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PICTURE-HESITANT FUZZY-BASED DUAL-NORMALIZED MULTIPLE AGGREGATIONS FOR MATERIAL SELECTION IN A LIFT-BASED CONVERTER

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Abstract. *This paper addresses the challenge of material selection for lift-based Wave Energy Converters (WECs) by presenting a novel methodology that integrates fuzzy information representation and Multi-Criteria Decision-Making (MCDM) techniques. The aim is to provide decision-makers with a robust framework for optimizing material choices despite uncertainties and limited field data. The methodology combines a material selection approach tailored for lift-based WECs with a new fuzzy information representation technique, probabilistic picture hesitant fuzzy sets (P-PHFSs). The results underscore the potential of these methods for reducing the risk of machine failures in WEC technology. The proposed method contributes to the development of WEC technology by providing a systematic and flexible framework for decision-makers to optimize material choices and improve the reliability and performance of WEC systems.*

Key words*: Material life cycle, Wave energy converter, Decision making, Fuzzy logic, Probabilistic picture hesitant fuzzy set, Preference selection index*

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1. INTRODUCTION

Wave energy has seen commercialization in the past decade, driven by government support, private investment, and the offshore energy sector's efforts to combat climate change. Wave energy, combined with wind and wave power, can help carbonize coastal energy systems and achieve zero waste energy, and large-scale WECs are expected soon [1].

Lift-based WECs show high potential for competitiveness in the offshore sector due to their immersed mode capability and passive stalling in storm conditions stress and potential mechanical failure [2]. Numerous efforts have been made to develop methods for quantifying and preventing wear damage to offshore infrastructure. Offshore constructions, like wave energy converters, are susceptible to random loading due to the fluctuation of ocean waves. The WECs can be complex due to the unique structural hydrodynamic interactions of each wave energy converter. Accurate fatigue damage models can help create a durable and cost-effective structural WEC, reducing its leveled energy cost. Analytical models for assessing and quantifying fatigue damage in WEC structures must be developed during the design stage [3].

The development of hydrodynamic models to predict electrical performance has formed a significant part of the research on lift-based WECs. Common risk reduction measures for wave energy converters include digital twins, adaptive control systems, and suitable materials. The development of solutions that minimize the risk of failure is crucial for enhancing the technical readiness level (TRL) of lift-based WECs [4]. This study focuses on lift-based WECs. This form of WEC generates lift forces using rotating hydrofoils. Lift-based WECs can operate submerged and use pitch control to reduce hydrofoil load fluctuations, but loading variations cannot be avoided due to the unpredictable nature of different waves within sea states [5]. The structure of hydrofoils allows for the estimation of fatigue injury to lift-based WECs using a probabilistic approach, rather than a deterministic approach, under specific sea conditions [6].

Multi-criteria decision-making (MCDM) is used to make complex decisions based on multiple factors. The objective is to identify the optimal sites for WECs based on their performance across various parameters [7]. Numerous studies have demonstrated the effectiveness of MCDM methods in identifying suitable locations for renewable energy sources like wind and solar electricity [8]. The study on wave energy is currently lacking in depth. The lift-based WEC material selection process comprises five stages: criteria selection, data normalization, criteria weights, alternative assessment, and outcomes validation.

An MCDM, which assesses alternatives based on expert opinions and specific criteria, has gained popularity as a viable study area [9]. The uncertainty and ambiguity in the decision-making process have made it challenging for decision-makers to evaluate and choose the best option in MCDM challenges [10]. Interest in fuzzy sets (FSs) [11] and their classical expansions, including interval-valued FSs (IVFSs) [12], intuitionistic FSs (IFSs) [13], interval-valued IFSs [14], hesitant fuzzy sets (HFS) [15] and picture FSs (PFSs) [16] has been significant in research and development. The concept of hesitant fuzzy sets (HFSs), which enable the degree of an element's membership to be represented by a collection of alternative values [17].

Ali et al., [18] introduced the picture's hesitant fuzzy element (PHFSs), an extension of HFSs consisting of positive membership degree, neutral membership degree, and negative membership degree functions. We introduce probabilistic picture hesitant fuzzy sets (P-

PHFSs) to improve their effectiveness by considering the likelihood of each member in the PHFE. P-PHFSs are highly effective as they can represent membership degrees, their probabilities, and their positive, neutral, and negative probabilities [19]. The study explores the effectiveness and efficiency of the performance selection index (PSI) method in resolving machining MCDM issues [20].

This study uses P-PHFSs and fuzzy DNMA techniques to develop material selection characteristics for lift-based WECs. Material fitness-for-purpose methodologies are crucial in preventing the failure of innovative technologies and thereby reducing investment loss. The DNMA is a utility theory-based method that employs two distinct normalization procedures and three aggregation strategies [21]. The DNMA method has been compared to other utility-theory-based MCDM techniques for the first time in terms of its benefits. This study's implications extend beyond lift-based WECs to other submerged marine energy-collecting methods operating near the ocean's free surface. The study introduces P-PHFSs, a tool that simplifies complex assessment information representation in decision-making situations, including operations, score function, accuracy function, and comparison approach.

The framework introduces a distinctive material selection method in lift-based WECs, employing fuzzy double normalized-based multiple aggregations (DNMA) as an MCDM. An emphasizes material fitness-for-purpose to avoid technological failure and financial losses. It applies to numerous stages of the product cycle, including lift-based wave energy converters. This study has implications for additional submerged marine energy-collecting devices that operate near the ocean's surface. The sensitivity analysis is used to evaluate the accuracy of the scenario assessment, considering uncertainties or changes in values.

The remainder of this study is organized as follows: The literature review is discussed in Section 2. The basic concepts are presented in Section 3. Section 4 provides the proposed methodology and an evaluation framework. A case study is applied to the method for material selection for lift-based WECs in Section 5. Further, the results and discussion of the case study are in Section 6. Finally, a summary of the findings, limitations, and future work is in Section 7.

2. Literature Review

The material selection architecture for lift-based WECs is based on seven criteria: structure dependability, hydrodynamic efficacy, offshore maintenance, corrosion resistance, production cost, eco-friendliness, and shelf life. The lift-based WEC consortium's three-year Horizon 2020 research project, which concluded in 2023, identified critical criteria that significantly increased the TRL of lift-based WECs [22].

The device's rotor is produced by the hydrofoils and center shaft, while the stator serves as the stationary component of the WEC. The lift WEC project's final idea involves a floating prototype, which reduces slamming and high loads through submergence and passive stalls, potentially saving installation and maintenance costs [23].

An MCDM is a crucial operational research method in engineering fields, where problem solutions are determined by multiple independent and often conflicting criteria. Although MCDM techniques are aimed at managing quantitative values, their integration with fuzzy set theory can provide answers in situations where managing qualitative values is difficult. This paper presents an MCDM strategy for a new device's material selection challenge, assuming a team of specialists conducts the evaluation. Based on the primary material selection criteria and lift-based WEC development stage evaluate using P-PHFS and the fuzzy DNMA method. The lift-based WEC idea is explained, with hydrofoils as the demonstration case for the framework's structural component [24].

Mzili et al., [25] developed a unique decision-support technology that combines hesitant linguistic term collection, the DNMA technique, and a basic decision-making process. The applicability of this method has been demonstrated in estimating geographic sites for retail shopping malls using fuzzy linguistic information.

Farooq [26] discussed processing and connections of probabilistic hesitation fuzzy elements (PHFE) information, proposing a method for ranking PHFEs based on score and deviation values, with the comparison technique reflecting absolute priority. Tian et al., utilized the tomada de decisao interativa multicriterio (TODIM) approach to model decision-making perceptions in prospect theory, incorporating probabilistic hesitant fuzzy information [27]. Song and Chen have developed a new MADM technique using distance and the complex proportional assessment (COPRAS) method for a PHF environment [28]. The preference selection index (PSI) method is simpler to comprehend than other MCDM approaches due to its statistical calculation of total preference values without relative weight. The PSI technique is beneficial for assessing optimal alternatives in cases of controversy regarding criteria relevance and requires fewer numerical calculations [29] and [30]. The study presents an MCDM material selection for lift-based WECs, demonstrating the device's hydrofoils to fill a research gap. Select the best composition for the optimum performance of the metallic alloy [31]. Selected the rank of flexible manufacturing system (FMS) flexibility [32]. Determined the optimum phase combination of biodegradable composites [33]. The method based on the removal effects of criteria (MEREC) integrated PSI-MCDM approach was used to select India's green renewable energy source [34].

We introduced P-PHFSs, a unique method for accurately and effectively describing complex assessment information for decision-makers [35] and [36]. The objective of this work is to use the fuzzy PSI-DNMA technique to develop an ordered material selection method for lift-based WECs. The fuzzy PSI-DNMA approach was utilized to rank each criterion and alternate material for hydrofoils, addressing uncertainty.

3. PRELIMINARIES

3.1. Picture Hesitant Fuzzy Set

Let X be a fixed set, a picture hesitant fuzzy set (PHFS) M on X is defined by

$$M = \left\{ \left\langle x, \phi(x), \chi(x), \psi(x) \right\rangle \mid x \in X \right\} \tag{1}$$

where, $\phi(x) = \{\sigma \mid \sigma \epsilon \phi(x)\}$, $\chi(x) = \{\varsigma \mid \varsigma \epsilon \chi(x)\}$, and $\psi(x) = \{\tau \mid \tau \epsilon \psi (x)\}$ are three sets of possible values in [0,1], indicating the possibility of positive (PMD), neutral (NeMD), and negative (NMD) membership degrees. The degrees mentioned above satisfy the requirement of $0 \leq \sigma^+ + \varsigma^+ + \tau^+ \leq 1$. As a convenience, $m = \{x, \phi(x), \chi(x), \psi(x)\}$ PHFE, denoted by $m = (\phi, \chi, \psi)$.

3.2. Probabilistic Picture Hesitant Fuzzy Set

Let X be a fixed set, a probabilistic picture hesitant fuzzy set (P-PHFS) M on X is defined by

$$M = \left\{ \left\langle x, \phi(x) \mid s(x), \chi(x) \mid t(x), \psi(x) \mid u(x) \right\rangle \mid x \in X \right\} \tag{2}$$

where, $\phi(x)|s(x)$, $\chi(x)|t(x)$ and $\psi(x)|u(x)$ contains a number elements, $\phi(x)$, $\chi(x)$, and $\psi(x)$ denote the possibility (PMD), (NeMD), and (NMD) of $x \epsilon X$ to the set M, respectively. Here $s(x)$, $t(x)$, and $u(x)$ are related with probabilistic information. Furthermore, $\phi(x)|s(x)$, $\chi(x)|t(x)$, and $\psi(x)|u(x)$ satisfy the requirement of $0 \le \sigma^+ + \varsigma^+ + \tau^+ \le 1$, and s_i, t_j, $u_k \epsilon$ [0,1].

$$\sum_{i=1}^{\#\phi} s_i = 1, \sum_{j=1}^{\#\chi} t_j = 1, \sum_{k=1}^{\#\psi} u_k = 1$$

where, $s_i \epsilon s(x)$, $t_j \epsilon t(x)$, and $u_k \epsilon u(x)$. The notation of $\#\phi$, $\#\chi$, and $\#\psi$ indicate the total number of elements in, $\phi(x)|s(x)$, $\chi(x)|t(x)$, and $\psi(x) \mid u(x)$ respectively. For convenience, $m = \{x, \phi(x)|s(x), \chi(x)|t(x), \psi(x)|u(x)\}$ a P-PHFE, denoted by $m = \{\phi|s, \chi|t, \psi|u\}$.

3.3. Basic Operations

Let , $m_1 = (\phi_1|s_1, \chi_1|t_1, \psi_1|u_1)$ and $m_2 = (\phi_2 |s_2, \chi_2 |t_2, \psi_2|u_2)$ be three P-PHFEs, $\vartheta > 0$, then m^c is the complement of m, and P-PHFE operations can be defined as:

$$m^c = (\phi \mid s_\phi, \chi \mid t_\chi, \psi \mid u_\psi) = \bigcup_{\sigma \in \phi, \varsigma \in \chi, \tau \in \psi} (\{\tau \mid u_\tau\}, \{\varsigma \mid t_\varsigma\}, \{\sigma \mid s_\sigma\})$$
$$m_1 \oplus m_2 = \bigcup_{\substack{\sigma_1 \in \phi_1, \varsigma_1 \in \chi_1, \tau_1 \in \psi_1 \\ \sigma_2 \in \phi_2, \varsigma_2 \in \chi_2, \tau_2 \in \psi_2}} (\{\sigma_1 + \sigma_2 - \sigma_1\sigma_2 \mid s_{\sigma_1} s_{\sigma_2}\}, \{\varsigma_1\varsigma_2 \mid t_{\varsigma_1} t_{\varsigma_2}\}, \{\tau_1\tau_2 \mid u_{\tau_1} u_{\tau_2}\}$$
$$m_1 \otimes m_2 = \bigcup_{\substack{\sigma_1 \in \phi_1, \varsigma_1 \in \chi_1, \tau_1 \in \psi_1 \\ \sigma_2 \in \phi_2, \varsigma_2 \in \chi_2, \tau_2 \in \psi_2}} (\{\sigma_1\sigma_2 \mid s_{\sigma_1} s_{\sigma_2}\}, \{\varsigma_1 + \varsigma_2 - \varsigma_1\varsigma_2 \mid t_{\varsigma_1} t_{\varsigma_2}\}, \{\tau_1 + \tau_2 - \tau_1\tau_2 \mid u_{\tau_1} u_{\tau_2}\}$$
$$\vartheta m = \bigcup_{\sigma \in \phi, \varsigma \in \chi, \tau \in \psi} (\{1 - (1-\sigma)^\vartheta \mid s_\sigma\}, \{\varsigma^\vartheta \mid t_\varsigma\}, \{\tau^\vartheta \mid u_\tau\})$$
$$m^\vartheta = \bigcup_{\sigma \in \phi, \varsigma \in \chi, \tau \in \psi} (\{\sigma^\vartheta \mid s_\sigma\}, \{1 - (1-\varsigma)^\vartheta \mid t_\varsigma\}, \{1 - (1-\tau)^\vartheta \mid u_\tau\})$$

3.4. Score and Accuracy Function

Let be a P-PHFE, then the score $S(m)$ and accuracy functions $H(m)$ are defined by

$$S(m) = \frac{\left(1 + \frac{1}{\#\phi} \sum_{i=1}^{\#\phi} (\sigma_i s_i) - \frac{1}{\#\chi} \sum_{i=1}^{\#\chi} (\varsigma_i t_i) - \frac{1}{\#\psi} \sum_{i=1}^{\#\psi} (\tau_i u_i)\right)}{2} \tag{3}$$

$$H(m) = \frac{\left(1 + \frac{1}{\#\phi} \sum_{i=1}^{\#\phi} (\sigma_i s_i) + \frac{1}{\#\chi} \sum_{i=1}^{\#\chi} (\varsigma_i t_i) + \frac{1}{\#\psi} \sum_{i=1}^{\#\psi} (\tau_i u_i)\right)}{2} \tag{4}$$

Let $m_1 = (\phi_1|s_1, \chi_1|t_1, \psi_1|u_1)$ and $m_2 = (\phi_2|s_2, \chi_2|t_2, \psi_2|u_2)$ be two P-PHFEs, then, if $S(m_1) > S(m_2)$ then $(m_1) > (m_2)$, if $S(m_1) < S(m_2)$ then $(m_1) < (m_2)$, and if $S(m_1) = S(m_2)$ then $(m_1) = (m_2)$. If $H(m_1) > H(m_2)$ then $(m_1) > (m_2)$, if $H(m_1) < H(m_2)$ then $(m_1) < (m_2)$, if $H(m_1) = H(m_2)$ then $(m_1) = (m_2)$.

4. Proposed Methodology

An integrated PSI-DNMA approach is utilized in the material selection procedure illustrated in Fig. 1 for parametric optimization problems.

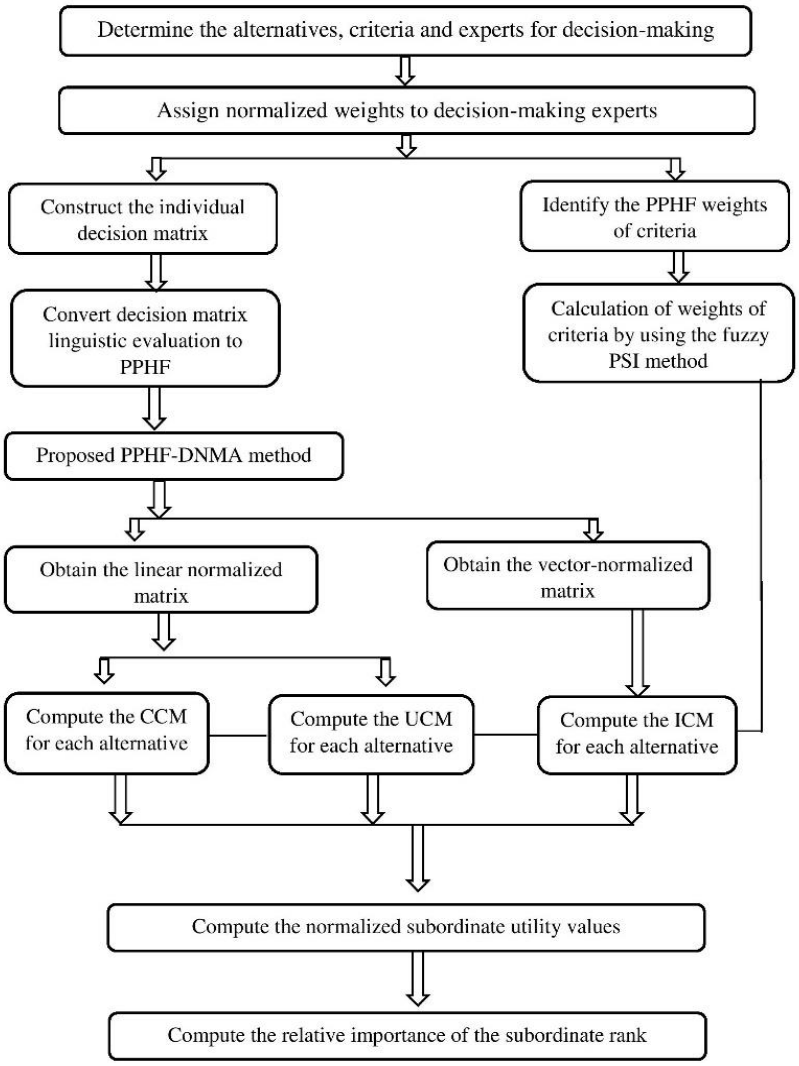

Fig. 1 Method of solving an optimization problem

4.1. Preference Selection Index Method

The PSI approach is utilized to address fuzzy decision-making issues in material selection, particularly in addressing debates about the relevance of attribute. The PSI approach to change weights, considering the contrast strength of each criterion and the contradictory nature of assessment criteria.

Step 1: Create the initial decision matrix

$$\aleph = \left[\hbar_{ij}\right]_{m\times n} = \begin{pmatrix} \hbar_{11} & \cdots & \hbar_{1n} \\ \vdots & \ddots & \vdots \\ \hbar_{m1} & \cdots & \hbar_{mn} \end{pmatrix} \tag{5}$$

Step 2: The normalized decision matrix is determined by calculating its elements using the following equations.

$$\bar{\hbar}_{ij} = \begin{cases} \dfrac{\hbar_{ij}}{\hbar_{ij}^{\max}} & \text{for beneficial criteria} \\ \dfrac{\hbar_{ij}^{\min}}{\hbar_{ij}} & \text{for cost criteria} \end{cases} \tag{6}$$

Step 3: Calculate the mean values of the normalized performances in response to each

$$\Im = \frac{1}{n}\sum_{i=1}^{n}\bar{\hbar}_{ij} \tag{7}$$

Step 4: Calculate the variation of preferences in response to each criterion.

$$\wp_j = \sum_{i=1}^{m}(\bar{\hbar}_{ij} - \Im)^2 \tag{8}$$

Step 5: Calculate the deviations of the response preference for each criterion.

$$\mho_j = 1 - \wp_j \tag{9}$$

Step 6: Compute the criteria weights.

$$\varpi_j = \frac{\mho_j}{\sum_{j=1}^{n}\mho_j} \tag{10}$$

4.2. Double Normalized Based Multiple Aggregation Method

Liao and Wu introduced the DNMA approach to the literature, which is an innovative method for ranking alternatives. Two normalized approaches and three distinct joining functions (full compensation, incomplete compensation, and incomplete compensatory) to implement a compensation system.

Step 1: The decision matrix's normalization.

$$\hbar_{ij}^{1N} = 1 - \frac{\left|\hbar_{ij} - t_j\right|}{\max\left\{\max_i \hbar_{ij}, t_j\right\} - \min\left\{\min_i \hbar_{ij}, t_j\right\}} \tag{11}$$

$$\hbar_{ij}^{2N} = 1 - \frac{\left|\hbar_{ij} - t_j\right|}{\sqrt{\sum_{i=1}^{m}\left(\hbar_{ij}\right)^2 + \left(t_j\right)^2}} \tag{12}$$

Where $d_{ij} = d(\hbar_{ij}, \hbar_j)$, $\hbar_j$ represents the goal value for the criteria C_j.

$$h_j = \begin{cases} \max_i \hbar_{ij} & \text{beneficial criteria} \\ \min_i \hbar_{ij} & \text{non-beneficial criteria} \end{cases}$$

The normalized decision matrices are represented as $\hbar^{1N}$ and $\hbar^{2N}$, respectively.

$$\begin{cases} \hbar_{ij}^{1N} = \hbar_{ij}^{1N} \big/ \max_i \hbar_{ij}^{1N} \\ \hbar_{ij}^{2N} = \hbar_{ij}^{2N} \big/ \max_i \hbar_{ij}^{1N} \end{cases}$$

Step 2: Compute of criteria weights. The fuzzy PSI technique calculates criteria weights based on the decision matrix's information, using an objective method for attributes like entropy. The basic conceptual approach of the PSI method for solving MCDM problems is described in Subsection 4.1.

Step 3: Determine the subordinate utility values and rank.

Complete compensatory model (CCM) $\mho_1\left(P_i\right) = \sum_{j=1}^{n} \varpi_j \hbar_{ij}^{1N}$ (13)

Un-compensatory model (UCM) $\mho_2\left(P_i\right) = \max_{j=1} \varpi_j \left(1 - \hbar_{ij}^{1N}\right)$ (14)

Incomplete compensatory model (ICM) $\mho_3\left(P_i\right) = \prod_j \left(\hbar_{ij}^{1N}\right)^{\varpi_j}$ (15)

Step 4: The normalized subordinate utility values

$$\mho_q^N(P)=\frac{\mho_q(P_i)}{\sqrt{\sum_{i=1}^{m}\left(\mho_q(P_i)\right)^2}} \tag{16}$$

where q=1,2,3 and i=1,2,...,m. The subordinate rank of each alternative is determined by the descending order of $\mho_1(P_i)$ and $\mho_3(P_i)$, and the ascending order of $\mho_2(P_i)$.

Step 5: Rank the alternatives. Assigning weights to the (CCM), (UCM), and (ICM)

$$R_s(P_i)=\begin{cases} \omega_1 * \sqrt{\xi\left(\mho_1^N(P_i)/\max\limits_i \mho_1^N(P_i)\right)^2+(1-\xi)\left(\dfrac{m-\gamma_1(P_i)+1}{m}\right)^2} \\ -\omega_2 * \sqrt{\xi\left(\mho_2^N(P_i)/\max\limits_i \mho_2^N(P_i)\right)^2+(1-\xi)\left(\dfrac{\gamma_2(P_i)}{m}\right)^2} \\ \omega_3 * \sqrt{\xi\left(\mho_3^N(P_i)/\max\limits_i \mho_3^N(P_i)\right)^2+(1-\xi)\left(\dfrac{m-\gamma_3(P_i)+1}{m}\right)^2} \end{cases} \tag{17}$$

where $\xi \in [0, 1]$ indicates the relative significance of the subordinate values and is weighted by ω_1, ω_2, ω_3, satisfying $\omega_i \in [0, 1]$. The rankings of all alternatives can be determined by utilizing the descending order of $R_s(P_i)$ for i=1,2,…,m.

5. CASE STUDY

This case study uses a lift-based WEC with a fiberglass wave floating structure, consisting of feathers and an essential shaft as the rotor and a stator as the stationary component. Structural reliability refers to an asset's ability to function as planned for a specific period under specific technical and atmospheric conditions. Evaluating these criteria can be challenging due to their unclear and quantitative nature. The fuzzy PSI-DNMA approach is used to evaluate various criteria, establishing a ranking level based on factors. Fig. 2 illustrates the phase of the hydrofoil concept for demonstration purposes.

Five materials, including aluminum alloys, offshore steel, high-strength steel, CFRC, and GFRP, have been assessed for use in wave energy converters based on seven criteria, including structure dependability, hydrodynamic efficacy, offshore maintenance, corrosion resistance, production cost, eco-friendliness, and self-life.

Aluminum alloys (M_1) - Aluminum alloys are widely used in modern industrial and consumer products due to their lightweight, corrosion-resistant, and versatile properties, including aircraft, automobiles, building materials, electrical conductors, and packaging materials Aluminum silicon alloys are fluid, durable, and castable, suitable for various applications like engine blocks. Aluminum is commonly alloyed with copper, zinc, zirconium, lithium, silicon, magnesium, nickel and lead in small proportions.

High-strength offshore steel (M_2) - High-strength offshore steel is specially designed and manufactured for use in offshore constructions including oil rigs, platforms and other marine applications. These steels have superior mechanical qualities, including better tensile strength, yield strength, and toughness than ordinary structural steels. The steel industry has developed advanced, ultra-high-strength steels in the last two decades, an offshore- grade structural steel used in the offshore sector.

Offshore steel (M_3) - Offshore steel is a type of steel material that is developed and manufactured, particularly for use in offshore constructions including oil and gas platforms, drilling rigs, and other maritime facilities. These constructions are subjected to extreme circumstances such as severe weather, corrosive seawater, and the requirement to bear large loads and dynamics. These criteria guarantee that the steel satisfies strict specifications for mechanical qualities, chemical composition, and other variables.

Carbon Fiber Reinforced Composite (CFRC) (M_4) - The CFRC is a form of composite material in which carbon fibers are inserted in a matrix material, usually a polymer resin. The combination of carbon fibers and matrix results in a composite material with improved mechanical characteristics, such as high strength-to-weight ratio, stiffness, and durability.

Carbon steel, a low-cost material used in refineries and petrochemical facilities for pipelines and valves, is primarily composed of carbon and iron compounds, but its poor corrosion resistance makes it less suitable for offshore conditions.

Glass Fiber Reinforced Plastic (GFRP) (M_5) - The GFRP, also known as Fiberglass Reinforced Plastic (FRP), is a composite material consisting of glass fibers embedded in a polymer matrix. This composite material combines the high strength and stiffness of glass fibers with the plasticity and mold ability of a plastic matrix, usually a thermosetting resin such as polyester or epoxy. GFRP is a fiber-reinforced plastic, similar to graphite-reinforced plastic, made from plastic reinforced with thin glass fibers, which can be chopped strand mats (CSM) or woven cloth.

5.1. Determining the Criteria Weights

The decision matrix (H) is being initiated. The alternative (m) score, as per Table 1, corresponds to the attributes (n) of the relevant P-PHF element .

Step 1: Experts can express their material selection aspirations using P-PHF numbers, which are summarized in the P-PHF decision matrix using Eq. (2), as shown in Table 2.

Step 2: Eq. (6) is used to obtain the normalized result matrix shown in Table 3.

Step 3: The mean values of normalized performances for each criterion are computed using data from Table 3 and Eq. (7). $\mathfrak{J}$ = {0.7482, 0.7274, 0.7678, 0.7240, 0.7596, 0.7940, 0.7914}

Step 4: Eq. (8) is used to calculate the results of the variance of preferences according to each criterion value shown in Table 4.

Step 5: The preference value is obtained by dividing the deviation of each criterion value using Eq. (9). $\mho_j$ = {0.8633, 0.8714, 0.8729, 0.8719, 0.8713, 0.8664, 0.8637}.

Step 6: The criteria weights are determined using Eq. 10. w_j = {0.1420, 0.1432, 0.1435, 0.1433, 0.1436, 0.1424, 0.1419}

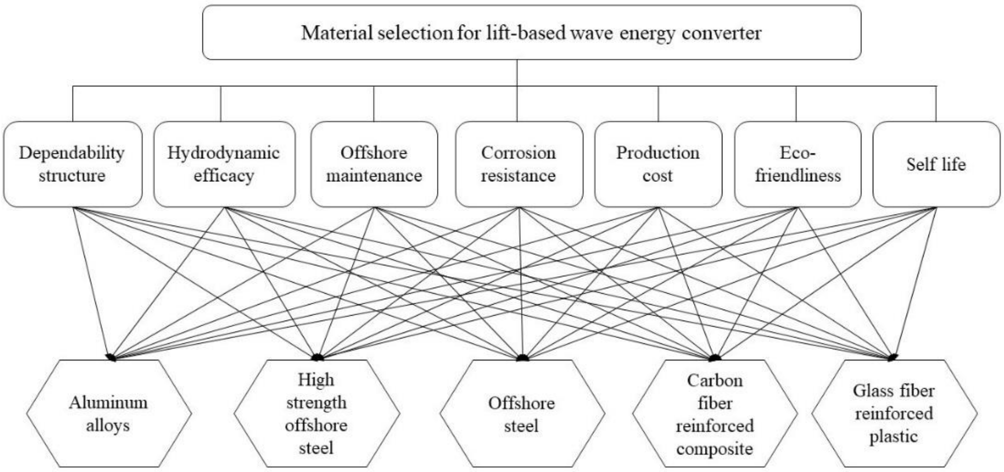

Fig. 2 Hierarchical organization of the material selection of lift base WEC

Table 1 The P-PHF number-based linguistic conversion scale

Linguistic variable	P-PHF Number
Very Low	(0.1, 0.2, 0.4)
Low	(0.3, 0.5, 0.7)
Medium Low	(0.4, 0.3, 0.6)
Equal	(0.5, 0.5, 0.5)
High	(0.8, 0.5, 0.3)
Absolutely High	(1, 0.4, 0.6)

Table 2 P-PHF decision matrix

<table>
<tr><th></th><th>C1</th><th>C2</th><th>C3</th><th>C4</th></tr>
<tr><td>M1</td><td>({0.13 | 0.15, 0.18 | 0.25, 0.21 | 0.6}
{0.16 | 0.28, 0.25 | 0.32, 0.04 | 0.4}
{0.05 | 0.53, 0.14 | 0.27, 0.23 | 0.2})</td><td>({0.25 | 0.12, 0.17 | 0.32, 0.14 | 0.56}
{0.1 | 0.46, 0.05 | 0.42, 0.03 | 0.12}
{0.46 | 0.61, 0.2 | 0.39})</td><td>({0.32 | 0.44, 0.1 | 0.33, 0.3 | 0.23}
{0.13 | 0.47, 0.23 | 0.3, 0.08 | 0.23}
{0.09 | 0.13, 0.05 | 0.4, 0.09 | 0.47})</td><td>({0.21 | 0.34, 0.03 | 0.43, 0.05 | 0.23}
{0.1 | 0.15, 0.13 | 0.25, 0.23 | 0.6}
{0.2 | 0.32, 0.11 | 0.42, 0.43 | 0.26})</td></tr>
<tr><td>M2</td><td>({0.56 | 0.3, 0.27 | 0.42, 0.53 | 0.28}
{0.23 | 0.2, 0.2 | 0.52, 0.18 | 0.28}
{0.14 | 0.38, 0.02 | 0.42, 0.03 | 0.2})</td><td>({0.08 | 0.25, 0.41 | 0.32, 0.23 | 0.43}
{0.31 | 0.23, 0.16 | 0.77}
{0.21 | 0.16, 0.17 | 0.24, 0.25 | 0.6})</td><td>({0.15 | 0.27, 0.32 | 0.55, 0.16 | 0.18}
{0.43 | 0.36, 0.44 | 0.53, 0.35 | 0.11}
{0.02|0.25, 0.09 | 0.75})</td><td>({0.55 | 0.19, 0.05 | 0.81}
{0.2 | 0.16, 0.14 | 0.84}
{0.17 | 0.18, 0.11 | 0.4, 0.16 | 0.42})</td></tr>
<tr><td>M3</td><td>({0.28 | 0.15, 0.12 | 0.35, 0.06 | 0.5}
{0.31 | 0.12, 0.17 | 0.32, 0.23 | 0.56}
{0.05 | 0.02, 0.03 | 0.78, 0.01 | 0.2})</td><td>({0.41 | 0.44, 0.22 | 0.56}
{0.3 | 0.22, 0.11 | 0.33, 0.15 | 0.45}
{0.08 | 0.23, 0.17 | 0.43, 0.16 | 0.34})</td><td>({0.06 | 0.68, 0.12 | 0.12, 0.11 | 0.2}
{0.27 | 0.56, 0.6 | 0.34, 0.02 | 0.1}
{0.11|0.5, 0.03|0.23, 0.07|0.27})</td><td>({0.15 | 0.38, 0.22 | 0.36, 0.18 | 0.26}
{0.04 | 0.46, 0.23 | 0.54}
{0.1|0.4, 0.13|0.26, 0.17 | 0.34})</td></tr>
<tr><td>M4</td><td>({0.13 | 0.9, 0.05 | 0.1}
{0.34 | 0.32, 0.24 | 0.42, 0.22 | 0.26}
{0.53 | 0.13, 0.46 | 0.43, 0.36 | 0.44})</td><td>({0.32 | 0.26, 0.21 | 0.42, 0.11 | 0.32}
{0.08 | 0.45, 0.2 | 0.55}
{0.32 | 0.74, 0.12 | 0.12, 0.22 | 0.14})</td><td>({0.31 | 0.59, 0.2 | 0.11, 0.1 | 0.3}
{0.22 | 0.11, 0.11 | 0.33, 0.3 | 0.56}
{0.01 | 0.36, 0.27 | 0.26, 0.38 | 0.38})</td><td>({0.14 | 0.66, 0.1 | 0.14, 0.21 | 0.2}
{0.32 | 0.31, 0.22|0.43, 0.19|0.26}
{0.42 | 0.22, 0.38 | 0.78})</td></tr>
<tr><td>M5</td><td>({0.18 | 0.2, 0.21 | 0.31, 0.07 | 0.49}
{0.03 | 0.4, 0.1 | 0.12, 0.15 | 0.48}
{0.32 | 0.54, 0.28 | 0.22, 0.29 | 0.24})</td><td>({0.14 | 0.54, 0.21 | 0.1, 0.03 | 0.36}
{0.31 | 0.83, 0.27 | 0.12, 0.29 | 0.05}
{0.26 | 0.64, 0.19 | 0.24, 0.18 | 0.12})</td><td>({0.11 | 0.2, 0.27 | 0.55, 0.23 | 0.25}
{0.18 | 0.27, 0.17 | 0.3, 0.13 | 0.43}
{0.32 | 0.75, 0.3 | 0.15, 0.31 | 0.1})</td><td>({0.29 | 0.42, 0.16 | 0.32, 0.02 | 0.26}
{0.14 | 0.63, 0.13 | 0.37}
{0.07 | 0.36, 0.46 | 0.22, 0.26 | 0.42})</td></tr>
</table>

<table>
<tr><th>C5</th><th>C6</th><th>C7</th></tr>
<tr><td>({0.43 | 0.43, 0.23 | 0.23, 0.13 | 0.34}
{0.03 | 0.24, 0.13 | 0.53, 0.11 | 0.23}
{0.21 | 0.19, 0.17 | 0.36, 0.18 | 0.45})</td><td>({0.32 | 0.26, 0.15 | 0.43, 0.11 | 0.31}
{0.02 | 0.65, 0.12 | 0.35}
{0.3 | 0.37, 0.29 | 0.22, 0.28 | 0.41})</td><td>({0.21 | 0.24, 0.14 | 0.11, 0.02 | 0.65}
{0.5 | 0.14, 0.3 | 0.86}
{0.02 | 0.25, 0.01 | 0.12, 0.2 | 0.63})</td></tr>
<tr><td>({0.16 | 0.25, 0.12 | 0.45, 0.17 | 0.3}
{0.04 | 0.43, 0.23 | 0.26, 0.2 | 0.31}
{0.09 | 0.67, 0.3 | 0.12, 0.2 | 0.21})</td><td>({0.19 | 0.28, 0.14 | 0.32, 0.16 | 0.4}
{0.09 | 0.57, 0.3 | 0.33, 0.15 | 0.1}
{0.16 | 0.37, 0.11 | 0.63})</td><td>({0.04 | 0.32, 0.3 | 0.68}
{0.3 | 0.44, 0.28 | 0.13, 0.29 | 0.43}
{0.23 | 0.11, 0.34 | 0.42, 0.2 | 0.47})</td></tr>
<tr><td>({0.32 | 0.66, 0.36 | 0.21, 0.15 | 0.13}
{0.19 | 0.45, 0.28 | 0.12, 0.16 | 0.43}
{0.02 | 0.27, 0.05 | 0.32, 0.34 | 0.41})</td><td>({0.14 | 0.78, 0.11 | 0.22}
{0.3 | 0.33, 0.21 | 0.4, 0.1 | 0.27}
{0.4 | 0.65, 0.37 | 0.22, 0.29 | 0.13})</td><td>({0.26 | 0.42, 0.29 | 0.11, 0.17 | 0.47}
{0.2 | 0.55, 0.31 | 0.21, 0.27 | 0.24}
{0.19 | 0.27, 0.14 | 0.73})</td></tr>
<tr><td>({0.24 | 0.54, 0.13 | 0.22, 0.02 | 0.24}
{0.08 | 0.37, 0.34 | 0.63}
{0.31 | 0.27, 0.03 | 0.73})</td><td>({0.15 | 0.37, 0.07 | 0.16, 0.01 | 0.47}
{0.3 | 0.28, 0.4 | 0.28, 0.29 | 0.44}
{0.01 | 0.48, 0.37 | 0.36, 0.38 | 0.16})</td><td>({0.12 | 0.33, 0.03 | 0.11, 0.04 | 0.56}
{0.07 | 0.55, 0.09 | 0.16, 0.1 | 0.29}
{0.34 | 0.44, 0.12 | 0.21, 0.35 | 0.35})</td></tr>
<tr><td>({0.14 | 0.17, 0.24 | 0.83}
{0.22 | 0.37, 0.16 | 0.1, 0.11 | 0.53}
{0.04 | 0.16, 0.09 | 0.32, 0.18 | 0.52})</td><td>({0.2 | 0.55, 0.19 | 0.3, 0.43 | 0.15}
{0.02 | 0.27, 0.26 | 0.73}
{0.3 | 0.51, 0.29 | 0.49})</td><td>({0.12 | 0.62, 0.15 | 0.38}
{0.16 | 0.11, 0.07 | 0.89}
{0.02 | 0.22, 0.3 | 0.28, 0.29 | 0.5})</td></tr>
</table>

Table 3 Normalized P-PHF score decision matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
M_1	0.9296	0.8135	1	0.8637	0.8800	1	0.8631
M_2	1	0.8707	0.8972	0.8143	0.9202	0.9979	0.9740
M_3	0.9068	1	0.8738	0.8183	0.8922	0.9292	0.9672
M_4	0.7878	0.8617	0.9231	1	1	0.9072	0.9445
M_5	0.8651	0.8184	0.9126	0.8480	0.8652	0.9295	1

Table 4 Preference variation values

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
M_1	0.0329	0.0074	0.0539	0.0195	0.0145	0.0424	0.0051
M_2	0.0633	0.0205	0.0167	0.0081	0.0257	0.0415	0.0333
M_3	0.0251	0.0743	0.0112	0.0088	0.0175	0.0183	0.0309
M_4	0.0015	0.0180	0.0241	0.0761	0.0577	0.0128	0.0234
M_5	0.0136	0.0082	0.0209	0.0153	0.0111	0.0183	0.0434

5.2. Determining Priorities of Alternatives

Step 1: Table 5 displays the results of linear normalization using Eq. (11). Table 6 displays the results of vector normalization using Eq. (12).

Step 2: The fuzzy PSI method is used for determining criteria weights.

Step 3: Table 7 presents the values obtained from Eqs. (13), (14), and (15) for computing the utility functions CCM, UCM, and ICM.

Step 4: The normalized subordinate utility values are calculated using Eq. (16), as illustrated in Table 8.

Step 5: The performance values of the alternative are calculated using Eq. (17).

Experts provide ξ = 0.5, ω_1 = 0.5, ω_2 = 0.2, and ω_3 = 0.3 as appropriate values for considering.

Table 9 displays the estimated performance values and ranking of the alternatives.

Table 5 Linear normalized P-PHF decision matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
M_1	0.6684	0	1	0.3079	0.1252	1	0
M_2	1	0.3068	0.1859	0	0.4434	0.9779	0.8102
M_3	0.5607	1	0	0.0260	0.2247	0.2387	0.7610
M_4	0	0.2584	0.3909	1	1	0	0.5947
M_5	0.3642	0.0261	0.3077	0.2137	0	0.2408	1

Table 6 Vector normalized P-PHF decision matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7
M_1	0.9954	0.9873	1	0.9916	0.9924	1	0.9915
M_2	1	0.9913	0.9934	0.9878	0.9952	0.9998	0.9984
M_3	0.9940	1	0.9919	0.9881	0.9933	0.9956	0.9980
M_4	0.9860	0.9907	0.9951	1	1	0.9942	0.9966
M_5	0.9912	0.9877	0.9944	0.9904	0.9913	0.9956	1

Table 7 Values of CCM, UCM, and ICM

	CCM	UCM	ICM
M_1	0.4429	0.4473	0.9592
M_2	0.5306	0.4476	0.9666
M_3	0.4008	0.4481	0.9617
M_4	0.4645	0.4448	0.9633
M_5	0.3066	0.4482	0.9519

Table 8 Normalized subordinate utility values and rank order

Alternatives	Descending		Ascending		Descending	
	$\mho_1^{N(P)}$	rank order	$\mho_2^{N(P)}$	rank order	$\mho 3^{N(P)}$	rank order
M_1	0.4549	3	0.4473	4	0.4465	3
M_2	0.5449	1	0.4476	3	0.4500	1
M_3	0.4116	4	0.4481	2	0.4477	4
M_4	0.4770	2	0.4447	5	0.4484	2
M_5	0.3148	5	0.4482	1	0.4432	5

Table 9 Performance values

Alternatives	Ranking values	Ranking order
M_1	0.4384	3
M_2	0.6352	1
M_3	0.3675	4
M_4	0.5472	2
M_5	0.2293	5

6. Results and Discussion

This section analyzes the outcomes of solving the fuzzy MCDM problem for material selection in a lift-based WEC. The materials used include aluminum alloy, high-strength offshore steel, offshore steel, CFRC, and GFRP. The materials are evaluated for their structural dependability, hydrodynamic efficacy, offshore maintenance, corrosion resistance, production cost, eco-friendliness, and shelf life, as previously discussed in subsection 5.1. Subsection 5.2 solves the P-PHF-DNMA algorithm by reversing the actual ratings of total cost and environmental effect.

The results indicate that high-strength offshore steel is a suitable material for hydroelectric power in lift-based WECs and serves as a viable alternative. The conceptual design phase utilizes weighting parameters to select materials with robust dependability structure and high hydrodynamic efficiency. Marine steel is a popular choice in offshore oil and gas because of its high exhaustion and maximum power. The material is also resistant to erosion and corrosion, ensuring minimal power generation loss. The study suggests that novel approaches must meet specific criteria such as stability and hydrodynamic efficacy to be considered suitable for their intended purpose and operation.

The CFRC is criticized for its high cost and significant environmental impact, which outweigh its structural dependability benefits. The aluminum alloy has emerged as a significant competitor to offshore steel options. The findings align with numerous marine renewable experiments, typically conducted in-house at universities or local research centers, involving small-scale prototype manufacturing.

The WEC project, based on lifts, requires more thorough scrutiny of decision-making weighing elements as it progresses. As the number of TRLs increases, it is possible to decrease danger by implementing design changes and protective mechanisms. Structural dependability is not equally weighted, but uncertainties in ratings are expected to decrease with more studies and larger-scale devices, focusing on manufacturing costs and environmental impact.

The study reveals that the material options for lift-based WECs vary depending on the design stage, as illustrated in Fig. 3. Composites are the most cost-effective, maintenance-intensive, and environmentally friendly materials for mass manufacturing lift-based WECs due to their higher environmental impact. Major wave energy businesses like Ocean Energy use offshore steel for devices, with weighting variables varying between commercialization and conceptual stages. The future material options for WEC's hydrofoil may include CFRC and GFRP, evaluated for cost-effectiveness, structural reliability, and environmental competitiveness.

The reduction in uncertainty in fatigue and ultimate strength properties and the assumption that CFRC and GFRP are more eco-friendly than offshore steel and aluminum options are achieved. Material selection is consistent with advances in offshore renewable structures such as wind turbines that demand improved structural reliability and affordability. Further research is needed in the comprehensive design stage, considering manufacturing costs, hydrodynamic efficiency, fatigue stress, and carbon footprint assessment, reflecting current developments in offshore renewable frameworks.

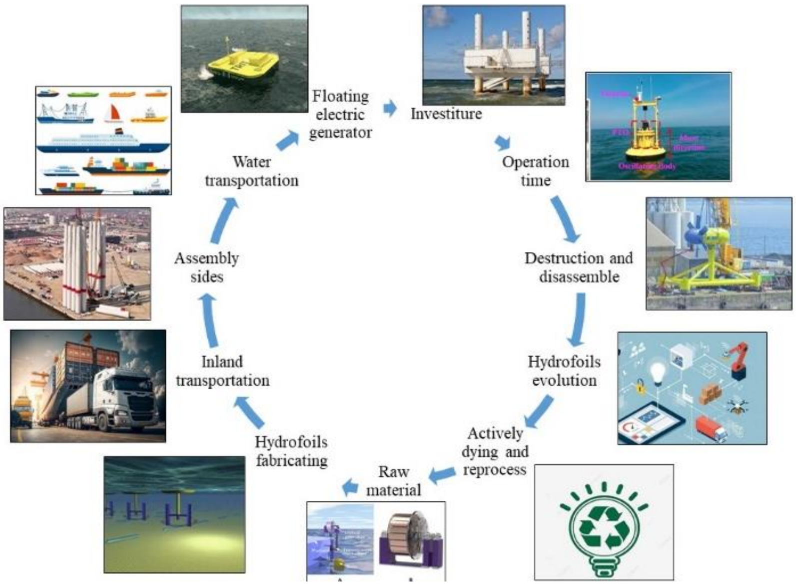

Fig. 3 The material life cycle process for lift-based WEC

6.1. Comparative Analysis of Different Ranking Techniques

The correlation coefficient between ranking scores can be utilized for pragmatic confirmation and agreement. This proposed method can be considered a global approach for comparing decision outcomes in real-world applications.

A comparison study is done using MCDM procedures based on several ranking algorithms to determine the ranking's stability. In many complicated decision-making situations, the robustness and reliability of alternative ranking scores are assessed by comparing the results of one model to those of other accessible and recognized approaches. The PSI-DNMA-based model's reliability was evaluated by a comparison of various commonly used methods, including TOPSIS [37], VIKOR [38], WASPAS [39], COPRAS [40], CRADIS [41], and EDAS [42]. The chosen methods were deemed advantageous due to their numerous advantages, broad applicability, and ability to swiftly identify options in a multi-criteria selection scenario. The ranking results are given in Table 10 and Fig. 4.

The method used slightly influenced the rankings of other quarters. The correlation between findings obtained through different methods is determined using WS coefficient and Weighted Spearman's coefficient (rw). Figs. 5 and 6 display a comparison of ranks using Spearman Order Correlation.

Table 10 The comparison results are presented in a ranked order

	TOPSIS	VIKOR	WASPAS	COPRAS	CRADIS	EDAS
M_1	0.4224	0.5770	0.4629	0.9816	0.5596	0.3959
M_2	0.5088	0.0000	0.4734	1.0000	1.0000	0.7085
M_3	0.4863	0.5721	0.4711	0.9882	0.5490	0.5053
M_4	0.4599	1.0000	0.4325	0.9945	0.5697	0.5367
M_5	0.3364	0.5785	0.4594	0.9639	0.3822	0.1144

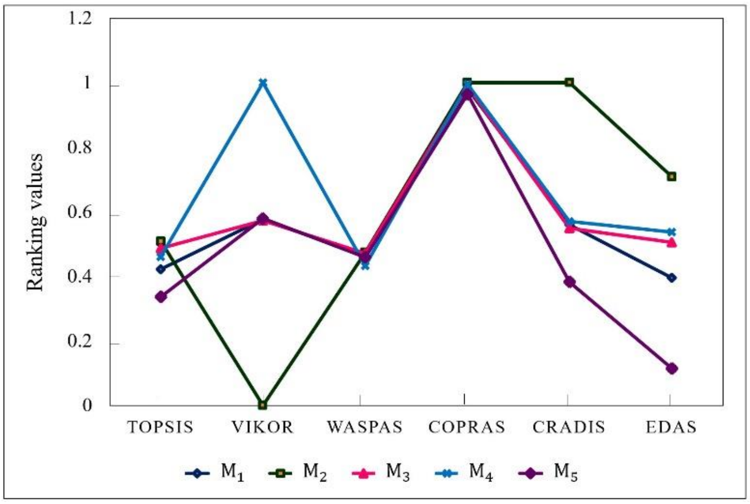

Fig. 4 Comparison of various F-MCDM methods

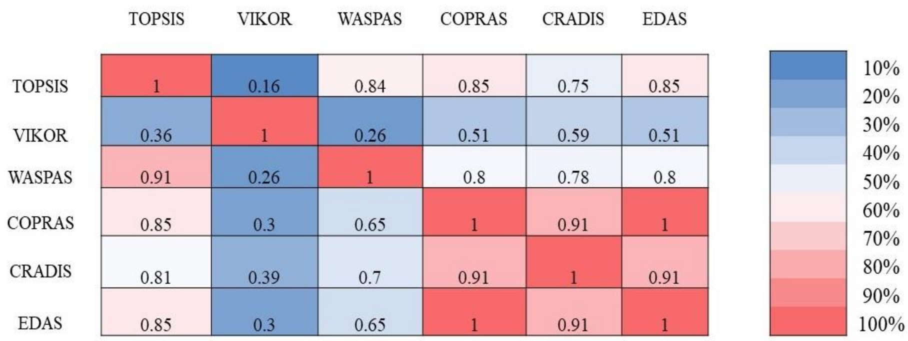

Fig. 5 Correlation between the ranking values of WS

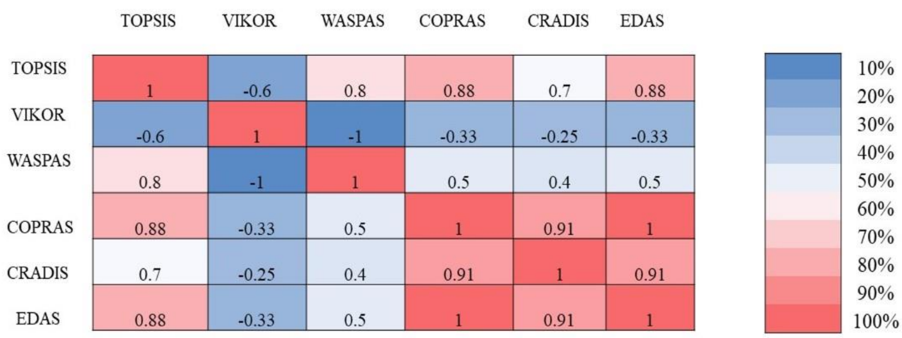

Fig. 6 Correlation between the ranking values of RW

6.2. Sensitivity Analysis

Sensitivity analysis is a crucial decision-making technique that compares a model's results to other accessible and well-structured methods to evaluate the resilience and reliability of alternative ranking scores. Sensitivity analysis investigates the impact of the δ parameter on the ranking of alternatives in the proposed PSI-DNMA technique. Table 11 provides a concise summary of the results. The alternative's ranking is determined to be $M_5 < M_3 < M_1 < M_4 < M_2$ based on the results. We conclude that when δ changes from 0.1 to 0.9 using proposed method, M_2 is the best option. Fig. 7 depicts the graphical representation of the δ variation possibilities.

The ranking of the alternatives remained the same when the relative importance of the parameter was changed. This effectively explains why the proposed method of ranking is unaffected by parameters. This demonstrates the dependability and durability of the suggested framework.

Table 11 The PSI-DNMA method's findings rank in the order of parameters

	δ = 0.1	δ = 0.2	δ = 0.3	δ = 0.4	δ = 0.5	δ = 0.6	δ = 0.7	δ = 0.8	δ = 0.9
M_1	0.3094	0.3835	0.4028	0.4211	0.4384	0.4550	0.4709	0.4863	0.5011
M_2	0.6352	0.6604	0.6515	0.6432	0.6352	0.6277	0.6204	0.6135	0.6068
M_3	0.2382	0.2864	0.3154	0.3423	0.3676	0.3749	0.4141	0.4357	0.4563
M_4	0.5073	0.5650	0.5570	0.5514	0.5472	0.5404	0.5418	0.5402	0.5390
M_5	0.0411	0.0998	0.1484	0.1910	0.2294	0.2482	0.2972	0.3279	0.3568

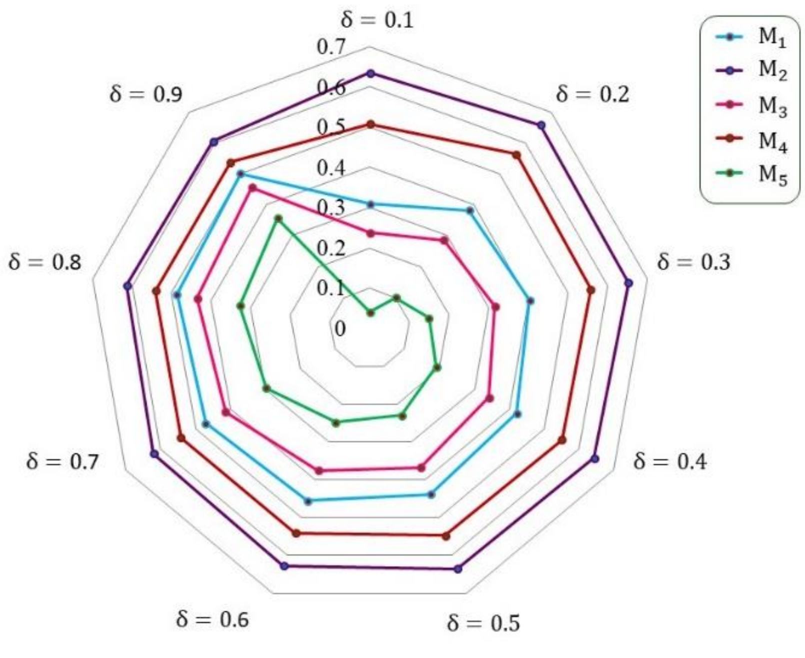

Fig. 7 Influence of δ parameter onto the solution

7. Conclusion

This study introduces a novel hybrid MCDM technique for solving practical decision-making issues, with primary contributions listed below. We introduced a novel method, P-PHFSs, to enhance the comprehension of complex assessment data by decision-makers. P-PHFSs are more effective in managing decision-makers fuzzy judgments due to their ability to express positive, neutral, and negative membership degrees and provide accompanying probabilistic information. Optimal material selection based on our approach can result in cost savings with more economical materials without compromising performance. This innovative combination enhances the ability to handle uncertainty and ambiguity in decision-making processes, providing a more robust and flexible framework for material selection in engineering applications.

The framework introduces a distinctive material selection method in lift-based WECs, employing fuzzy DNMA as an MCDM. Expert opinion was used to identify and assess key hydrofoil characteristics, a unique and original activity for this type of device. The team of experts uses fuzzy logic selecting and inability setting to assess essential hydrofoil material selection criteria, allowing for flexible and rigorous evaluation of lift-based WECs. The framework emphasizes material fitness-for-purpose to prevent technological failure and financial losses. This applies to various stages of the product cycle, including lift-based wave energy converters. The study suggests that further submerged marine energy-collecting devices operating near the ocean’s surface may be beneficial.

The paper presents a probabilistic picture hesitant fuzzy set-PSI-DNMA strategy for MCDM problem implementation, considering uncertain, indeterminate, and inconsistent information. The proposed strategy integrates the PSI method for objective weight and incorporates fundamental operations and the score accuracy function with P-PHFS for flexibility during the energy process. The PSI-DNMA model is utilized to evaluate the material selection for lift-based WECs, focusing on sustainability in P-PHFS. We discuss factors such as structure dependability, hydrodynamic efficiency, offshore maintenance, corrosion resistance, eco-friendliness, self-life, and production cost when choosing materials for lift-based WEC.

Future research will explore the dependability of structures using Einstein t-norm and t-conorm or Hamacher t-norm and t-conorm for analyzing P-PHFS operations and constructing aggregation operators. The study will explore consensus-building procedures using P-PHFSs, a crucial aspect of group decision-making, to ensure an acceptable outcome for many experts. The MCDM analysis predicts that composite solutions like CFRP and GFRP will become more cost-effective and environmentally friendly, with CFRP emerging as a viable alternative. Competing with steel alternatives may require significant cost and environmental reduction efforts.

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