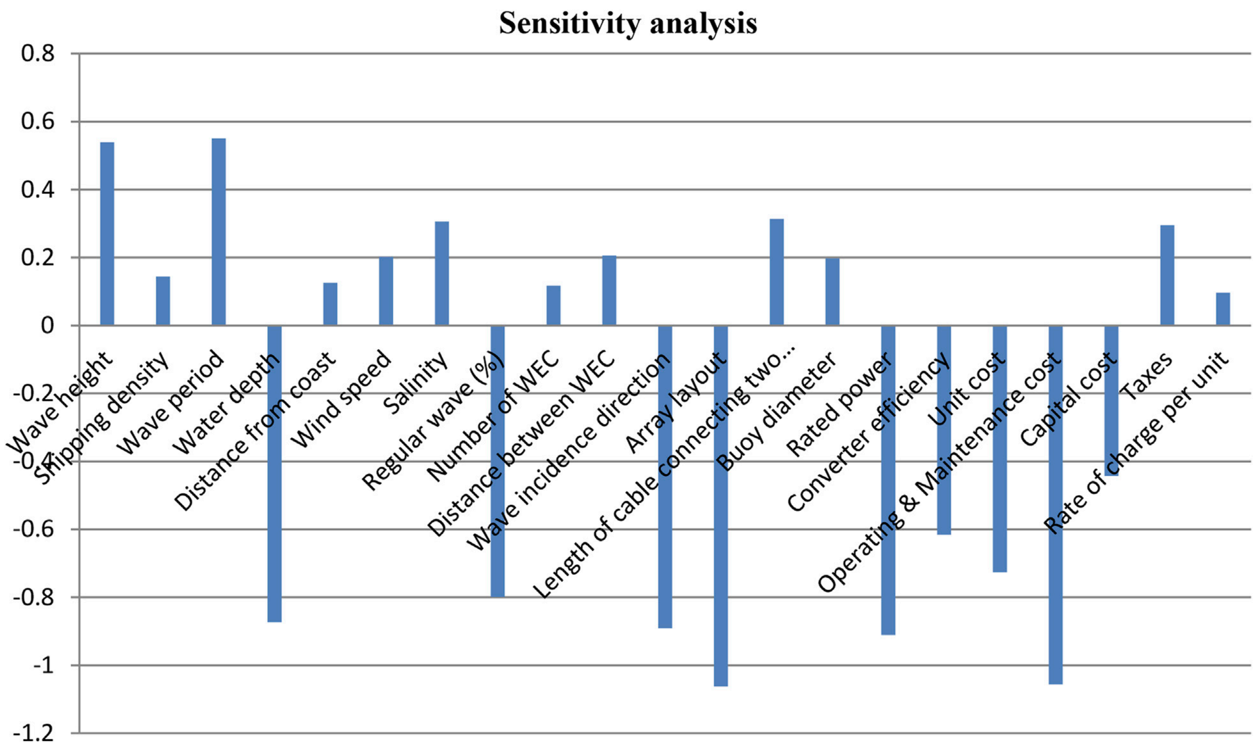

FIGURE 4
Figure depicting the input variable's sensitivity analysis.

distance from the coast, wind speed, salinity, regular wave, number of WECs, the distance between WECs, wave incidence direction, array layout, length of cable connecting to shore, buoy diameter, rated power, converter efficiency, unit cost, operating and maintenance costs, capital costs, taxes and rate of energy charge per unit) there is a change in output, which depicts the sensitivity of the model with respect to each of its inputs in Figure 4. The most sensitive parameter was wave period, and the least sensitive was array layout.

6 Conclusion

The goal of this research is to evaluate the likelihood of wave energy farms failing. In this case, 12 alternative models were created using MCDM approaches and polynomial neural networks. Each model's performance was estimated using performance indicators such as RMSE, MAE, r, and PBIAS. The model with the best performance efficiency was used to forecast the chance of failure. The selected model was also utilized to determine the likelihood of failure in five areas along the Indian coastal strip. The length of the cable connecting the converter (as determined by the X and P chart methods), the distance between WEC (as determined by the R Chart method), and converter efficiency (as determined by the citation frequency) were found to be the most important parameters in terms of failure probability.

Among the 12 models, the 21ANG1 developed model was found to have the highest performance efficiency (18.959). According to the sensitivity analysis results, the sensitivity and weight of importance of the variables are in exact coherence. The case study results show that the Chennai region has the highest failure probability compared to the other four regions, whereas the Kikanada coastal belt has the lowest chance of failure. This means that farms installed in the Kikanada region have the potential for higher conversion efficiency than in the Chennai region. Although the model has some drawbacks, such as if the method of ranking or decision making is changed, then the importance of the parameter may also change, and this will also impact the results. Again, the selected factors may also change if more resources are analyzed**.** Such drawbacks can be compensated for if specific policies are initiated so that uniformity among all the feasibility methods can be maintained.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/Supplementary Material.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

Acknowledgments

The authors thank the support of the National Research and Development Agency of Chile (ANID), ANID/Fondap/15110019.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2022.1009987/full#supplementary-material

References

Abanades, J., Greaves, D., and Iglesias, G. (2014). Wave farm impact on the beach profile: A case study. *Coast. Eng.* 86, 36–44. doi:10.1016/j.coastaleng.2014.01.008

Allen, T. T. (2006). *Introduction to engineering statistics and six sigma: Statistical quality control and design of experiments and systems.* Springer Science & Business Media.

Aragonés-Beltrán, P., Chaparro-Gonzalez, F., Pastor-Ferrando, J. P., and Pla-Rubio, A. (2014). An AHP (Analytic Hierarchy Process)/ANP (Analytic Network Process)-based multi-criteria decision approach for the selection of solar-thermal power plant investment projects. *Energy* 66, 222–238. doi:10.1016/j.energy.2013.12.016

Bódai, T., and Srinil, N. (2015). Performance analysis and optimization of a box-hull wave energy converter concept. *Renew. Energy* 81, 551–565. doi:10.1016/j.renene.2015.03.040

Brooke, J. (2003). *Wave energy conversion*, 6. Elsevier.

Buckley, J. J. (1985). Fuzzy hierarchical analysis. *Fuzzy sets Syst.* 17 (3), 233–247. doi:10.1016/0165-0114(85)90090-9

Carrasco, A., Ferreira, O., Matias, A., and Freire, P. (2012). Flood hazard assessment and management of fetch-limited coastal environments. *Ocean Coast. Manag.* 65, 15–25. doi:10.1016/j.ocecoaman.2012.04.016

Chang, D.-Y. (1996). Applications of the extent analysis method on fuzzy AHP. *Eur. J. operational Res.* 95 (3), 649–655. doi:10.1016/0377-2217(95)00300-2

Chen, M.-F., Tzeng, G.-H., and Ding, C. G. (2008). Combining fuzzy AHP with MDS in identifying the preference similarity of alternatives. *Appl. Soft Comput.* 8 (1), 110–117. doi:10.1016/j.asoc.2006.11.007

Cheng, Y., Chen, X., Dai, S., Ji, C., and Cocard, M. (2021). Wave energy extraction for an array of dual-oscillating wave surge converter with different layouts. *Appl. Energy* 292, 116899. doi:10.1016/j.apenergy.2021.116899

Chiu, Y.-C., Chen, B., Shyu, J. Z., and Tzeng, G. H. (2006). An evaluation model of new product launch strategy. *Technovation* 26 (11), 1244–1252. doi:10.1016/j.technovation.2005.09.002

Choupin, O., Pinheiro Andutta, F., Etemad-Shahidi, A., and Tomlinson, R. (2021). A decision- making process for wave energy converter and location pairing. *Renew. Sustain. Energy Rev.* 147, 111225. doi:10.1016/j.rser.2021.111225

Despotovic, M., Nedic, V., Despotovic, D., and Cvetanovic, S. (2016). Evaluation of empirical models for predicting monthly mean horizontal diffuse solar radiation. *Renew. Sustain. Energy Rev.* 56, 246–260. doi:10.1016/j.rser.2015.11.058

Duncan, A. J. (1956). The economic design of | barX charts used to maintain current control of a process. *J. Am. Stat. Assoc.* 51 (274), 228–242. doi:10.2307/2281343

Gatzert, N., and Kosub, T. (2016). Risks and risk management of renewable energy projects: The case of onshore and offshore wind parks. *Renew. Sustain. Energy Rev.* 60, 982–998. doi:10.1016/j.rser.2016.01.103

Ghosh, S., Chakraborty, T., Saha, S., Majumder, M., and Pal, M. (2016). Development of the location suitability index for wave energy production by ANN and MCDM techniques. *Renew. Sustain. Energy Rev.* 59, 1017–1028. doi:10.1016/j.rser.2015.12.275

Gray, J., Chen, J., Hearn, T., Hendricks, E. S., Lavelle, T. M., and Martin, J. R. (2016). "Thermodynamics of gas turbine cycles with analytic derivatives in OpenMDAO," in Proceeding of the 57th AIAA/ASCE/AHS/ASC Structures, Structural Dynamics, and Materials Conference, San Diego, California, USA, January 2016 (IEEE).

Greaves, D., Conley, D., Magagna, D., Aires, E., Chambel Leitao, J., Witt, M., et al. (2016). Environmental impact assessment: Gathering experiences from wave energy test centres in europe. *Int. J. Mar. Energy* 14, 68–79. doi:10.1016/j.ijome.2016.02.003

Guanche, R., de Andres, A., Simal, P., Vidal, C., and Losada, I. (2014). Uncertainty analysis of wave energy farms financial indicators. *Renew. Energy* 68, 570–580. doi:10.1016/j.renene.2014.02.046

Gupta, H. V., Sorooshian, S., and Yapo, P. O. (1999). Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. *J. Hydrol. Eng.* 4 (2), 135–143. doi:10.1061/(asce)1084-0699(1999)4:2(135)

Hmd, A., and Wu, F. (2011). Support vector machine approach to for longitudinal dispersion coefficients in streams. *Appl. Soft Comput.* 11 (2), 2902–2905.

Ivakhnenko, A. (1971). Polynomial theory of complex systems. *IEEE Trans. Syst. Man. Cybern.* SMC-1, 364–378. doi:10.1109/tsmc.1971.4308320

Kasirian, M. N., and Yusuff, R. M. (2010). Application of AHP and ANP in supplier selection process-a case in an automotive company. *Int. J. Manag. Sci. Eng. Manag.* 5 (2), 125–135. doi:10.1080/17509653.2010.10671100

Katsaprakakis, D. A., and Christakis, D. G. (2014). Seawater pumped storage systems and offshore wind parks in islands with low onshore wind potential. A fundamental case study. *Energy* 66, 470–486. doi:10.1016/j.energy.2014.01.021

Köne, A. Ç., and Büke, T. (2007). An Analytical Network Process (ANP) evaluation of alternative fuels for electricity generation in Turkey. *Energy Policy* 35 (10), 5220–5228. doi:10.1016/j.enpol.2007.05.014

Lemke, F., and Müller, J.-A. (2003). Self-organising data mining. *Syst. Anal. Model. Simul.* 43 (2), 231–240. doi:10.1080/0232929031000136135

Luo, Z.-m., Zhou, J. z., Zheng, L. p., Mo, L., and He, Y. y. (2010). A TFN–ANP based approach to evaluate Virtual Research Center comprehensive performance. *Expert Syst. Appl.* 37 (12), 8379–8386. doi:10.1016/j.eswa.2010.05.044

Mackay, E. B., Bahaj, A. S., and Challenor, P. G. (2010). Uncertainty in wave energy resource assessment. Part 2: Variability and predictability. *Renew. energy* 35 (8), 1809–1819. doi:10.1016/j.renene.2009.10.027

Nariman-Zadeh, N., Darvizeh, A., Darvizeh, M., and Gharababaei, H. (2002). Modelling of explosive cutting process of plates using GMDH-type neural network and singular value decomposition. *J. Mater. Process. Technol.* 128 (1), 80–87. doi:10.1016/s0924-0136(02)00264-9

Noori, N., and Kalin, L. (2016). Coupling SWAT and ANN models for enhanced daily streamflow prediction. *J. Hydrology* 533, 141–151. doi:10.1016/j.jhydrol.2015.11.050

Pascual-González, J., Guillen-Gosalbez, G., Mateo-Sanz, J. M., and Jimenez-Esteller, L. (2016). Statistical analysis of the EcoInvent database to uncover relationships between life cycle impact assessment metrics. *J. Clean. Prod.* 112, 359–368. doi:10.1016/j.jclepro.2015.05.129

Rotty, R. M. (1979). Growth in global energy demand and contribution of alternative supply systems. *Energy* 4 (5), 881–890. doi:10.1016/0360-5442(79)90019-7

Saaty, T. L. (1999). "Fundamentals of the analytic network process," in *Proceedings of the 5th international symposium on the analytic hierarchy process*.

Saaty, T. L. (2004). Fundamentals of the analytic network process—dependence and feedback in decision-making with a single network. *J. Syst. Sci. Syst. Eng.* 13 (2), 129–157. doi:10.1007/s11518-006-0158-y

Saaty, T. L. (1980). *The analytic hierarchy process: Planning, priority setting, resources allocation*. New York: McGraw.

Saniga, E. M. (1989). Economic statistical control-chart designs with an application to $\bar{X}$ and R charts. *Technometrics* 31 (3), 313–320. doi:10.2307/3556141

Sharkey, F., Bannon, E., Conlon, M., and Gaughan, K. (2013). Maximising value of electrical networks for wave energy converter arrays. *Int. J. Mar. Energy* 1, 55–69. doi:10.1016/j.ijome.2013.06.002

Shaw, K., Shankar, R., Yadav, S. S., and Thakur, L. S. (2012). Supplier selection using fuzzy AHP and fuzzy multi-objective linear programming for developing low carbon supply chain. *Expert Syst. Appl.* 39 (9), 8182–8192. doi:10.1016/j.eswa.2012.01.149

Tan, P.-N., Steinbach, M., and Kumar, V. (2006). *Introduction to data mining*, 1. Boston: Pearson Addison Wesley.

Tan, X., Ma, K., Guo, W., and Huang, T. (2007). "An application of ANP with benefits, opportunities, costs and risks in supplier selection: A case study in a diesel engine manufacturing firm," in Proceeding of the Automation and Logistics, 2007 IEEE International Conference on, September 2007 (IEEE).

Velasquez, M., and Hester, P. T. (2013). An analysis of multi-criteria decision-making methods. *Int. J. Operations Res.* 10 (2), 56–66.

Willmott, C. J., and Matsuura, K. (2005). Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Clim. Res.* 30 (1), 79–82. doi:10.3354/cr030079

Xiao, J., He, C., and Jiang, X. (2009). Structure identification of Bayesian classifiers based on GMDH. *Knowledge-Based Syst.* 22 (6), 461–470. doi:10.1016/j.knosys.2009.06.005

Yang, Y. Q., Wang, S. Q., Dulaimi, M., and Low, S. P. (2003). A fuzzy quality function deployment system for buildable design decision-makings. *Automation Constr.* 12 (4), 381–393. doi:10.1016/s0926-5805(03)00002-5