Received: 7 July 2020 | Revised: 16 January 2021 | Accepted: 15 February 2021

DOI: 10.1049/rpg2.12168

IET Renewable Power Generation

The Institution of Engineering and Technology WILEY

ORIGINAL RESEARCH PAPER

A new extension of hesitant fuzzy set: An application to an offshore wind turbine technology selection process

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Funding information
National Research Foundation of Korea; Korean Government (MSIT), Grant/Award Number: NRF-2019R1G1A1006073

Abstract

Wind energy is an energy source that is naturally clean, safe and cheap. It comes from a variety of sources. The electric energy generated by a wind turbine manifests as kinetic energy throughout the earth. The energy received from the wind is clean and is permanently available and can be generated forever. Turbine characteristics also have an impact on wind energy production. The turbine properties within a wind farm are important in estimating the load on power generation and wind turbine energy. The amount of energy released is calculated according to the type of the turbine model applied. In many situations, the choices of turbine model can incur various vague and complicated hesitation situations. To manage this situation, a hesitant fuzzy set with the Multi Criteria Decision Making (MCDM) is used. In the present research, the newly proposed Normal Wiggly Hesitant Fuzzy-Criteria Importance Through Intercriteria Correlation (NWHF-CRITIC) and Normal Wiggly Hesitant Fuzzy-Multi Attribute Utility Theory (NWHF-MAUT) methods were employed to rank turbine models based on quality, power level, voltage, and capacity. As part of this process, the NWHF method was utilized to extract and gather deeper information from the decision-makers.

1 | INTRODUCTION

Energy is derived from the *panchabhutas* or the five classical elements ($\sigma\tau\omega\iota\chi\epsilon\iota\omega\nu$) that includes water, land, air, sky and fire. However, wind is a perpetually available energy. Even though the sun is the ultimate source of energy, in darkness, wind will yet be available. Wind can drive wind turbines to correct for power shortage situations. In most countries, the amount of energy generated by wind turbines exceeds the amount of energy that can be obtained from other renewable energy sources. Wind energy is considered to be one of the best new sources of renewable energy for control and mitigation of climate change and global warming. In Figure 1, the structure of a wind turbine is shown.

Wind power generation in India has increased many folds in recent years. The installed wind capacity as of 31 March 2019 was 36.625 GW. India has the fourth largest wind power installation in the world. The total wind power generation in India reached 62.03TWh in 2018–2019. This is considered to be 4.06% of the total power generation whereas in the world it is 5.29%. Wind power installation is increasing at a rate of 10% per year.

The MCDM method is applied to determine the correct solution to the problem of the best turbine selection and installation. The decision made by the MCDM method is subjected to various tests. Although there are many different mathematical models, the solution adopted by the MCDM model has a decisive role. Here, with the use of NWHF, the deeper and

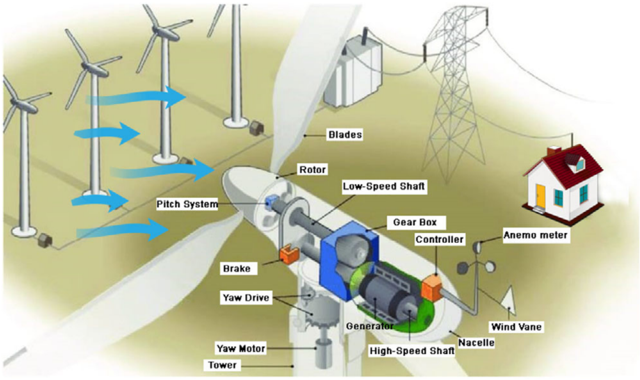


FIGURE 1 The structure of the wind turbine model

hesitant ideas of the decision-makers can be recorded and assessed. Specifically, the NWHF is used to express the vagueness and hesitation of decision-makers. In this paper, we propose the NWHF-CRITIC method to determine the criteria weights. The CRITIC method, in fact, is considered to be the best weight finding method. In addition, the NWHF-MAUT method is used to select the best of the alternative among the turbine models that are sorted by rank based on their characteristics.

With MCDM methods, some researchers have selected the AHP methodology for choosing wind turbine design and systems (Sagbansua and Balo, 2017) [1]. Also, it is used to identify suitable locations for wind farms (Ali et al., 2018) [2]. Indeed, when selecting the wind system, the location is considered as a very important factor. Wind farms in the west, particularly in the United States, have chosen the GIS-based dispatch and the AHP scale system to help the government to establish windmills and explain their benefits. Further, the type-2 fuzzy set theory with the AHP methodology has been employed to help decision-makers deal with complex factors when selecting environmental friendly wind turbine sites (Ayodele et al., 2018) [3]. Wind farm sites selected based on GPS systems typically are on beaches in countries like Saudi Arabia. In a complex environment, MCDM proceeds by evaluating each of the criteria using a variety of weight finding methods, such as entropy, and weight sum (Rehman and Khan, 2017) [4] along with several ranking methods such as, AHP, TOPSIS, VIKOR, MOORA, and others (Baseer, et al., 2017) [5]. These site selection methods are based not only on fuzzy MCDM, but also other accounting processes, such as OWA. In small countries like Oman for example, historical sites have been analyzed using the above methods (Yahyai et al., 2012) [6]. Thus, the overall capacity of a wind farm is assessed through the AHP system along with social, economic, location, and environmental factors. Some studies have emphasized islands as suitable locations for wind power installations. Meanwhile, in many countries too, offshore sites are important locations. Among the forms of renewable energy, wind is at the forefront of new development. The study about wind technologies have been carried out in several countries, for example, Iran, the use of MCDM with GPS technology search of new wind energy is part of Western Iran's 28% availability (Noorallahiet al., 2016) [7]. Turkey's wind energy and wind energy projects have been explored and elaborated in this study (Dursun et al., 2014) [8]. Wind turbine models in several technologies and structural infrastructures are essential for locating many parts of the world depending on onshore and offshore. For these, some researchers have analyzed and evaluated the selective compromise wind turbine model by the TOPSIS method in their articles (Kolious et al., 2016) [9]. In developing countries such as China, low-cost wind power generation has been studied. In summary, wind farm performance is ranked with the AHP method (Lee et al., 2009) [10]; meanwhile, to remove ambiguity in critical situations for decision-makers in their analysis of windmill alternatives, fuzzy set theory, Intuitionistic fuzzy set theory, and Interval-valued intuitionistic fuzzy set theory are used (Onar et al., 2015) [11] (Aikhude, 2018) [12].

MCDM is essential to Operations Research and the resolution of problems in critical decision-making situations. For use with the MCDM method (Bhole and Deshmukh, 2018) [13] have proposed several methods, including MAUT/MAVT, TOPSIS, ELECTRE, PROMOTHEE, AHP, and GP. Degirmenci et al., (2018) [14] have identified geographic information systems using the MCDM method. Diemuodeke et al. (2018) [15] illustrated by MCDM an energy system map for home energy storage and backup diesel generators. Farhadinia et al. (2018) [16] introduced the concept of entropy measure of interval-transformed Hesitant Fuzzy Linguistics. (Freitas et al., 2013) [17] considered the MAUT method as an extension of the AHP method. Garg et al. (2015) [18] identified an entropy based weight finding method using the MCDM approach. Gocmen et al. (2016) [19] derived an IT estimator approach for an individual turbine. The main features and wind power generation strategies of wind farms are described by Gocmen et al. (2016) [20]. Haghighat Mamaghani et al. (2016) [21] described the use of photovoltaic panels, wind turbines and diesel generators in a unique power generation system for rural electrification. Kinzel et al., (2012) [22] analyzed the characteristics of vertical-axis wind turbines. Lee et al. (2012) [23] evaluated the wind turbine model means of MCDM. Mahdy and Bahaj (2018) [24] proposed some offshore wind turbine models. Mollerstrom et al. (2019) [25] summarized and introduced an all vertical axis wind turbine project of 100 KW capacity. Grid code technical requirements for linking wind farms to electric power systems have been published by Tsili and Papathanassiou in 2009 [26].

A probabilistic fuzzy technique was defined by Liu and Li (2005) [27]. In this MAUT method, the evaluation of criteria is carried out by importance of criteria (Velasquez and Hester, 2013) [28]. An improvised MAUT theory was introduced by Dyer et al. (1992) [29]. The popular weight finding method known as Criteria Importance Through Inter-Criteria Correlation (CRITIC) was introduced by Diakoulaki et al. (1995) [30]. This method provides the compact structure of a selected problem. Many researchers have used this CRITIC method in real life applications. For example, Madic and Radovanovic used it when calculating the weights of criteria (2015) [31]. Kazan and Ozdemir (2014) [32] used the CRITIC method to calculate stock trading. Narayanamoorthy et al. (2019) [33]utilized the MCDM approach to select reclaimed water. Narayanamoorthy et al. (2019) [34] employed the VIKOR method for industrial robot selection. Ren et al. (2017) [35] introduced a new extension of the hesitant fuzzy sets, namely, the dual hesitant fuzzy set. Ren et al. (2018) [36] introduced as the extension of the hesitant fuzzy set, the NWHFs. Rodriguez et al. (2012) [37] applied the linguistic hesitant fuzzy term to decision making. Torra (2010) [38] introduced the hesitant fuzzy set and adapted it for decision making (Torra and Narukawa, 2009) [39]. Ye (2014) [40] addressed a new approach entailing the use of a correlation coefficient with dual hesitant fuzzy set. Haaren, R.V. Fthenakis, V (2011) discussed about wind farm selection using SMCA [41]. Tegou, L. I et al.(2010) analysed the environmental management framework for wind farm siting [42].

In the present study, we attempt to fill the evident research gap by investigating the process of the selection of the best offshore wind turbine model. Many researchers have expressed their opinion on onshore wind turbine models. The key factors leading to our research are the following.

- MCDM can be used as a mathematical logical method of solving problems characterized by hesitations of decision-makers in choosing the best alternative from among a given set. Most of the MCDM problems in the ranking process are based on criteria evaluation. Generally, many complex factors and hesitations may be involved in examining and choosing wind turbine attributes.
- The MCDM approach has not yet been applied as a mathematical model for offshore wind turbine model selection. This technique can be used to select the most suitable model for offshore wind farms; also, it can provide a solution for the selected application after it has been subjected to different classifications.
- A lot of research has been done on the fuzzy set, intuitionistic fuzzy set and the hesitant fuzzy set. Here, we chose an offshore wind turbine model with NWHFs. Also, we used both CRITIC and MAUT in NWHFs. The CRITIC method uses the standard deviation and correlation coefficient to determine the weights of the criteria. MAUT is also one of the best outranking methods among the MCDM techniques.
- Offshore wind turbine models are generally capable of producing large amounts of electricity. Therefore, we chose this type of wind turbine model for our application in the present research.
- The new extension of Hesitant Fuzzy Set, NWHF, is used to resolve the hesitation thoughts and confusion of decision-makers. Here, the NWHF helps to rectify the decision-makers' deep and complex hesitations. For this scenario, we selected five wind turbine models, their selected criteria, and also the amounts of power generated.

  The main motivation of this research:

- Our main motivation for the present research is to choose the best high power generation model for an offshore wind farm and also to introduce the outranking system to NWHFs that helps to resolve the deep hesitation of decision-makers when selecting the best offshore wind turbine model.
- We also describe the offshore wind turbine models and their characteristics according to voltage, hub height and rotor blade details.
- Several criteria have been used to evaluate the accuracy of offshore wind turbines and characterize the analytical results.

  We introduced new mathematical logic systems, namely, the NWHF-CRITIC and the NWHF-MAUT methods, to select the most suitable wind turbine model.
- We also introduce a new, modified score function for NWHFs. This function is used to calculate the average values of our elements in NWHFs.
- Our sensitivity analysis of the wind turbine selection process shows how the results change according to a change in the weight values.
- The solution is analyzed based on the operation and maintenance cost, cost factor, reliability, and technical characteristics. These criteria are addressed by NWHFs, an extension of the HFMCDM system. The NWHFs make the best decision by clarifying the deep and hesitant thoughts of the decision-makers.

The paper is organized as follows. In Section 2, the preliminaries of mathematical modeling and basic operations are given. In Section 3, the theorem and proof of the proposed method is provided. In addition to these, the technologies of the various wind turbine models and their properties are presented. In Section 4, new methods of mathematical logic, the NWHF-CRITIC and the NWHF-MAUT methods, are introduced. In Section 5, those methods are evaluated by numerical analysis. In Section 6, the selected methods are discussed. In Section 7, the entropy weighted and methods are compared. In Section 8, a sensitivity analysis on the selected application is performed. Finally, Section 9 draws conclusions.

2 | PRELIMINARIES

In this section, we discuss some preliminaries of the proposed NWHF-critic and the NWHF-MAUT method.

Definition 2.1. Let ϑ be a finite hesitant fuzzy reference set of [0, 1]. The form of a hesitant fuzzy set is as follows.

$$H = \left\{ < \eta, \mathfrak{h}_H(\eta) / \eta \in \vartheta \right\},$$

where $\mathfrak{h}_H(\vartheta)$ is a set of numbers from [0,1]. The possible membership degrees of the element $\eta \in \vartheta$ to the set H and $\mathfrak{h}_H(\eta)$ are called the hesitant fuzzy elements [38].

Definition 2.2. An NWTHF, $\tilde{A}$ on z is in terms of a function $f_{\tilde{A}}(\mathfrak{z})$ will return various HWTFNs as [36]:

$$\tilde{A}_{NW} = \left\{ \left\langle \mathfrak{z}, f_{\tilde{A}}(\mathfrak{z}) \right\rangle \mathfrak{z} \in Z \right\},$$

where $f_{\tilde{A}}(\mathfrak{z})$ is called an HTFE and it will give various numerable NWTHFNs. Further,

$$f_{\tilde{A}}(\mathfrak{z}) = \left\{ \delta_i = \left(\delta_i^L, \delta_i^M, \delta_i^U \right) / \delta_i \in f_{\tilde{A}}(\mathfrak{z}), \quad i = 1, 2, \dots, \# f_{\tilde{A}}(\mathfrak{z}) \right\},$$

where δ_i are triangular NWHFs and $\delta_i^L \leq \delta_i^M \leq \delta_i^U$. $\# f_{\tilde{A}}(\mathfrak{z})$ is the number of triangular NWHFNs. Then, NWTHFs satisfy the condition of membership function, $\varphi_{\tilde{\delta}} : R \to [0, 1]$ given by:

$$\varphi_{\tilde{\delta}}(z) = \begin{cases} \dfrac{z - \delta^L}{\delta^M - \delta^L} & \mathrm{s} \in [\delta^{\mathrm{L}}, \theta^{\mathrm{M}}] \\ \dfrac{z - \delta^U}{\delta^M - \delta^U} & \mathrm{s} \in [\delta^{\mathrm{M}}, \delta^{\mathrm{U}}]' \\ 0 & \text{otherwise} \end{cases}$$

where, δ^L, δ^M and δ^U represent the lower, middle, upper value of NWTHFs, respectively.

Definition 2.3. Some preliminary operations in NWTHFEs are defined [36]. Here, we choose two NWTHFEs as $f^*_{\tilde{A}}$ and $f^{*1}_{\tilde{A}}$. Then,

(1) $f^*_{\tilde{A}} \oplus f^{*1}_{\tilde{A}} = \{(\delta^L_1 + \delta^L_2 - \delta^L_1\delta^L_1, \delta^M_1 + \delta^M_2 - \delta^M_1\delta^M_1, \delta^U_1 + \delta^U_2 - \delta^U_1\delta^U_2)/\delta_1 \in f^*_{\tilde{A}}, \delta_2 \in f^{*1}_{\tilde{A}}\}$

(2) $f^*_{\tilde{A}} \otimes f^{*1}_{\tilde{A}} = \{\delta^L_1\delta^L_2, \delta^M_1\delta^M_2, \delta^U_1\delta^U_2/\delta_1 \in f^*_{\tilde{A}}, \delta_2 \in f^{*1}_{\tilde{A}}\}$

(3) $(f^*_{\tilde{A}})^\lambda = \{((\delta^L_1)^\lambda, (\delta^M_1)^\lambda, (\delta^U_1)^\lambda)/\delta_1 \in f^*_{\tilde{A}}\}\ \lambda > 0.$

(4) $\lambda f^*_{\tilde{A}} = \{(1 - (1 - \delta^L_1)^\lambda, 1 - (1 - \delta^M_1)^\lambda, 1 - (1 - \delta^U_1)^\lambda)/\delta_1 \in f^*_{\tilde{A}}\}\ \lambda > 0.$

Definition 2.4. Let $h = \alpha_1, \alpha_2 \dots, \alpha_{\#h}$ be the NWHFE [36]. Then the mean value is

$$\bar{h} = \frac{1}{\#h}\sum_{i=1}^{\#h}\alpha_i.$$

Definition 2.5. Let $h = \alpha_1, \alpha_2 \dots, \alpha_{\#h}$ be the NWHFE. By the mean value definition, we find the standard deviation of h as [36],

$$\sigma_h = \sqrt{\frac{1}{\#h}\sum_{i=1}^{\#h}(\alpha_i - \bar{h})^2}.$$

Here, $\tilde{f} : h \to [0, \sigma_h]$ satisfies $\tilde{\alpha}_i = \sigma_h \in \frac{(\alpha_i - \bar{h})^2}{2\sigma_h^2}$. The interval range of α_i is $[\alpha_i - \tilde{f}(\alpha_i), \alpha_i + \tilde{f}(\alpha_i)]$

Definition 2.6. The degree of real preference h is [36],

$$rpd(\tilde{h}) = \begin{cases} \displaystyle\sum_{i=1}^{\#\tilde{h}}\tilde{\alpha}_i\left(\frac{\#\tilde{h} - i}{\#\tilde{h} - 1}\right) & \text{if h} < 0.5 \\ 1 - \displaystyle\sum_{i=1}^{\#\tilde{h}}\tilde{\alpha}_i\left(\frac{\#\tilde{h} - i}{\#\tilde{h} - 1}\right) & \text{if h} > 0.5 \\ 0.5 & \text{if h} = 0.5 \end{cases}. \tag{1}$$

Definition 2.7. Let $D = \{(s, h(s))/s \in S\}$ be a hesitant fuzzy set on the reference set S [36]. Then, D can be denoted as:

$$D_{NWHF} = \{\langle s, h(s), \varphi(h(s))\rangle s \in S\}, \tag{2}$$

where $h(s)$ is the hesitant fuzzy element in the hesitant fuzzy set D. Here, $h(s)$ represents the membership value of NWHFs.

$$\begin{aligned} \varphi(h(s)) = \{\tilde{\delta}_1, \tilde{\delta}_2 \dots, \tilde{\delta}_{\#h(s)}\}, \tilde{\delta}_1 &= \{\delta^L_i, \delta^M_i, \delta^U_i\} \\ &= \{\max(\delta_i - \tilde{f}(\delta_i), 0), (2rpd(\tilde{h}(s)) - 1)\tilde{f}(\delta_i) + \delta_i, \\ &\min(\delta_i + f(\tilde{\delta}_i), 1)\}, \end{aligned}$$

δ_i is the value of $h(s)$. In the above equation, δ_i is the wiggly element in $\tilde{f}(\delta_i)$. Here, real preference degree of $h(s)$ is denoted by $rpd(\tilde{h}(s))$.

Definition 2.8. For NWHFE, let $\langle h, \varphi(h)\rangle$ be the membership mean value denoted as $\bar{h}$ and σ_h representing the standard deviation of NWHFs [36].

$$S_{NWHF}(\langle h, \varphi(h)\rangle) = \left[\alpha(\bar{h} - \sigma h) + (1 - \alpha)\left(\frac{1}{\#h}\sum_{i=1}^{\#h}\tilde{\bar{\delta}}_i - \sigma_{\bar{\delta}_i}\right)\right],$$

where,

$$\tilde{\bar{\delta}}_i = \frac{\delta^L_i + \delta^M_i + \delta^U_i}{3},$$

$$\sigma_{\tilde{\bar{\delta}}_i} = \sqrt{(\delta^L_i)^2 + (\delta^M_i)^2 + (\delta^U_i)^2 - (\delta^L_i\delta^M_i) - (\delta^L_i\delta^U_i) - (\delta^M_i\delta^U_i)}.$$

Here, $\alpha \in (0, 1)$.

In the next theorem, we derive the properties of some operations in NWHFs. We follow the operation of the NWHFEs as:

$$\begin{aligned} &\langle h_1, \varphi(h_1)\rangle\hat{\oplus}\langle h_2, \varphi(h_2)\rangle\hat{\oplus}\langle h_3, \varphi(h_3)\rangle\hat{\oplus}\langle h_4, \varphi(h_4)\rangle \\ &\quad = \{\big(\cup_{\nu_1\in h_1, \nu_2\in h_2, \nu_3\in h_3, \nu_4\in h_4} \\ &\nu_1 + (\nu_2 + \nu_3 + \nu_4 - \nu_2\nu_3\nu_4) \\ &\qquad - \nu_1(\nu_2 + \nu_3 + \nu_4 - \nu_2\nu_3\nu_4), \big) \\ &\big(\cup_{\nu_1\in\varphi(h_1), \nu_2\in\varphi(h_2), \nu_3\in\varphi(h_3)}\nu_1 \oplus \nu_2 \oplus \nu_3 \oplus \nu_4\big)\} \\ &\quad = \{\big(\cup_{\nu_1\in h_1, \nu_2\in h_2, \nu_3\in h_3, \nu_4\in h_4}((\nu_1 + \nu_2 + \nu_3 - \nu_1\nu_4) \\ &\qquad + \nu_4 - (\nu_1 + \nu_2 + \nu_3 - \nu_1\nu_4)\nu_4)\big) \\ &\big(\cup_{\tilde{\nu_1}\in\varphi(h_1), \nu_2\in\varphi(h_2), \nu_3\in\varphi(h_3), \tilde{\nu_4}\in\varphi(h_4)}\big) \\ &\tilde{\nu_1} \oplus \tilde{\nu_2} \oplus \tilde{\nu_3} \oplus \tilde{\nu_4}\} \\ &\quad = \langle h_1, \varphi(h_1)\rangle\hat{\oplus}\langle h_2, \varphi(h_2)\rangle\hat{\oplus}\langle h_3, \varphi(h_3)\rangle\hat{\oplus}\langle h_4, \varphi(h_4)\rangle. \end{aligned}$$

Theorem 2.1. *Let* $\langle h_1, \varphi(h_1)\rangle, \langle h_2, \varphi(h_2)\rangle, \langle h_3, \varphi(h_3)\rangle$ *and* $\langle h_4, \varphi(h_4)\rangle$ *be four NWHFEs. Then,*

1. $$\lambda\left(\langle h_1, \varphi(h_1)\rangle \hat{\oplus} \langle h_2, \chi(h_2)\rangle \hat{\oplus} \langle h_3, \chi(h_3)\rangle\right) = \lambda\langle h_1, \varphi(h_1)\rangle \hat{\oplus} \lambda\langle h_2, \varphi(h_2)\rangle \hat{\oplus} \lambda\langle h_3, \varphi(h_3)\rangle.$$

2. $$(\langle h_1, \varphi(h_1)\rangle \hat{\otimes} \langle h_2, \chi(h_2)\rangle \hat{\otimes} \langle h_3, \varphi(h_3)\rangle)^{\lambda} = (\langle h_1, \varphi(h_1)\rangle)^{\lambda} \hat{\otimes} (\langle h_2, \varphi(h_2)\rangle)^{\lambda} \hat{\otimes} (\langle h_3, \varphi(h_3)\rangle)^{\lambda}.$$

3. $$((\langle h_1, \varphi(h_1)\rangle)^{\lambda_1})^{\lambda_2} = (\langle h_1, \varphi(h_1)\rangle)^{\lambda_1 \lambda_2}, \lambda_1 > 0, \lambda_2 > 0.$$

Proof.

(1)
$$\begin{aligned}
&\Rightarrow \lambda(\langle h_1, \varphi(h_1)\rangle \hat{\oplus} \langle h_2, \varphi(h_2)\rangle \hat{\oplus} \langle h_3, \varphi(h_3)\rangle) \\
&\quad = \left(\cup_{\nu_1 \in h_1, \nu_2 \in h_2, \nu_3 \in h_3}, 1 - \left(1 - (\nu_1 + \nu_2 + \nu_3 - \nu_1\nu_4)\right.\right. \\
&\qquad \left.\left. + \nu_4 - (\nu_1 + \nu_2 + \nu_3 - \nu_1\nu_2\nu_3)\right)^{\lambda}\right), \\
&\qquad \left(\cup_{\tilde{\nu}_1 \in \varphi(h_1) \tilde{\nu}_2 \in \varphi(h_2) \tilde{\nu}_3 \in \varphi(h_3)} \lambda(\tilde{\nu}_1 \oplus \tilde{\nu}_2 \oplus \tilde{\nu}_3)\right) \\
&= \{\left(\cup_{\nu_1 \in h_1, \nu_2 \in h_2, \nu_3 \in h_3} 1 - (1 - \nu_1)^{\lambda}(1 - \nu_2)^{\lambda}(1 - \nu_3)^{\lambda}\right), \\
&\qquad \left(\cup_{\tilde{\nu}_1 \in \varphi(h_1) \tilde{\nu}_2 \in \varphi(h_2) \tilde{\nu}_3 \in \varphi(h_3)} \lambda\tilde{\nu}_1 \oplus \lambda\tilde{\nu}_2 \oplus \lambda\tilde{\nu}_3\right)\} \\
&= \{(\cup_{\nu_1 \in h_1, \nu_2 \in h_2, \nu_3 \in h_3} 1 - (1 - \nu_1)^{\lambda} \\
&\quad + 1 - (1 - \nu_2)^{\lambda} + 1 - (1 - \nu_3)^{\lambda}) \\
&\quad - ((1 - (1 - \nu_1)^{\lambda})(1 - (1 - \nu_2)^{\lambda}) \\
&\quad \times (1 - (1 - \nu_3)^{\lambda}), \lambda\tilde{\nu}_1 \oplus \lambda\tilde{\nu}_2 \oplus \lambda\tilde{\nu}_3)\} \\
&= \lambda\langle h_1, \varphi(h_1)\rangle \hat{\oplus} \lambda\langle h_2, \varphi(h_2)\rangle \hat{\oplus} \lambda\langle h_3, \varphi(h_3)\rangle.
\end{aligned}$$

(2)
$$\begin{aligned}
&\Rightarrow \left(\langle h_1, \varphi(h_1)\rangle \hat{\otimes} \langle h_2, \varphi(h_2)\rangle \hat{\otimes} \langle h_3, \varphi(h_3)\rangle\right)^{\lambda} \\
&= \left\{ \left(\cup_{\nu_1 \in h_1, \nu_2 \in h_2, \nu_3 \in h_3} (\nu_1\nu_2\nu_3)^{\lambda}\right), \right. \\
&\qquad \left. \left(\cup_{\tilde{\nu}_1 \in \varphi(h_1) \tilde{\nu}_2 \in \varphi(h_2) \tilde{\nu}_3 \in \varphi(h_3)} (\tilde{\nu}_1 \otimes \tilde{\nu}_2 \otimes \tilde{\nu}_3)\right) \right\} \\
&= \{\left(\cup_{\nu_1 \in h_1, \nu_2 \in h_2, \nu_3 \in h_3} \nu_1^{\lambda}\nu_2^{\lambda}\nu_3^{\lambda}\right), \\
&\qquad \left(\cup_{\tilde{\nu}_1 \in \varphi(h_1) \tilde{\nu}_2 \in \varphi(h_2) \tilde{\nu}_3 \in \varphi(h_3)} \tilde{\nu}_1{}^{\lambda}\tilde{\nu}_2{}^{\lambda}\tilde{\nu}_3{}^{\lambda}\right)\} \\
&= (\langle h_1, \varphi(h_1)\rangle)^{\lambda} \hat{\otimes} (\langle h_2, \varphi(h_2)\rangle)^{\lambda} \hat{\otimes} (\langle h_3, \varphi(h_3)\rangle)^{\lambda}.
\end{aligned}$$

(3)
$$\begin{aligned}
&\Rightarrow ((\langle h_1, \varphi(h_1)\rangle)^{\lambda_1})^{\lambda_2} \\
&= \{\left(\cup_{\nu_1 \in (h_1)} (\nu_1^{\lambda_1})^{\lambda_2}\right), \left(\cup_{\tilde{\nu}_1 \in \varphi(h_1)} (\tilde{\nu}_1{}^{\lambda_1})^{\lambda_2}\right)\} \\
&= \{\left(\cup_{\nu_1 \in (h_1)} \nu_1^{\lambda_1\lambda_2}\right), \left(\cup_{\tilde{\nu}_1 \in \varphi(h_1)} \tilde{\nu}_1{}^{\lambda_1\lambda_2}\right)\} \\
&= (\langle h_1, \varphi(h_1)\rangle)^{\lambda_1\lambda_2} \text{ where } \lambda_1, \lambda_2 > 0.
\end{aligned}$$

□

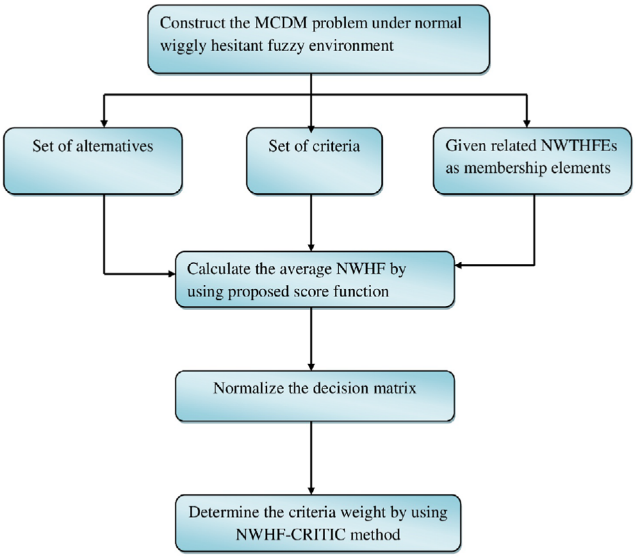


FIGURE 2 Procedure of the NWHF-CRITIC method

TABLE 1 NWHF decision matrix

	P_1	P_2	$\cdots$	P_n
Q_1	$\langle h_{11}, \eta(h_{11})\rangle$	$\langle h_{12}, \eta(h_{12})\rangle$	$\cdots$	$\langle h_{1n}, \eta(h_{1n})\rangle$
Q_2	$\langle h_{21}, \eta(h_{21})\rangle$	$\langle h_{22}, \eta(h_{22})\rangle$	$\cdots$	$\langle h_{2n}, \eta(h_{2n}),\rangle$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Q_m	$\langle h_{m1}, \eta(h_{m1})\rangle$	$\langle h_{m2}, \eta(h_{m2})\rangle$	$\cdots$	$\langle h_{mn}, \eta(h_{mn})\rangle$

3 | PROBLEM DESCRIPTION

3.1 | Algorithm for the proposed weight finding method (NWHF-CRITIC)

We propose a new outranking method and weight finding method for NWHFs. Here, we develop the NWHFs with the MCDM problem. Let $Q = \{Q_1, Q_2 \ldots, Q_m\}$ and $P = \{P_1, P_2 \ldots, P_n\}$ be two sets of m alternatives and n criteria, respectively.

Let us consider the performance of the alternatives $Q_i (i = 1, 2 \ldots, m)$ with respect to the criteria $P_j (j = 1, 2 \ldots, n)$ calculated by the NWHFE. The hierarchical structure of the proposed NWHF-MAUT is shown in Figure 2.

$$\tilde{h}_{ij} = \{\tilde{\eta}_{ij} \in \tilde{h}_{ij}\}, \tag{3}$$

$$\tilde{h}_{ij} = \{[\eta(h_{\eta_{ij}})]/\varphi(h_{\beta_{ij}}) \in \tilde{\beta}_{ij}\}. \tag{4}$$

Step 1:

Construct the NWHFDM following Table 1,

$$\tilde{H} = \tilde{h}_{ij} = [\tilde{h}_{ij}]_{m \times n} \tag{5}$$

$$= \{\tilde{\eta}_{ij} \in \tilde{h}_{ij}\} = \{\eta(h_{\eta_{ij}})/\eta(h_{\eta_{ij}}) \in \tilde{\eta}_{ij}\}.$$

Step 2:

Determine the score function in reference to NWHFE as,

$$S_{NW}(\langle h,\eta(h)\rangle) = \alpha(\bar{h}-\sigma_h) + (1-\alpha)\left(\frac{1}{h}\sum_{i=1}^{\#h}\tilde{\bar{v}} - \sigma_{\tilde{\bar{v}}_i}\right). \tag{6}$$

Step 3:

The normalization of the NWHDM matrix is calculated by using the equation

$$NWH_{ij}^{*} = \frac{h_{ij} - min(h_{ij})}{max(h_{ij}) - min(h_{ij})}. \tag{7}$$

The normalized performance of normal wiggly is NWH_{ij}^{*}. It is based on the i^{th} alternative and j^{th} criteria.

Step 4:

Standard deviation and correlation of criteria are used to find weights of the criteria. $W_{j(NW)}$s denote the normal wiggly DM weights and the calculation procedure is given as follows:

$$W_{j(NW)} = \frac{C_{j(NW)}}{\sum_{j=1}^{n} C_{j(NW)}}, \tag{8}$$

where the quantity of information about the criteria is $C_{j(NW)}$.

$$C_{j(NW)} = \sigma_j \sum_{j=1}^{n}(1 - r_{jj}). \tag{9}$$

Here, $\sigma_{j(NW)}$, r_{jj} is the standard deviation and the correlation between the two criteria, respectively.

3.2 | Algorithm for the proposed outranking method (NWHF-MAUT)

In the MCDM technique, ranking is important for sorting the alternatives. There are several types of outranking methods that are followed by many researchers. In this research paper, we use one of the most popular outranking methods named the MAUT (multi-attribute utility theory). Here, we extend this to the NWHF. The proposed algorithm of the NWHF-MAUT is given in the following steps. The procedure of NWHF-MAUT method is shown as hierarchical structure in Figure 3.

Step 1:

Constructing the decision matrix is based on selected criteria and alternatives.

Step 2:

The criteria weights are formulated by the CRITIC method.

Step 3:

Based on the selected criteria and the alternatives, we make the NWHD matrix $H_{(NW)}$.

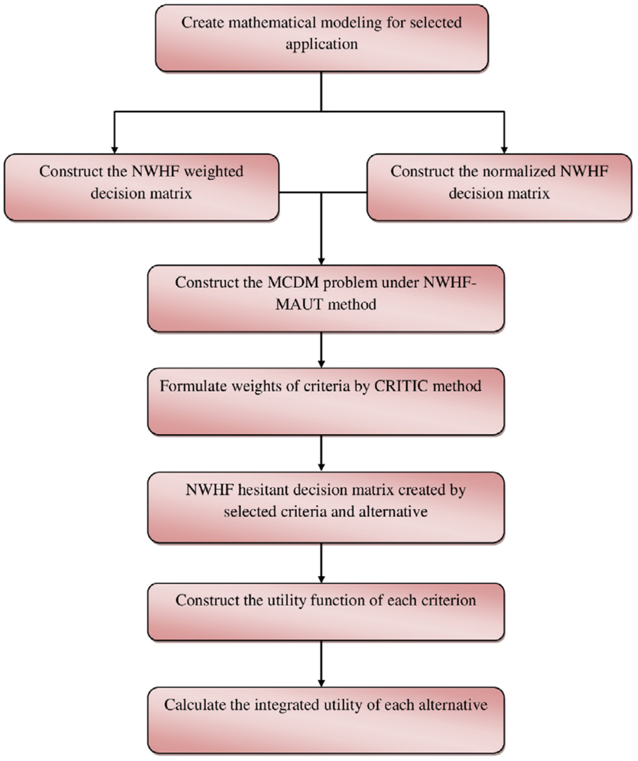


FIGURE 3 The hierarchical structure of the NWHF-MAUT method

Step 4:

The utility function of the criteria is constructed dependent upon the beneficial and the cost criteria.

$$U_j(h_{ij(NW)}) = \frac{h_{ij(NW)} - \min(h_{ij(NW)})}{\max(h_{ij(NW)}) - \min(h_{ij(NW)})}, \tag{10}$$

$$U_j(h_{ij(NW)}) = \frac{\max(h_{ij(NW)}) - (h_{ij(NW)})}{\max(h_{ij(NW)}) - \min(h_{ij(NW)})}, \tag{11}$$

where i is alternative and j is criteria. The utility function of beneficial and cost criteria is $U_{j(NW)}$.

Step 5:

Constructing the integrated utility of each alternative,

$$U(A_i)_{(NW)} = \sum_{j=1}^{n} W_{j(NW)}\, U_{j(NW)}\ (hij)_{(NW)}. \tag{12}$$

Here, $U(A_i)_{(NW)}$ is the utility function of each alternative, $W_{j(NW)}$ is criteria weight, $h_{ij(NW)}$ is the hesitant decision matrix and $U_j(h_{ij(NW)})$ denotes the utility function of each of the criteria.

The MAUT method is ranked to the alternative by the order of the highest alternative integrated utility value.

4 | TECHNOLOGY OF WIND TURBINES

The wind turbine produces electricity by using the force of the wind to rotate wind turbine rotor blades and ultimately charge a generator thereby. Wind energy is a permanent energy source and is safer than energy derived from most of the fuels. Wind turbines do not emit any harmful greenhouse gases. Moreover, they incur fewer side-effects and problems than all other modes of non-renewable energy generation and do not require much land or water for their setup.

Wind turbines are categorized into the following three types according to their operation.

(i) Wind turbine in horizontal axis
(ii) Wind turbine in vertical axis
(iii) Ducted wind turbine

Turbines are power transfer mechanisms. Wind turbines are chosen based on their properties, the regulation of the environment and their suitability. The technical choices include the speed of the atmospheric conditions associated with the wind and the density of the air. The technical features include the refined area and turbine height. Wind energy includes technologies such as wind power, wind speed and ambient technology available in a given area. A wind turbine cannot convert all wind into energy due to inefficiencies accruing from the Betz law, rotor blade friction and drag, gearbox losses, and generator and converter losses [11]. The following equation is used for finding the wind energy.

$$P = 1/2 * \rho * A * v^3. \tag{13}$$

The output of turbine power is

$$P_T = 1/2 * \rho * A * v^3 * C_p. \tag{14}$$

In above equation, C_p represents the ratio of power extracted by the turbine where C_p is given as:

$$C_p = P_T / P_W. \tag{15}$$

The maximal possible Betz limit C_p is $16/27$. P_T represents the wind power potential, A represents the swept area, V is the velocity of wind, and ρ is the air density. More than any other renewable energy, the amount of energy received from the wind has increased. Over the last 10 years, wind power has been established in India and has seen a huge growth in power generation. The growth of wind farms installed over the last 5 years is given in Table 2. Figure 4 represents the graphical representation of growth of wind farms.

The technology of wind energy is changing everyday. Different wind turbine models are evaluated by their wind power. Wind force is calculated on different heights from the ground level, including wind speed and density of air. Wind turbines designed according to the wind speeds are classified in Table 3. The air is cleaned by the wind turbine. Wind turbines emit low levels of carbon. In the fiscal year 2017, air pollution was reduced by 189 million tons of carbon pollution. In the growing field of wind power generation, onshore–offshore wind turbines are to be planned based on the most suitable locations for power generation.

TABLE 2 Installed wind power capacity and generation in India

Year	2014 -2015	2015 -2016	2016 -2017	2017 -2018	2018 -2019
Installed capacity(MW)	23,447	26,777	32,280	34,046	36,625
Generation(GWh)	28,214	28,604	46,011	52,666	64,036

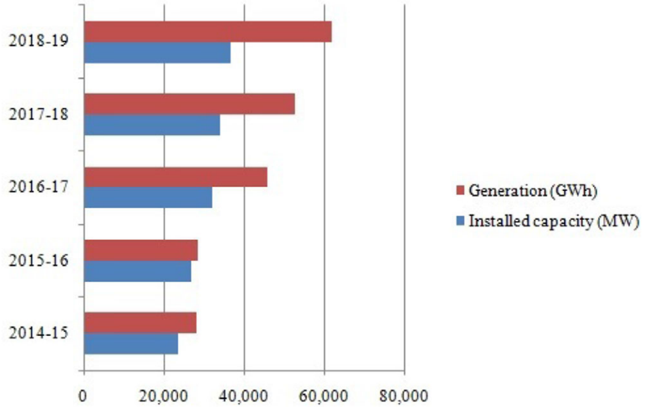


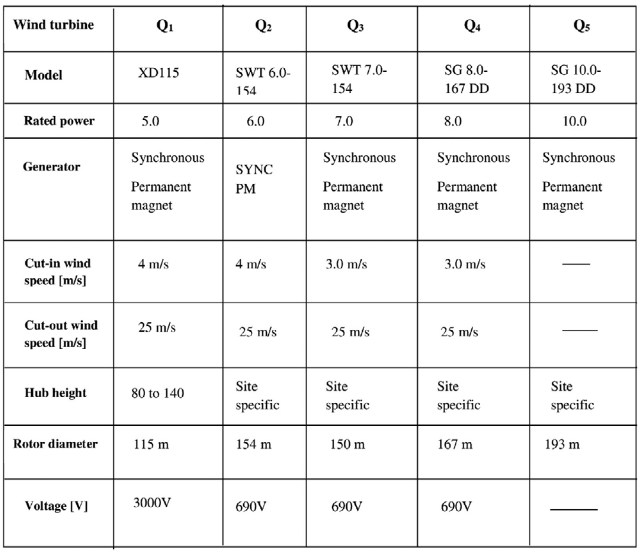
FIGURE 4 Graphical representation of wind production and power

5 | ILLUSTRATIVE EXAMPLE

In this illustrative section, the wind turbine models suitable for the proposed mathematical logical method are taken as alternatives. They are selected to serve the world and the people on the basis of certain criteria. The wind turbine model alternatives are based on their characteristics and criteria. The growth of the wind turbine industry, in fact, is the driving growth in the world market. The installation of the wind turbine has increased

TABLE 3 Wind turbine classes

Class	Average wind speed	Wind turbulence
IA	10	16%
IB	10	14%
IC	10	12%
IIA	8.5	16%
IIB	8.5	14%
IIC	8.5	12%
IIIA	7.5	16%
IIIB	7.5	14%
IIIC	7.5	12%



Wind turbine	Q_1	Q_2	Q_3	Q_4	Q_5
Model	XD115	SWT 6.0-154	SWT 7.0-154	SG 8.0-167 DD	SG 10.0-193 DD
Rated power	5.0	6.0	7.0	8.0	10.0
Generator	Synchronous Permanent magnet	SYNC PM	Synchronous Permanent magnet	Synchronous Permanent magnet	Synchronous Permanent magnet
Cut-in wind speed [m/s]	4 m/s	4 m/s	3.0 m/s	3.0 m/s	——
Cut-out wind speed [m/s]	25 m/s	25 m/s	25 m/s	25 m/s	——
Hub height	80 to 140	Site specific	Site specific	Site specific	Site specific
Rotor diameter	115 m	154 m	150 m	167 m	193 m
Voltage [V]	3000V	690V	690V	690V	———

FIGURE 5 Characteristics of selected offshore wind turbine models

considerably since the early days. Hence, decision-making for the selection of the wind turbine technology is a real-time issue. The characteristics upon which the optimal selection is to be done mathematically to avoid financial loss and loss of selection time. In this illustrative example, the characteristics of the selected offshore wind turbines are presented in Figure 5. The alternatives are: $Q_1 \rightarrow XD115$

$Q_2 \rightarrow SWT - 6.0 - 154$
$Q_3 \rightarrow SWT - 7.0 - 154$
$Q_4 \rightarrow SG - 8.0 - 167DD$
$Q_5 \rightarrow SG - 10.0 - 193DD$

Selection of these models is based on the literature review, their respective characteristics, and their power output. The selection criteria are:

P_1 → **Characteristics of machine**
P_2 → **Operation and maintenance cost**
P_3 → **Cost factor**
P_4 → **Reliability**
P_5 → **Technical characteristics**

The characteristics of the wind turbine alternatives considered are the magnitude of the power output, the wind speed, and the nature of the blades. Some additional properties regarding the selected offshore wind turbine are shown in Figure 6. After selecting the best five models and their criteria, the mathematical logic proposed here is ranked by the NWHF-CRITIC and NWHF-MAUT methods. The wind turbine model most suitable for the current situation finally is chosen. The solution entails solving the mathematical logic by sequencing. In Figure 6, the hierarchical structure of the alternatives and criteria are formulated.

Main result

Initially, we make a decision matrix of the NWHF values in the ascending order, as given in Table 4. This decision matrix includes five criteria and five alternatives.

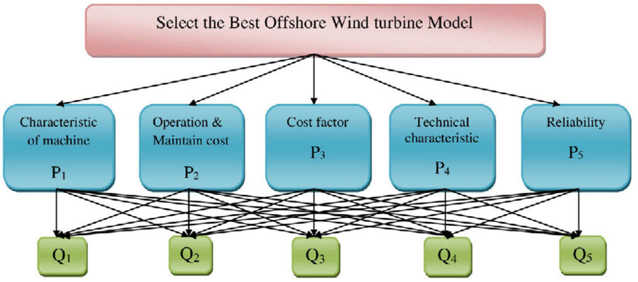


FIGURE 6 Hierarchical structure of selected application

TABLE 4 Normal wiggly hesitant decision matrix

	P_1	P_2	P_3	P_4	P_5
Q_1	(0.3, 0.4, 0.6)	(0.4, 0.5, 0.6)	(0.7, 0.8, 0.8)	(0.2, 0.4, 0.4)	(0.7, 0.8, 0.9)
Q_2	(0.5, 0.6, 0.8)	(0.5, 0.6, 0.7)	(0.3, 0.5, 0.5)	(0.4, 0.5, 0.6)	(0.4, 0.5, 0.5)
Q_3	(0.6, 0.7, 0.9)	(0.3, 0.5, 0.6)	(0.5, 0.6, 0.6)	(0.3, 0.6, 0.7)	(0.6, 0.7, 0.7)
Q_4	(0.2, 0.3, 0.3)	(0.2, 0.3, 0.3)	(0.2, 0.4, 0.4)	(0.6, 0.7, 0.8)	(0.3, 0.5, 0.5)
Q_5	(0.7, 0.8, 0.9)	(0.1, 0.2, 0.4)	(0.1, 0.2, 0.3)	(0.5, 0.7, 0.7)	(0.2, 0.4, 0.4)

We determine the score function in reference to NWDHFE using (6).

First, we calculate the hesitant score matrix H_{ij} based on (6). In Table 5, we have given the score values of NWHF.

5.1 | The NWHF-CRITIC method

In this subsection, the weights of the criteria are calculated using (7). Next, we have to find the normalized values of the NWHFs. The resulting values are given in Table 6.

TABLE 5 Normal wiggly hesitant score matrix

	P_1	P_2	P_3	P_4	P_5
Q_1	0.311	0.4171	0.7247	0.2466	0.706
Q_2	0.4936	0.4986	0.3577	0.4162	0.3835
Q_3	0.6072	0.3959	0.5279	0.3946	0.6268
Q_4	0.2042	0.2042	0.2574	0.6254	0.3565
Q_5	0.706	0.0656	0.1029	0.5556	0.2574

TABLE 6 Normal wiggly hesitant normalized matrix

	P_1	P_2	P_3	P_4	P_5
Q_1	0.2128	0.8117	1	0	1
Q_2	0.5767	1	0.4097	0.4477	0.2811
Q_3	0.8031	0.7628	0.6834	0.3907	0.8231
Q_4	0	0.3201	0.2484	1	0.2209
Q_5	1	0	0	0.8157	0

TABLE 7 Value of correlation co-efficient of each criteria

	P_1	P_2	P_3	P_4	P_5
P_1	1	−0.2064	−0.3233	0.0175	−0.2422
P_2	−0.0613	1.0003	0.7373	−0.7381	0.6406
P_3	−0.3391	10.7373	1	−0.8998	0.5864
P_4	0.0177	−0.7381	−0.8998	1	−0.8519
P_5	−0.2422	0.6406	0.5864	−0.8159	1

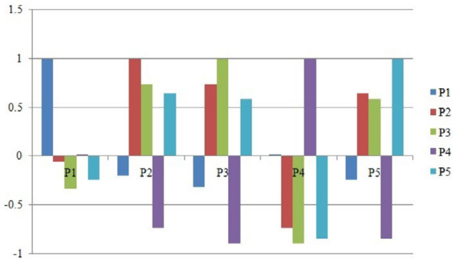


FIGURE 7 Values of correlation co-efficient of each criteria

The standard deviation and correlation coefficients are followed by calculation of the criteria weights and are denoted by $(W_{j(NW)})$. The weights of the criteria are constructed using (8). In Table 7, the values of pairwise comparison and standard deviation are given. In Figure 7, the correlation coefficient values are shown.

The proposed NWHF-CRITIC weights finding method is constructed according to the criteria of the highest value of standard deviation and the lowest value of correlation coefficient.

The criteria weight and quantity of information are calculated using Equations (8) and (9). The criteria quantity information is shown in Figure 8. The results for the weighted criteria are shown in Table 8. The weighted criteria are shown in Figure 9.

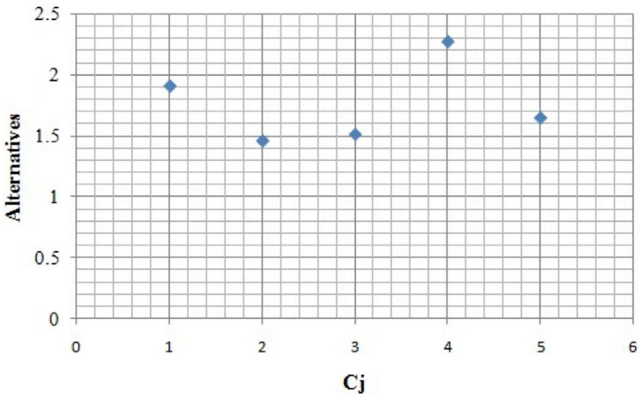


FIGURE 8 Quantity of information on criteria

TABLE 8 Value of correlation co-efficient of each criteria

Criteria	P_1	P_2	P_3	P_4	P_5
$(C_{j(NW)})$	1.9040	1.4564	1.5094	2.2663	8.7807
$(W_{j(NW)})$	0.2168	0.1658	0.1718	0.2581	0.1872

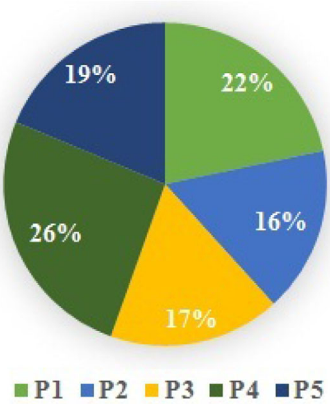


FIGURE 9 Criteria weight values

TABLE 9 Value of utility function of each criterion

	P_1	P_2	P_3	P_4	P_5
Q_1	0.2128	0.1882	0	0	1
Q_2	0.5767	0	0.5902	0.4477	0.2811
Q_3	0.8031	0.2372	0.3165	0.3907	0.8231
Q_4	0	0.6799	0.7515	1	0.2209
Q_5	1	1	1	0.8157	0

5.2 | The NWHF-MAUT method

In this subsection, NWHF is considered as an outranking method for the sorting of the selected alternatives. For that, we calculate each criterion's utility function. In addition, the utility function depends on the beneficial and cost criteria. The utility function of each criterion is determined by the Equations (10) and (11).

After finding these, we have to calculate the integrated utility of each alternative using (12). The weight of each criterion is assigned by the CRITIC method. The criteria utility function results are given in Table 9 and plotted in Figure 10.

In the following Table 10, we rank the selected alternatives in the descending order. The ranking of the selected alternatives is

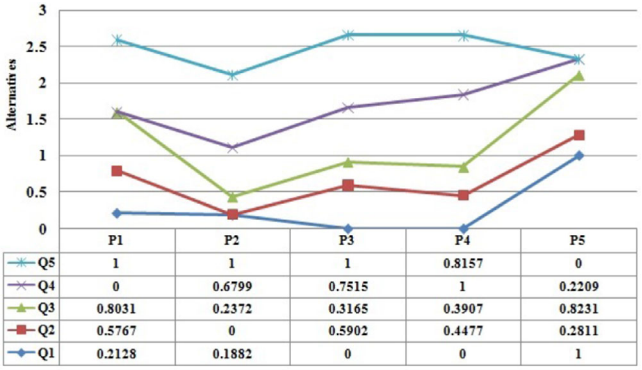


FIGURE 10 Value of utility function of each criterion

TABLE 10 Values of integrated utility functions of alternatives

	P_1	P_2	P_3	P_4	P_5	Total	Rank
Q_1	0.0461	0.0312	0	0	0.1872	0.2645	V
Q_2	0.1250	0	0.1013	0.1155	0.0526	0.3944	IV
Q_3	0.1741	0.0393	0.0543	0.1008	0.1541	0.5226	III
Q_4	0	0.1127	0.1291	0.2581	0.0413	0.5412	II
Q_5	0.2168	0.1658	0.1718	0.2105	0	0.7649	I

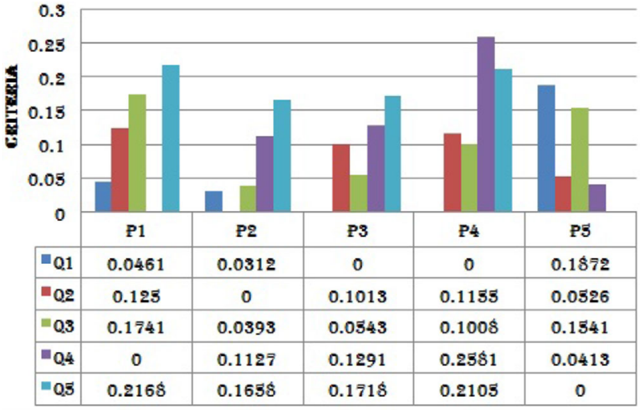


FIGURE 11 Values of integrated utility functions of alternatives

$Q_5 < Q_4 < Q_3 < Q_2 < Q_1$. Hence, $SG-10.0-193DD$ is the best offshore wind turbine system. In Figure 11, the integrated utility function of each alternative is shown. The ranking results are shown in Figure 12.

6 | DISCUSSION

The mathematical logic proposed in this section is applied to choose the best turbine model. The deeper information of the decision-maker is revealed in the course of the NWHF decision making. Aggregation is used to rank the alternatives, and NWTFN, three hesitant fuzzy values are found to determine the right solution. Our aim is to find the best model for the selected application using the outranking method for the NWHFs presented in this research article. We have also converted the new weight finding CRITIC method to the NWHF-CRITIC method and provided the theorem, the operation, and the score function. We converted the MAUT method to the NWHF-MAUT method for ranking of the corresponding solution methods. We selected wind turbine offshore models as alternatives and chose the right model through the NWHF-CRITIC and NWHF-MAUT methods. The NWHF-CRITIC weight finding method provides more solutions than most of the other weight finding methods. Other mathematical methods such as standard deviation and correlation are used in the NWHF-CRITIC method. This study is set out to find increases in wind energy in order to determine the proper installation of the wind turbine. The amount of wind energy depends on the turbine models. There will be many problems, as well as many confusions and hesitations in selecting the models. The solution presented in this paper can be of significant help to the decision-makers.

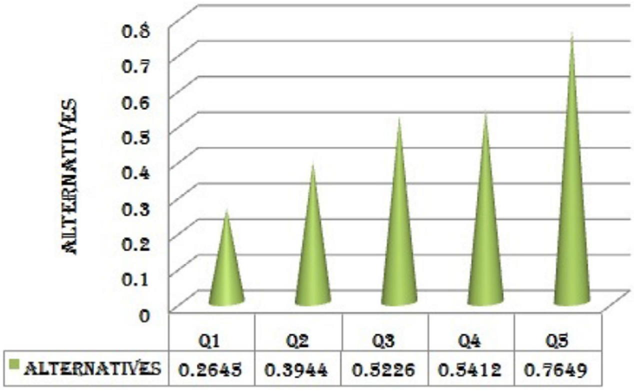


FIGURE 12 Ranking of alternatives

TABLE 11 Entropy weights of criteria

Criteria	P_1	P_2	P_3	P_4	P_5
$(E_{j(NW)})$	0.9472	0.9057	0.9010	0.9714	0.9579
$(W_{j(NW)})$	0.1666	0.2976	0.3125	0.0902	0.1328

7 | COMPARATIVE ANALYSIS

MCDM has been proposed under the NWHF environment. The CRITIC method for weight finding and the MAUT method for alternative finding are introduced under NWHF. The solutions obtained from the above are compared with other MCDM methods with identical values. Based on this comparison, the proposed methods viz., the HWHF-CRITIC and the NWHF-MAUT, provide a valid solution. Here, we compare NWHF-CRITIC with the weighted entropy, the results of which are listed in Table 11. Thus, we believe that the proposed mathematical logical methods, the NWHF-CRITIC and NWHF-MAUT methods, have been tested on the basis of comparison, and that these methods are valid in MCDM. The entropy criteria weight values are given in Table 11.

In Table 8 and Table 11, the sums of the weighted criteria are given in the same order. By using Equation (12) and the weighted entropy, the utility function of each alternative value is given in Table 11. The integrated utility functions of the alternatives using entropy weights are given in Table 12. Figure 12 shows a comparison of the CRITIC and the entropy ranking results. Figure 13 compares the results for the respective criteria. Then, Figure 14 shows how the utility function of each alternative changes when using the CRITIC and entropy weight finding methods. Further comparisons of the CRITIC and entropy weighted methods are shown in Figures 15–19.

TABLE 12 Integrated utility function of each alternative using entropy weight

	P_1	P_2	P_3	P_4	P_5	Total	Rank
Q_1	0.0354	0.0560	0	0	0.1328	0.2242	V
Q_2	0.0960	0	0.1844	0.0403	0.0373	0.358	IV
Q_3	0.1337	0.0705	0.0989	0.0352	0.1093	0.4476	III
Q_4	0	0.2023	0.2348	0.0902	0.0293	0.5566	II
Q_5	0.1666	0.2976	0.3125	0.0735	0	0.8502	I

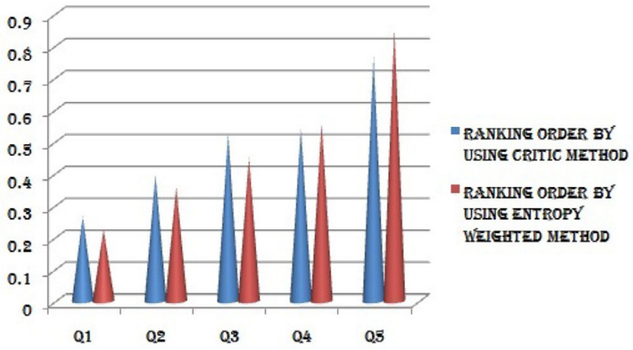


FIGURE 13 Ranking results for utility function of each alternative using CRITIC and entropy weighted methods

8 | SENSITIVITY ANALYSIS

The sensitivity analysis was conducted to determine the effects of changes in the weights of the criteria and changes in the data at the end of the offshore wind turbine selection. The offshore wind turbine models, such as XD115, SWT-6.0-154, SWT-7.0-154, SG-8.0-167 DD, and SG-10.0-193DD, were selected based on the characteristics of the machine, operation and maintenance cost, cost factor, reliability and technical characteristics criteria. In this analysis, the weight of a given criterion is determined by changing the weight of each criterion proportionally to the weights of the other criteria. In this research, we used the CRITIC method to determine the weights of the criteria. The weights obtained by the CRITIC method were 0.2168 for the characteristics of the machine, 0.1658 for the operation

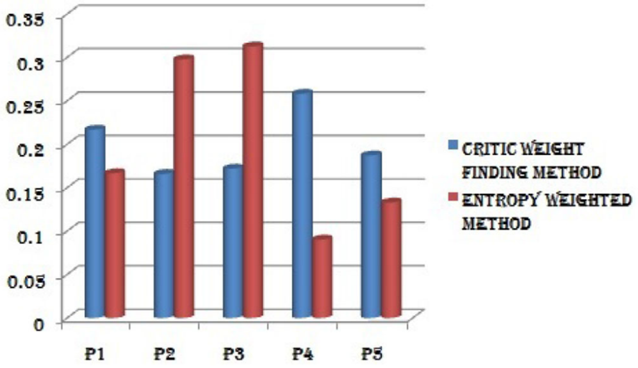


FIGURE 14 Comparison of the CRITIC and the entropy weighted values

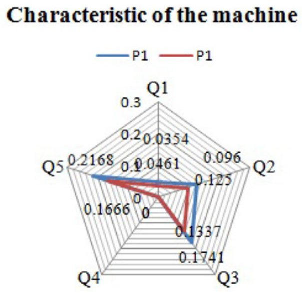


FIGURE 15 P_1 criterion weight comparison between CRITIC and entropy weighted methods

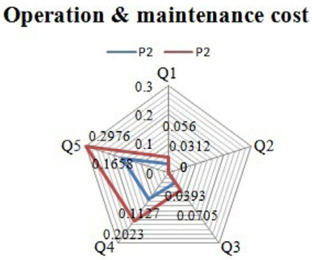


FIGURE 16 P_2 criterion weight comparison between CRITIC and entropy weighted methods

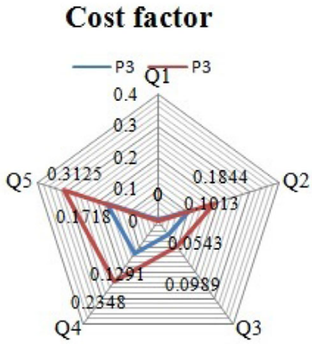


FIGURE 17 P_3 criterion weight comparison between CRITIC and entropy weighted methods

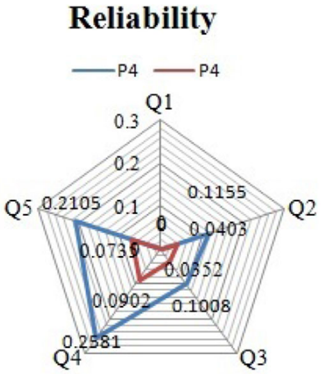


FIGURE 18 P_4 criterion weight comparison between CRITIC and entropy weighted methods

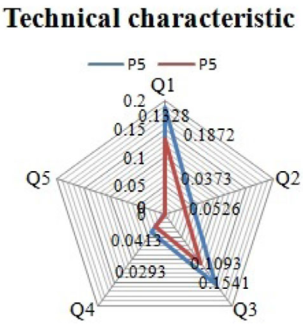


FIGURE 19 P_5 criterion weight comparison between CRITIC and entropy weighted methods

TABLE 13 Integrated utility function of each alternative, when $W_1 = 0.15$, $W_2 = 0.179$, $W_3 = 0.175$, $W_4 = 0.264$, $W_5 = 0.214$

	P_1	P_2	P_3	P_4	P_5	Total	Rank
Q_1	0.0319	0.0336	0	0	0.214	0.2795	V
Q_2	0.0865	0	0.1032	0.1181	0.0601	0.3679	IV
Q_3	0.1204	0.0424	0.0553	0.1031	0.1761	0.4973	III
Q_4	0	0.1217	0.1315	0.264	0.0472	0.5644	II
Q_5	0.15	0.179	0.175	0.2153	0	0.7193	I

and maintenance cost, 0.1718 for the cost factor, 0.2581 for reliability, and 0.1872 for technical characteristics, as shown in Table 8.

Case 1:

When the weight of the characteristics of the machine changes from 0.2168 to 0.15, the changes in the weights of the other criteria are given in Table 13. The weights of the other criteria are calculated as follows. The sum of the weights of the other criteria becomes 1−0.15 = 0.85. The sum of these weights is used to calculate the ratios of the weights of the other criteria. The weights of operation and maintenance cost is $W_2 = \frac{0.1658}{(1-0.2168)} \times 0.85 = 0.179$. Similarly, the weights of the cost factor, reliability and technical characteristics criteria are $W_3 = 0.175$, $W_4 = 0.274$ and $W_5 = 0.214$, respectively. Each new ranking of the integrated utility function is recalculated by the weight of these new criteria. As shown in Figure 20, in the selection of the characteristics of the machine criterion, there is no sensitivity. This is because its weight loss or increase shows an identical pattern with no change in the alternative ranking, namely, $SG - 10.0 - 193DD > SG - 8.0 - 167DD > SWT - 7.0 - 154 > SWT - 6.0 - 154 > XD115$.

The operation and maintenance cost criterion show a slight sensitivity to changes in their weights. Only the wind turbine model $SG - 10.0 - 193DD$ is best selected until the weight of the scale increases to 0.85. Table 13 presents the ranking of the utility function of each alternative for the changing of weight values to $W_1 = 0.15$, $W_2 = 0.179$, $W_3 = 0.175$, $W_4 = 0.264$, $W_5 = 0.214$. The results of sensitivity analysis of Case 1 are shown in Figures 22–26.

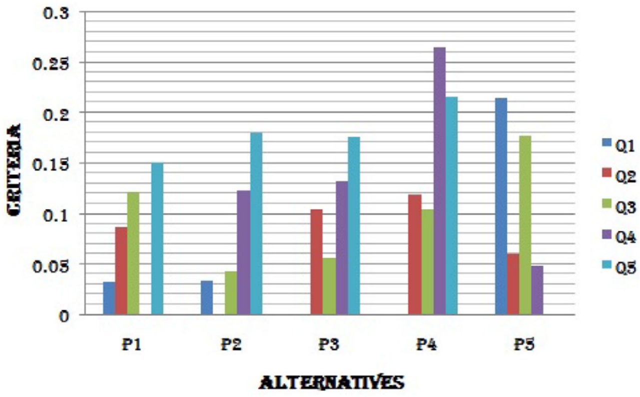


FIGURE 20 When $W_1 = 0.15$, $W_2 = 0.179$, $W_3 = 0.175$, $W_4 = 0.264$, $W_5 = 0.214$

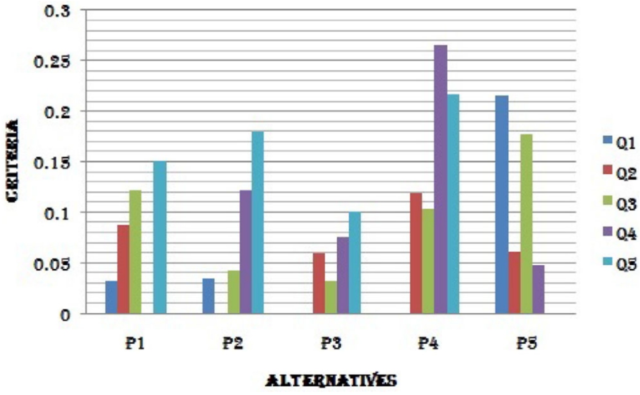


FIGURE 21 When $W_1 = 0.2168$, $W_2 = 0.1658$, $W_3 = 0.1$, $W_4 = 0.2581$, $W_5 = 0.1872$

Case 2:

The operation and maintenance cost, and cost factor criteria have similar weight values. Therefore, Table 8 gives the changes in the values of the other criteria when the weight of the cost factor criterion is reduced to 0.1. The current rank order is $SG - 10.0 - 193DD > SET - 7.0 - 154 > SG - 8.0 - 167DD > SWT - 6.0 - 154 > XD115$. Cost is an

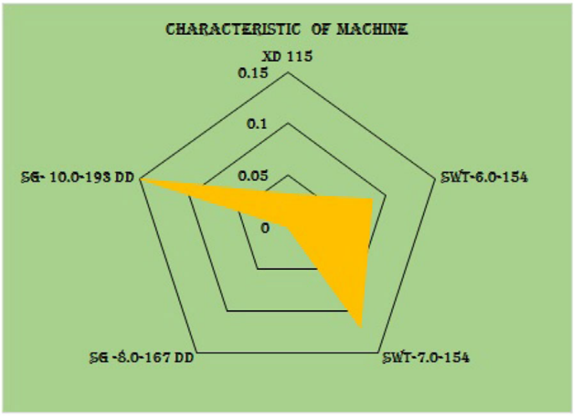


FIGURE 22 P_1- Characteristics of machine

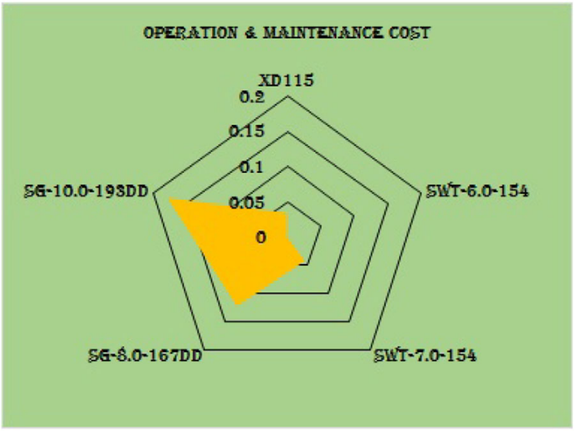


FIGURE 23 P_2- Operation and maintenance cost

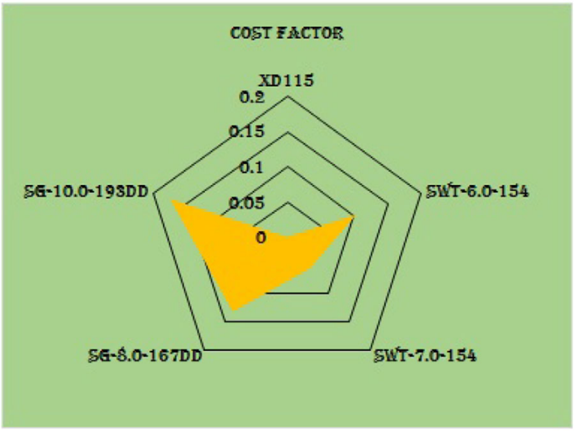


FIGURE 24 P_3- Cost factor

important criterion to the selection of this wind turbine model due to the fact that cost reflects the model's unique characteristics. There is no sensitivity to the other criteria, such as reliability and technical characteristics. The selected alternative is always $SG-10.0-193DD$. The reliability criterion is the most important one. But there is no sensitivity change in reliability. $SG-8.0-167DD$ is selected as the second best alternative until the weight increases above 0.85. The results of the sensitivity analysis are shown in Figure 21. Table 14 presents the ranking of the utility functions of the respective alternatives for the changing of weight values to $W_1=0.2168$, $W_2=0.1658$, $W_3=0.1$, $W_4=0.2581$, and $W_5=0.1872$. The results of sensitivity analysis of Case 2 are shown in Figures 27–31.

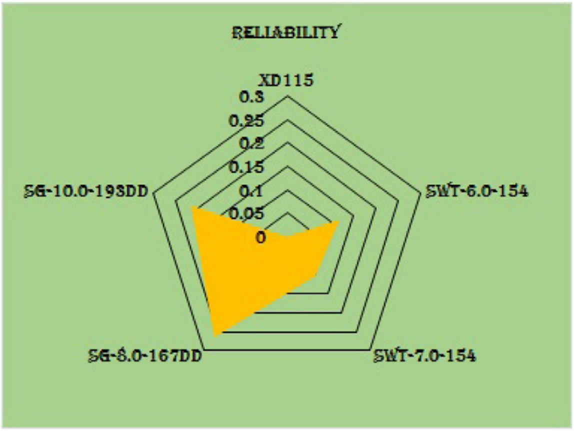


FIGURE 25 P_4- Reliability

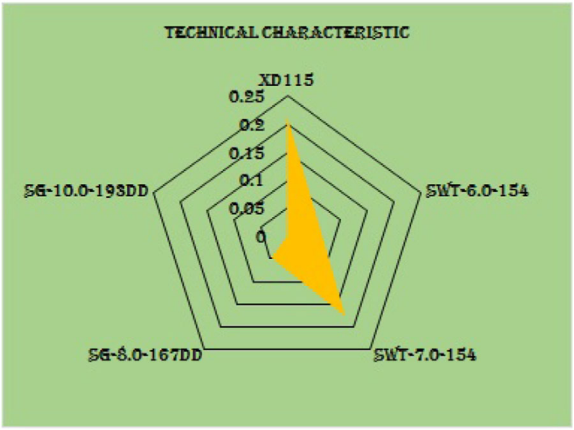


FIGURE 26 P_5- Technical characteristic

TABLE 14 Integrated utility function of each alternative, when $W_1=0.2168$, $W_2=0.1658$, $W_3=0.1$, $W_4=0.2581$, $W_5=0.1872$

	P_1	P_2	P_3	P_4	P_5	Total	Rank
Q_1	0.0461	0.0312	0	0	0.1872	0.2645	V
Q_2	0.1250	0	0.0590	0.1155	0.0526	0.3521	IV
Q_3	0.1741	0.0393	0.0316	0.1008	0.1540	0.4998	II
Q_4	0	0.1127	0.0751	0.2581	0.0413	0.4872	III
Q_5	0.2168	0.1658	0.1	0.2105	0	0.6931	I

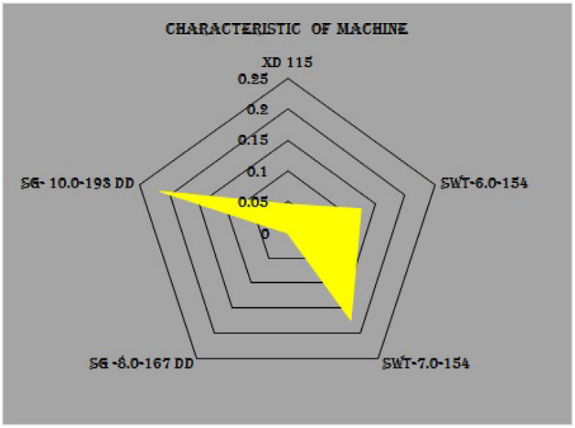


FIGURE 27 P_1- Characteristics of machine

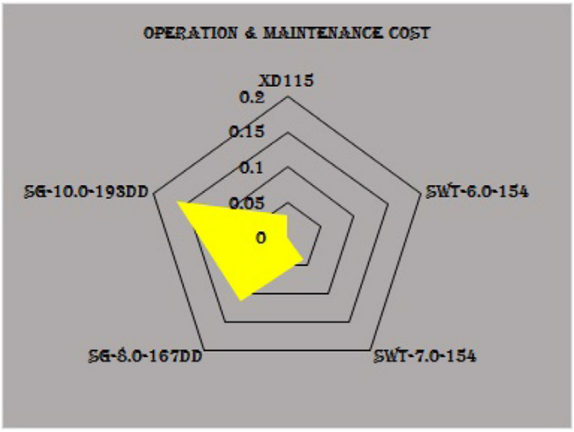


FIGURE 28 P_2- Operation and maintenance cost

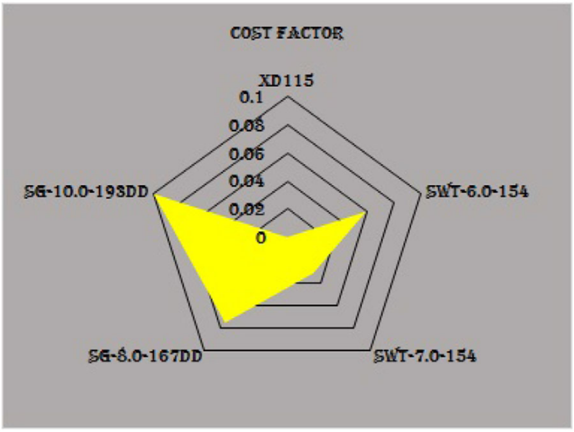


FIGURE 29 P_3- Cost factor

9 | CONCLUSION

Energy is a precious resource that must be assiduously developed, husbanded, and conserved. Even though energy is available in a variety of different forms in our country, the overall amount available is not sufficient due to a growing population, environmental change, increase in the number of vehicles, economic growth, and other issues. To compensate for these changes, we are forced to look for alternative energy. A perpetual source of energy that is naturally cleaner and more readily available, that is to say, wind, should be studied and applied for the purposes of energy savings. This renewable energy has no deleterious effects on society or nature. The establishment of a wind farm can reduce power shortages and improve the country's quality of production in the stock market. The hesitant fuzzy values considered in the NWHF method can reveal the hesitation situations of decision-makers in seeking to select the best wind turbine models. In the present study, we converted the two best MCDM methods, CRITIC and MAUT, to the NWHF-CRITIC and NWHF-MAUT methods, respectively, and selected the best solutions using them. The NWHF-CRITIC method is used for weight finding and for NWHF-MAUT ranking. Based those processes, $Q_5 \rightarrow SG - 10.0 - 193DD$ was selected as the best alternative followed by $Q_4 \rightarrow SG - 8.0 - 167DD$, $Q_3 \rightarrow SWT - 7.0 - 154$, $Q_2 \rightarrow SWT - 6.0 - 154$ and $Q_1 \rightarrow XD115$ in that order.

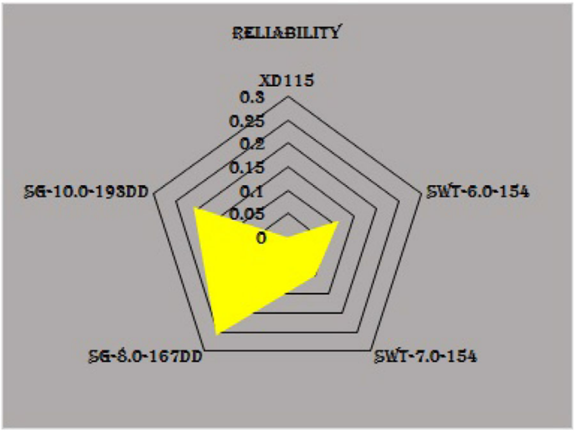


FIGURE 30 P_4- Reliability

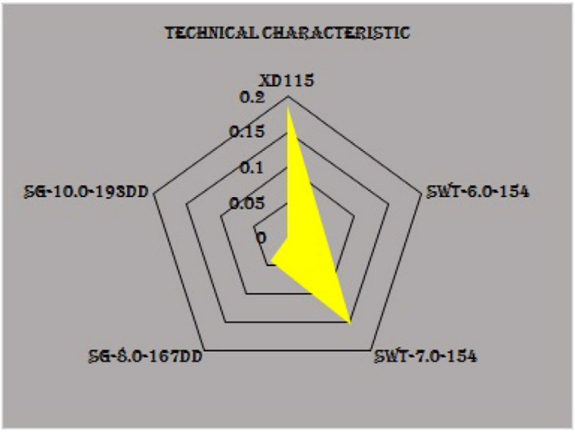


FIGURE 31 P_5- Technical characteristic

NOMENCLATURE

AHP	Analytical hierarchy process
CRITIC	Criteria Importance Through Intercriteria Correlation
MAVT	Multi Attribute Value Theory
DM	Decision Making
ELECTRE	Elimination Et ChoixTraduisant la REalite
GIS	Geographic Information System
GP	Goal Programming
GP	Goal Programming
GPS	Global Positioning System
GW	Gigawatt
MAUT	Multi Attribute Utility Theory
MCDM	Multi-Criteria Decision Making
MCDM	Multi-Criteria Decision Making
MOORA	Multi - Objective Optimization on the Basis of Ratio Analysis

MW	Megawatt
NWHF	Normal Wiggly Hesitant Fuzzy
NWHFDM	Normal Wiggly Hesitant Fuzzy Decision Making
NWHFE	Normal Wiggly Hesitant Fuzzy Element
NWTHFE	Normal Wiggly Triangular Hesitant Fuzzy Element
NWTHFN	Normal Wiggly Triangular Hesitant Fuzzy Number
NWTHFS	Normal Wiggly Triangular Hesitant Fuzzy Set
PROMOTHEE	Preference Ranking Organization METHod for Enrichment of Evaluations
ROV	Range of Value
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
TWh	Terawatt hours
VIKOR	VIsekriterijumsko KOmpromisno Rangiranje

ACKNOWLEDGEMENTS

This work was supported by a National Research Foundation (NRF) of Korea Grant funded by the Korean Government (MSIT) (Grant NRF-2019R1G1A1006073).

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How to cite this article: Narayanamoorthy, S., et al.: A new extension of hesitant fuzzy set: An application to an offshore wind turbine technology selection process. IET Renew. Power Gener. 15, 2340–2355 (2021). https://doi.org/10.1049/rpg2.12168