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# COMPREHENSIVE DISTANCE-BASED RANKING METHOD FOR EVALUATING HYDRAULIC CONVERTERS IN TIDAL STREAM TURBINES UTILIZING PICTURE FERMATEAN FUZZY SET

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**Abstract**. *In recent years, advancements in hydrokinetic technology and the growing demand for renewable energy have heightened interest in water-based energy extraction. This study proposes a new fuzzy information representation technique, Probabilistic Picture Fermatean Fuzzy Sets (PPFFSs), to investigate the selection of hydrokinetic energy harnessing technologies (HEHT) for various marine and river-based applications. To address the complexity of multiple criteria and alternatives, we developed a new integrated multi-criteria decision-making (MCDM) model that incorporates logarithmic percentage change-driven objective weighting (LOPCOW) and comprehensive distance-based ranking (COBRA) approaches. We define PPFFS as the definition of basic functions and the provision of information scoring and accurate operational processes. According to the results, the efficiency factor is the most important criterion, and the Seagen tidal stream turbine outperforms all other tidal turbines. The findings are supported by experimental data from the HEHT and a comparison of how two hydrokinetic energy converters can improve efficiency. As a result, hydrokinetic systems are one of the greatest sustainable energy solutions for distant communities and small-scale applications.*

**Key words**: *Multi criteria decision making, Hydraulic converter, Tidal stream turbine, Picture Fermatean fuzzy set, Comprehensive distance based ranking*

## 1. INTRODUCTION

Tidal energy has a global capacity of 120 GW and is capable of generating up to 150 TWh annually [1]. Unlike other renewable energy sources, wave energy offers long-term

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predictability, abundant resources and high energy density, albeit with high maintenance costs. Developing an effective and cost-effective wave energy device suitable for various water flow conditions has emerged as a significant challenge [2].

The decision to use hydraulic tidal turbines was a significant step in the development and implementation of tidal energy systems. Wave energy, as a sustainable and renewable energy source, has attracted worldwide attention because of its sustainability and potential contribution to the global energy system [3]. However, choosing the right tidal turbine requires careful consideration of various aspects, including cost, efficiency, resilience, environmental impact and maintenance concerns. These criteria are often intertwined and subject to multiple uncertainties [4].

Since the construction of a horizontal-axis tidal stream turbine is comparable to that of a horizontal-axis wind turbine, many of its blades resemble wind turbine blades. Currently, tidal stream turbines are primarily developed using blade element momentum (PEM) theory, which is also used to investigate their hydrodynamic properties [5]. Optimization is usually required following the initial design phase to maximize the operating efficiency of tidal stream turbines. This optimization often uses a genetic algorithm, focusing mainly on the distribution of blade chord length, turning angle, and thickness [6].

It involves progressively more sophisticated methods that can efficiently manage ambiguous and imprecise data [7]. Fuzzy set theory has emerged in recent years as a useful technique for dealing with uncertainty in MCDM situations. However, due to ambiguity and uncertainty among decision makers (DMs), it is challenging and confusing to evaluate the performance of each choice and choose the best one for MCDM difficulties [8]. Fermatean fuzzy set (FFS) differs from other extensions of fuzzy set theory by its greater flexibility in describing fuzzy and imprecise information. FFS builds on the concept of intuitionistic fuzzy sets by including a parameter that allows subtle expressions of hesitancy [9].

This paper presents a new method for selecting hydraulic tidal turbines, combining comprehensive distance-based ranking (COBRA) and logarithmic percentage change driven objective weighting (LOPCOW) with probabilistic Fermatean fuzzy sets. While the COBRA technique best combines multiple criteria and produces a compromise solution that balances opposing objectives, the LOPCOW approach is widely recognized for its ability to manage quantitative and qualitative criteria [10].

Building on the strengths of both methods, the proposed Picture Probabilistic Fermatean Fuzzy Set-Based LOPCOW-COBRA strategy creates a robust and all-encompassing decision framework. The technique effectively integrates the uncertainty and partial truth values associated with various criteria, including probabilistic FFS [11].

The PPFFS is a novel extension of the traditional fuzzy set, incorporating both the probabilistic and Fermatean fuzzy paradigms. This combination allows PPFFS to capture higher levels of uncertainty and ambiguity compared to standard fuzzy sets and other extensions. In particular, PPFFS improves the ability to model and analyze situations where information is not only imprecise but also inherently probabilistic.

By integrating the probabilistic component with Fermatean fuzzy sets, PPFFS provides a more fine-grained representation of uncertainty that accommodates both membership degree and non-membership degree with an additional layer of probabilistic uncertainty. The dual nature of PPFFS allows for a more robust decision-making framework, especially in data-scarce or highly variable environments. PPFFS can be adapted to various application domains, making it a versatile tool for complex decision-making scenarios.

A comprehensive MCDM technique, the COBRA method, combines multiple criteria into a compromise solution. This method balances the requirements to identify the optimal turbine alternative by carefully weighing the trade-offs between several performance parameters [12]. By using the PFFS and COBRA methods, this work aims to provide a systematic and rigorous approach to hydraulic tidal turbine selection. We provide a robust framework that improves decision-making in the face of uncertainty while improving the validity and reliability of the selection process. A case study illustrates how the suggested technique is applicable and practical in real situations.

As stated earlier, these methods are equivalent to ranking alternatives using distance from an established reference point. It is useful to find out which of these methods is better than using Euclidean distances to calculate the distance between positive and negative ideals. So far, the literature has not established a methodology for ranking alternatives based on the combined effect of multiple types of distances from different reference sites, which is precisely the research gap that this work attempts to fill.

As a result, a new recommended approach was developed that incorporates all the advantages of the distance-based methods discussed earlier in this paper, without the need to consider all distances. The goal of establishing a new MCDM is to develop a more accurate, reliable, consistent, understandable, simple to use, and less cumbersome method. In addition to the previously stated goals, the underlying reason for using the technique proposed in this study is to make DMs more complete and reliable.

Despite progress in fuzzy set theory and MCDA techniques, it is still necessary to accurately capture the uncertainty and probabilistic integrity of the wave turbine selection criteria. An innovative approach to overcome these limitations is to combine the PFFS and LOPCOW-COBRA methods. The fuzzy COBRA deterministic decision framework and improved uncertainty representation of PFFS are used in the proposed method. Considering the complexity and unpredictability involved, this combination provides a more accurate and reliable way to select hydraulic tidal stream turbines.

The study's remaining segment is divided into the following sections: The literature review will be included in Section 2. The primary ideas are explained in Section 3. A suggested evaluation methodology and framework are provided in Section 4. An algorithm for selecting the optimal tidal stream turbines for renewable hydroelectric power is applied to assess the strategies in Section 5. Discussion of the results, comparison and sensitivity analyses are provided in Section 6. In Section 7, the results and future work are summarized.

## 2. Literature Review

Hydraulic tidal turbine selection is a complex issue involving trade-offs of many performance, cost, and environmental factors [13]. Conventional approaches often fall short of capturing the ambiguity and complexity inherent in this decision-making process [14]. This review of the literature examines current strategies and emphasizes the advantages of PPFFS and the COBRA technique to overcome these problems.

Factors in renewable energy systems are complex and variable, including wave energy, requiring sophisticated decision-making techniques [15]. Several MCDA techniques have been used in studies to solve selection problems for renewable energy. For example, Solangi et al [16] evaluated renewable energy solutions using analytic hierarchy process

(AHP) and Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS), emphasizing the value of considering various factors when making decisions. Specific research has applied MCDA and fuzzy logic to the problem of tidal turbine selection in the context of tidal energy. To select the best tidal turbines, Chisale and Lee [17] used the fuzzy TOPSIS method, demonstrating the effectiveness of fuzzy approaches in this field.

The study found that the arrays had little effect on water levels and maximum water levels, both of which are connected with flood risk. However, the tidal turbine arrays had a greater impact on the tidal currents. The flow velocity field, suspended sediment levels, and faecal bacteria levels rose along the arrays while decreasing upstream and downstream [18]. The model demonstrated the importance of including the interaction of the turbines and the flow in assessing the potential power output by comparing the difference in the estimated power output of the various arrays, both with and without the impact of energy extraction by the turbines in the model [19].

The research elucidates the critical significance of bathymetry in wake recovery and fatigue design, offering vital information for real-world turbine array planning. Turbine locations beyond 1.5D upstream of the ridge have a higher rate of wake recovery due to a favourable pressure gradient, whereas places beyond 3D downstream of the ridge have greater turbulence intensity [20].

Fuzzy set theory is a way to deal with ambiguity and imprecision in human judgment. It is widely used for decision-making in various fields [21]. Fuzzy sets (FSs) and their classical extensions such as interval-valued FSs [22], hesitant FSs [23], neutrosophic FSs [24], Fermatean FSs [25], and spherical FSs [26] have received much attention as very convenient operators of evaluation data. Fuzzy set extensions, Pythagorean FSs [27], and intuitionistic FSs [28] have improved the ability to express uncertainty. Senapati and Yagar [29] extended these ideas using FFS, which allows more flexibility and improves uncertainty modeling. Several decision-making scenarios use the FFS framework, demonstrating its effectiveness in dealing with inherent uncertainty problems.

As a result, many researchers have extended the FS index to solve the problem of uncertainty in various domains such as engineering, medicine, and decision-making [30]. FFSs, like Pythagorean and intuitionistic FSs, can handle a large degree of uncertainty and accurately and effortlessly reflect human error judgments during decision-making [31]. Inspired by the dominance of FFSs, many studies have used it to solve challenging MCDM problems. For example, extended the application of the weighted aggregated sum product assessment (WASPAS) approach to specific health care waste disposal facilities in an FFS system [32]. FFS aggregation functions were used in the study by [33] to test the Covid-19 capabilities. FFSs were used in [34] study to overcome parameter uncertainty in capital budgeting.

The work of [35] used FFS parameters and scoring function to solve fuzzy traffic problems. In order to select a bridge, the research of optimized TOPSIS with FFSs [36]. Using TOPSIS with FFSs, a study by [37] determined which purification most effectively reduced COVID-19 and suggested a few Einstein averaging operators. A study by [38] used ELimination Et Choix Traduisant la REalite (ELECTRE), WASPAS and preference ranking organization method for enrichment evaluation (PROMETHEE-II) in the FFS system for laboratory selection for Covid-19 testing. Fuzzy sets handle data unpredictability better when they contain a probabilistic component. Developed by [39], probabilistic fuzzy sets combine fuzzy logic with probability theory to provide a robust framework for handling uncertainty. This strategy is effectively used in environmental science, technology, and economics.

MCDM approaches are important resources when making decisions considering multiple factors. Methods like the VIKOR technique, TOPSIS, and AHP are commonly used [40]. In the field of operations research, MCDM is concerned with the development of mathematical and computational tools that assist decision-makers in their subjective evaluation of predefined criteria [41]. As an objective assessment, there are several MCDM strategies, each with pros and cons. The MultiAtributive Ideal-Real Comparative Analysis (MAIRCA) [42], TOPSIS [43], Elimination and Choice Expressing Reality (ELECTRE) [44], and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) [45] are some of these methods. Using a straightforward mathematical tool that exhibits a high degree of consistency concerning changes in the nature and character of the criteria, this approach facilitates decision-making. This method's ability to calculate the probability of each option accounts for its merit. Measuring the discrepancy between ideal and actual estimates provides the basic premise of MAIRCA.

More recently, Krstic et al., [46] presented the COBRA approach, which is an extension of the decision-making toolset. It seeks a middle ground where all factors are balanced, which is useful when trade-offs are required in difficult decision-making situations. The literature demonstrates that decision tools have progressed from traditional fuzzy sets to more complex fuzzy and probabilistic extensions and advanced MCDM procedures. However, the inclusion of PPFFS in the COBRA technique represents a significant advance in the field. This technique seeks to solve the complexity and unpredictability of the problem by providing a more comprehensive and efficient solution for the selection of hydraulic tidal turbines.

## 3. Preliminaries

### 3.1 Fermatean Fuzzy Set

Let $Z$ be a fixed set, a Fermatean fuzzy set (FFS) $P$ on $Z$ is defined $P = \{(z, \alpha(z), \beta(z)) \mid z \in Z\}$ the function $\alpha(z), \beta(z)$ from $z$ in [0,1] denotes the membership and non-membership degrees, respectively, which have to satisfy $0 \leq (\alpha(z))^3 + \beta(z))^3 \leq 1$.

### 3.2 Picture Fermatean Fuzzy Set

Let $Z$ be a fixed set, a picture Fermatean fuzzy set (PFFS) $P$ on $Z$ is defined as $P = \{(z, \alpha(z), \beta(z), \gamma(z)) \mid z \in Z\}$, where, $\alpha(z) = \{\phi=\{(\sigma, \varsigma) \mid \phi \in \alpha(z)\}, \beta(z) = \{\chi = (\mu, \varpi) \mid \chi \in \beta(z)\}$, and $\gamma(z)|= \{\delta=(\xi, \rho) \mid \delta \in \gamma(z)\}$ are three FFSs of 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 $0 \leq \phi^+ + \chi^+ + \delta^+ \leq 1$.

### 3.3 Picture Probabilistic Fermatean Fuzzy Set

Let $Z$ be a fixed set, a picture probabilistic Fermatean fuzzy set (PPFFS) $P$ on $Z$ is defined as, $P = \{(z, \alpha(z)|u(z), \beta(z)|v(z), \gamma(z)|w(z)) \mid z \in Z\}$, where, $\alpha(z)|u(z), \beta(z)|v(z)$ and $\gamma(z)|w(z)$ contains a number elements, $\alpha(z), \beta(z)$, and $\gamma(z)$ denote the possibility (PMD), (NeMD), and (NMD) of $z \in Z$ $0 \leq \phi+ + \chi+ + \delta+ \leq 1$ requirement to the set P, respectively.

Here *u(x)*, *v(x)*, and *z(x)* are associated with probabilistic data. Furthermore, $\alpha(z)|u(z)$, $\beta(z)|v(z)$, and $\gamma(z)|w(z)$ satisfy the requirement of $0 \le \phi^{+} + \chi^{+} + \delta^{+} \le 1$, and $u_i, v_j, w_k \in [0,1]$. $\sum_{i=1}^{\#\phi} u_i = 1, \sum_{j=1}^{\#\chi} v_j = 1, \sum_{k=1}^{\#\delta} w_k = 1$ where, $u_i \in u(z)$, $v_j \in v(z)$, and $w_k \in w(z)$.

### 3.4 Basic Operations

Let, $p = (\alpha|u, \beta|v, \gamma|w)$, $p_1 = (\alpha_1|u_1, \beta_1|v_1, \gamma_1|w_1)$ and $p_2 = (\alpha_2|u_2, \beta_2|v_2, \gamma_2|w_2)$ be three P-PPFFEs, $\kappa > 0$, then PPFFE operations are defined by,

$$p^c = (\gamma \mid w_\gamma, \beta \mid v_\beta, \alpha \mid u_\alpha) = \bigcup_{\phi\in\alpha,\chi\in\beta,\delta\in\gamma} (\{\delta \mid w_\delta\},\{\chi \mid v_\chi\},\{\phi \mid u_\phi\})$$

$$p_1 \oplus p_2 = \bigcup_{\substack{\phi_1\in\alpha_1,\chi_1\in\beta_1,\delta_1\in\gamma_1\\ \phi_2\in\alpha_2,\chi_2\in\beta_2,\delta_2\in\gamma_2}} (\{\phi_1 + \phi_2 - \phi_1\phi_2 \mid u_{\phi_1}u_{\phi_2}\},\{\chi_1\chi_2 \mid v_{\chi_1}v_{\chi_2}\},\{\delta_1\delta_2 \mid w_{\delta_1}w_{\delta_2}\}$$

$$p_1 \otimes p_2 = \bigcup_{\substack{\phi_1\in\alpha_1,\chi_1\in\beta_1,\delta_1\in\gamma_1\\ \phi_2\in\alpha_2,\chi_2\in\beta_2,\delta_2\in\gamma_2}} (\{\phi_1\phi_2 \mid u_{\phi_1}u_{\phi_2}\},\{\chi_1 + \chi_2 - \chi_1\chi_2 \mid v_{\chi_1}v_{\chi_2}\},\{\delta_1 + \delta_2 -$$
$$\delta_1\delta_2 \mid w_{\tau_1}w_{\tau_2}\}$$

$$\vartheta p = \bigcup_{\phi\in\alpha,\chi\in\beta,\delta\in\gamma} (\{1-(1-\phi)^\vartheta \mid \phi_\sigma\},\{\chi^\vartheta \mid \chi_\varsigma\},\{\delta^\vartheta \mid w_\delta\})$$

$$p^\vartheta = \bigcup_{\phi\in\alpha,\chi\in\beta,\delta\in\gamma} (\{\phi^\vartheta \mid u_\phi\},\{1-(1-\chi)^\vartheta \mid v_\chi\},\{1-(1-\delta)^\vartheta \mid w_\delta\})$$

### 3.5 Score and Accuracy Function

Let $p = (\alpha|u, \beta|v, \gamma|w)$ be a PPFFE, then the score ($S(p)$) and accuracy functions ($A(p)$) are defined as

$$S(p) = \frac{\left\{1+((\sigma_i u_i)^3 - (\varsigma_i u_i)^3 - (\mu_i v_i)^3 - (\varpi_i v_i)^3 - (\xi_i w_i)^3 - (\rho_i w_i)^3)\right\}}{2} \tag{1}$$

$$A(p) = \left\{1+((\sigma_i u_i)^3 + (\varsigma_i u_i)^3 + (\mu_i v_i)^3 + (\varpi_i v_i)^3 + (\xi_i w_i)^3 + (\rho_i w_i)^3)\right\} \tag{2}$$

Let $p_1 = (\alpha_1|u_1, \beta_1|v_1, \gamma_1|w_1)$ and $p_2 = (\alpha_2|u_2, \beta_2|v_2, \gamma_2|w_2)$ be two PPFFEs, then, if $S(p_1) > S(p_2)$ then $(p_1) > (p_2)$, if $S(p_1) < S(p_2)$ then $(p_1) < (p_2)$, and if $S(p_1) = S(p_2)$ then $(p_1) = (p_2)$. If $A(p_1) > A(p_2)$ then $(p_1) > (p_2)$, if $A(p_1) < A(p_2)$ then $(p_1) < (p_2)$, if $A(p_1) = A(p_2)$ then $(p_1) = (p_2)$.

## 4. Proposed Methodology

### 4.1 Logarithmic Percentage Change-driven Objective Weighting Method

The following steps were used to apply the LOPCOW technique.

**Step 1:** Create a decision matrix using PPFF preferences (refer to Definition 3.3). This involves comparing the set of alternatives (i=1,2,3…n) against the criteria (j=1,2,3…m) to populate the matrix with appropriate PPFF values.

$$K = k_{ij} = \begin{bmatrix} k_{11} & \cdots & k_{1n} \\ \vdots & \ddots & \vdots \\ k_{n1} & \cdots & k_{nm} \end{bmatrix} \tag{3}$$

**Step 2:** Compute the normalized decision matrix.

$$K_{ij} = \frac{k_{ij} - k_{\min}}{k_{\max} - k_{\min}} \quad \text{for beneficial criteria} \tag{4}$$

$$K_{ij} = \frac{k_{\max} - k_{ij}}{k_{\max} - k_{\min}} \quad \text{for non-beneficial criteria} \tag{5}$$

**Step 3:** Determines the percentage values for each criteria.

$$S_{ij} = \left| In \left( \frac{\sqrt{\dfrac{\sum_{i=1}^{m} K_{ij}{}^{2}}{m}}}{\varsigma} \right) 100 \right| \tag{6}$$

where ς and m represent the standard deviation and the number of alternatives.

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

$$w_{jLOPCOW} = \frac{s_{ij}}{\sum_{i=1}^{m} S_{ij}} \tag{7}$$

### 4.2 Comprehensive Distance-based Ranking Method

Using the COBRA approach, the largest capacity tidal stream turbine is selected as shown in Fig. 1. The steps of the COBRA method are listed below.

**Step 1:** Construct the decision matrix

$$K = [k_{ij}]_{m \times n} \tag{8}$$

**Step 2:** Compute the normalizes the values

$$F_{ij} = \frac{k_{ij}}{\max k_{ij}} \tag{9}$$

**Step 3:** Determine the weighted normalized the values

$$G = [F_{ij} \times w_{jLOPCOW}] \tag{10}$$

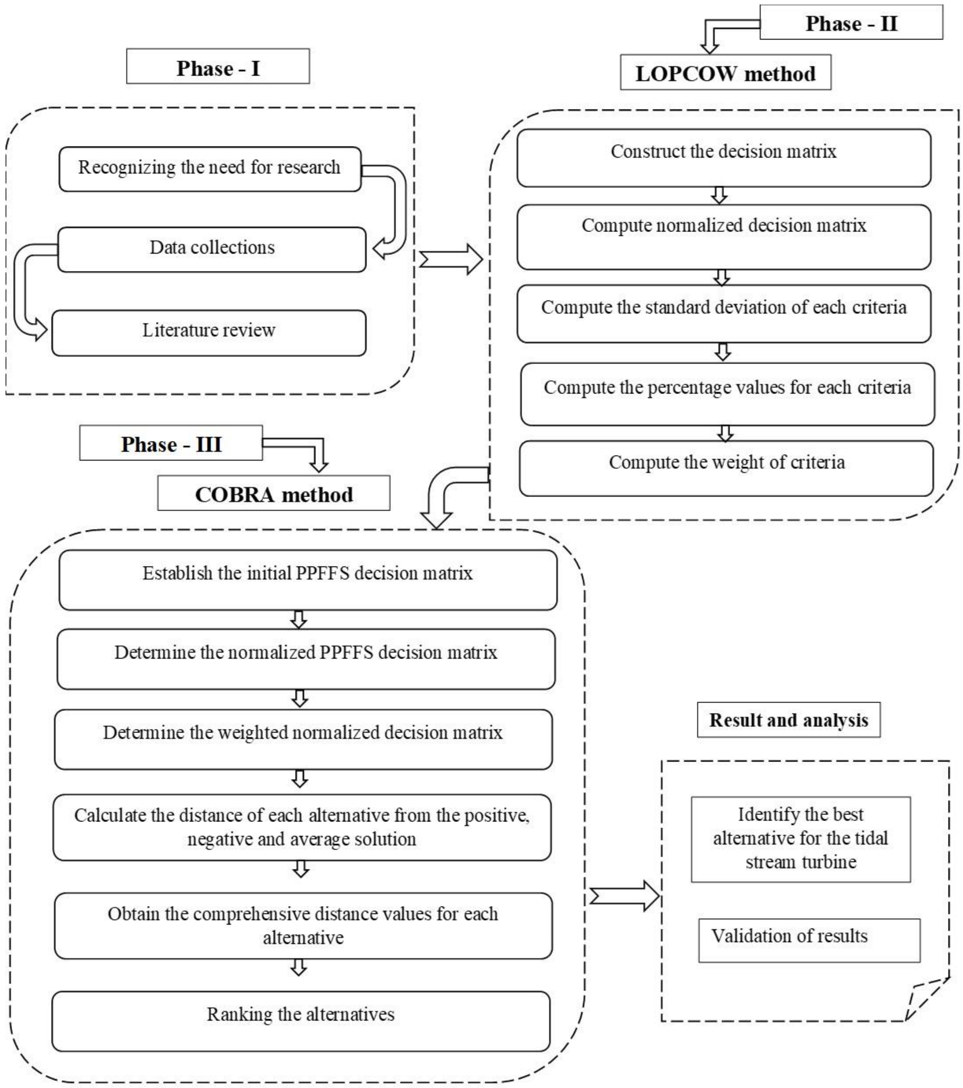


**Fig. 1** The flowchart depicts an optimal performance solving method

**Step 4:** Negative ideal, positive ideal and mean responses are calculated for each attribute. Equations (11) and (13) are used for the benefit attribute, while Eqs. (12) and (14) are used for the cost criterion.

$$NIS_j = \min\,(F_{ij} \times w_{jLOPCOW}) \tag{11}$$

$$NIS_j = \max\,(F_{ij} \times w_{jLOPCOW}) \tag{12}$$

$$PIS_j = \max\,(F_{ij} \times w_{jLOPCOW}) \tag{13}$$

$$PIS_j = \min\,(F_{ij} \times w_{jLOPCOW}) \tag{14}$$

$$AS_j = \frac{\sum_{i=1}^{m}(F_{ij} \times w_{jLOPCOW})}{m} \tag{15}$$

**Step 5:** The distances between the negative ideal *(d (NIS$_j$))* and positive ideal *(d (PISj))* solutions and from the average solution between negative *(d (AQ$^-_j$))* and positive *(d (AQ$^+_j$))* are calculated as follows.

$$d(Q_j) = d(\mathrm{E}(\mathrm{Q}_j)) + \delta \times d(\mathrm{E}(\mathrm{Q}_j)) \times d(\mathrm{T}(\mathrm{Q}_j)) \tag{16}$$

Equation (17) uses $Q_j$ to represent $PIS_j$, $AS_j$, $NIS_j$ and δ to show the correction coefficient obtained.

$$\delta = \max d(E(Q_j)) - \min d(E(Q_j)) \tag{17}$$

The Taxicab and Euclidean distances for the obtained positive ideal resolution are denoted by $T(Q_j)$ and $E(Q_j)$ in Eqs.(18) and (19), respectively.

$$d(T(PIS_j)_i) = \sum_{j=1}^{m} \left| PIS_j - F_{ij} \times w_{jLOPCOW} \right| \tag{18}$$

$$d(E(PIS_j)_i) = \sqrt{\sum_{j=1}^{m} \left( PIS_j - F_{ij} \times w_{jLOPCOW} \right)^2} \tag{19}$$

Also, the following calculation is performed for these distances for the negative ideal solution.

$$d(T(NIS_j)_i) = \sum_{j=1}^{m} \left| PIS_j - F_{ij} \times w_{jLOPCOW} \right| \tag{20}$$

$$d(E(NIS_j)_i) = \sqrt{\sum_{j=1}^{m} \left( PIS_j - F_{ij} \times w_{jLOPCOW} \right)^2} \tag{21}$$

$$d(T(AQ)\ ) = \kappa \left| AQ - F \times w \right| \tag{22}$$

$$d(E(AQ_j)^+{}_i) = \sqrt{\sum_{j=1}^{m} \kappa^+ \left( AQ_j - F_{ij} \times w_{jLOPCOW} \right)^2} \tag{23}$$

$$\kappa^+ = \begin{cases} 1 & \text{if} \quad AQ_j < F_{ij} \times w_{jLOPCOW} \\ 0 & \text{if} \quad AQ_j > F_{ij} \times w_{jLOPCOW} \end{cases} \tag{24}$$

$$d(T(AQ_j)^-{}_i) = \sum_{j=1}^{m} \kappa^- \left| AQ_j - F_{ij} \times w_{jLOPCOW} \right| \tag{25}$$

$$d(E(AQ_j)^-{}_i) = \sqrt{\sum_{j=1}^{m} \kappa^- \left( AQ_j - F_{ij} \times w_{jLOPCOW} \right)^2} \tag{26}$$

$$\kappa^- = \begin{cases} 1 & \text{if} \quad AQ_j > F_{ij} \times w_{jLOPCOW} \\ 0 & \text{if} \quad AQ_j < F_{ij} \times w_{jLOPCOW} \end{cases} \tag{27}$$

**Step 6:** Compute the comprehensive distance values *d(Ci)*

$$d(\mathrm{C}_i) = \frac{d(\mathrm{PIS}_j)_i - d(\mathrm{NIS}_j)_i - d(\mathrm{AQ}_j)^+{}_i + d(\mathrm{AQ}_j)^-{}_i}{4} \tag{28}$$

The optimal solution is determined by selecting the option with the lowest comprehensive distance value.

## 5. Selection of Tidal Stream Turbine for Hydrokinetic Energy Converter

The growing demand for sustainable energy sources has fueled much interest in wave energy. Similar to underwater wind turbines, tidal turbines convert the kinetic energy of tidal currents into electricity. This case study examines the process of selecting the optimal tidal turbine for a hydrokinetic energy converter project.

### 5.1 Alternatives

Scortrenewables tidal turbine ($P_1$): The revolutionary floating tidal turbine, called the SR2000, was developed by Scotrenewables Tidal Power, now called Orbital Marine Power. An important development in wave energy technology is the turbine. Unlike offshore-mounted systems, this design allows the turbine to be towed into place and anchored, reducing deployment and maintenance costs. Compared to conventional fixed turbines, the floating platform design has less impact on the marine environment and coastline [47]. The need for aggressive offshore operations reduces the possibility of towing the turbine to port for repairs.

Nauticity Colmat Tidal Turbine ($P_2$): The unique design of the Colmat Tidal Turbine aims to efficiently harvest tidal energy. Turbines usually use sophisticated hydrodynamic concepts to maximize energy extraction from tidal flow, while precise design details may vary. A Colmat tidal turbine produces electricity that can be used for many things, such as providing power maintaining grid stability, and providing green energy for industrial applications [48].

Seaflow tidal turbine ($P_3$): The offshore tidal turbine is an important step in the development of marine renewable energy, demonstrating the promise of harnessing tidal currents as a clean and sustainable source of electricity. It aims to collect the kinetic energy of tidal currents and convert it into power [49]. It consists of a horizontal-axis rotor with multiple blades similar to a wind turbine, but specially designed for underwater operation.

Vertent Power tidal turbine ($P_4$): An example of renewable energy technology is the Verdent Power tidal turbine, which uses tidal current energy to generate electricity [50]. It is a highly adaptable and environmentally friendly alternative to conventional tidal power plants that rely on massive infrastructure such as dams or barrages.

Seagen tidal turbine ($P_5$): Seagan is a twin-rotor tidal turbine that harnesses the power of tidal currents. It consists of two horizontal-axis rotors, each with multiple blades, arranged in a cross-beam construction. Rotors are positioned in the course of tidal currents, capturing energy as the waves come in and out [51]. Seagan has a capacity of about 1.2 MW, making it one of the largest wave energy systems in service at the time of its installation. It is capable of generating large amounts of renewable electricity for use in homes, companies, and other buildings.

RER hydro-tidal turbine ($P_6$): Hydrokinetic technology harnesses the energy of flowing water without the need for substantial dams or barriers to power the RER hydro-tidal turbine. This makes it possible to use natural water movements, including river currents and waves, to generate energy. Turbines can be placed in other aquatic habitats such as rivers, estuaries, and tidal streams [52]. Due to its adaptability, hydrokinetic energy can be used in places where other renewable energy sources are not practical.

### 5.2 Attributes

Availability ($C_1$): The availability of renewable energy is an important indicator for measuring the operational efficiency and reliability of energy systems. This has a direct impact on the efficiency and reliability of renewable energy sources in meeting energy demand.

Capacity factor ($C_2$): The efficiency factor is an important parameter for evaluating the efficiency of renewable energy systems because it reflects how efficiently a generator converts its capacity into actual energy output over time.

Conversion efficiency ($C_3$): The conversion efficiency of a device is the ratio of the energy converted into a usable form to the total energy available.

Economic ($C_4$): The installed capacity of a device is the total power it can generate when it is operating properly and at full power output. Traditionally, it refers to the installed capacity of an electrical generator in a device.

Power-Take-Off ($C_5$): A system incorporated into a renewable energy device converts energy from the physical motions of the device into usable forms such as electricity.

Survivability ($C_6$): The ability of a device to remain undamaged and operational in harsh environmental conditions.

## 6. RESULTS AND DISCUSSION

The results of the PPFFS based COBRA method for selecting hydraulic tidal stream turbines provide a new approach for decision making under uncertainty. This technique combines the advantages of COBRA with the flexibility of PPFFS to handle imprecise and unpredictable data. The evaluation used seven criteria, and six tidal turbine solutions were examined, each with varying performance levels across parameters.

### 6.1 Results of the Criteria Weights based on PPFFS-LOPCOW

Create a decision matrix with dimension m x n, where m is the number of alternative and n is the number of attribute. Using Definition 3.3 and the linguistic measure of Table 1, we construct Table 2, which shows the PPFFs decision matrix. The PPFFs score matrix is then calculated with Eq. (1). The normalized PPFFS score matrix was then constructed using Eq. (1) and is presented in Table 3.

**Table 1** Linguistic term and PPFFs numbers

| Linguistic variable | FFs Number |
|---|---|
| Very insignificant | (0.1, 0.8) |
| Not significant | (0.2, 0.7) |
| Slightly significant | (0.3, 0.6) |
| Medium significant | (0.5, 0.5) |
| Significant | (0.7, 0.3) |
| Very significant | (0.8, 0.4) |
| Absolutely significant | (0.9, 0.1) |

The equations described above were used to develop specifications for the six key criteria. The most essential factor in selecting techniques is the "power-take-off" value of 0.1835, followed by the "availability" value of 0.1771. However, "conversion efficiency" ranked third with a score of 0.1745. The strategy used the probabilistic properties of Fermatean fuzzy sets to account for the uncertainty in the decision process. Turbines are rated as most suitable based on their total scores across all criteria as shown in Fig. 2.

**Table 2** The PPFF decision matrix

| | $C_1$ | $C_2$ | $C_3$ |
|---|---|---|---|
| $P_1$ | {(0.5 \| 0.4, 0.3 \| 0.6), (0.4 \| 0.5, 0.2 \| 0.5), (0.5 \| 0.6, 0.3 \| 0.4)} | {(0.7 \| 0.4, 0.4 \| 0.6), (0.4 \| 0.2, 0.2 \| 0.8), (0.3 \| 0.4, 0.2 \| 0.6)} | {(0.2 \| 0.7, 0.4 \| 0.3), (0.3 \| 0.6, 0.9 \| 0.4), (0.4 \| 0.4, 0.6 \| 0.6)} |
| $P_2$ | {(0.7 \| 0.5, 0.5 \| 0.5), (0.6 \| 0.9, 0.4 \| 0.1), (0.2 \| 0.3, 0.1 \| 0.7)} | {(0.8 \| 0.7, 0.5 \| 0.3), (0.5 \| 0.5, 0.3 \| 0.5), (0.2 \| 0.6, 0.5 \| 0.3)} | {(0.6 \| 0.2, 0.3 \| 0.8), (0.8 \| 0.8, 0.4 \| 0.2), (0.2 \| 0.3, 0.7 \| 0.7)} |
| $P_3$ | {(0.4 \| 0.7, 0.3 \| 0.3), (0.7 \| 0.6, 0.2 \| 0.4), (0.5 \| 0.5, 0.3 \| 0.5)} | {(0.9 \| 0.9, 0.3\|0.1), (0.6 \| 0.6, 0.4 \| 0.4), (0.6 \| 0.9, 0.2 \| 0.1)} | {(0.6 \| 0.4, 0.4 \| 0.6), (0.5 \| 0.7, 0.7 \| 0.3), (0.5 \| 0.9, 0.8 \| 0.1)} |
| $P_4$ | {(0.2 \| 0.3, 0.1 \| 0.7), (0.4 \| 0.8, 0.1 \| 0.2), (0.6 \| 0.3, 0.2 \| 0.7)} | {(0.8 \| 0.2, 0.6 \| 0.8), (0.8 \| 0.3, 0.4 \| 0.7), (0.8 \| 0.1, 0.5 \| 0.9)} | {(0.8 \| 0.1, 0.5 \| 0.9), (0.2 \| 0.5, 0.1 \| 0.5), (0.9 \| 0.6, 0.5 \| 0.4)} |
| $P_5$ | {(0.8 \| 0.4, 0.5 \| 0.6), (0.7 \| 0.4, 0.5 \| 0.6), (0.7 \| 0.9, 0.4 \| 0.1)} | {(0.7 \| 0.1, 0.5 \| 0.9), (0.9 \| 0.8, 0.5 \| 0.2), (0.1 \| 0.7, 0.7 \| 0.3)} | {(0.1 \| 0.7, 0.7\| 0.3), (0.6 \| 0.2, 0.3 \| 0.8), (0.2 \| 0.3, 0.1 \| 0.7)} |
| $P_6$ | {(0.3 \| 0.2, 0.2 \| 0.8), (0.9 \| 0.1, 0.4 \| 0.9), (0.9 \| 0.2, 0.8 \| 0.8)} | {(0.6 \| 0.7, 0.5 \| 0.3), (0.3 \| 0.7, 0.2 \| 0.3), (0.4 \| 0.5, 0.1 \| 0.5)} | {(0.8 \| 0.4, 0.9 \| 0.6), (0.5 \| 0.6, 0.7 \| 0.4), (0.3 \| 0.8, 0.4 \| 0.2)} |

| $C_4$ | $C_5$ | $C_6$ |
|---|---|---|
| {(0.3 ∣ 0.5, 0.2 ∣ 0.5), (0.4 ∣ 0.4, 0.6 ∣ 0.6), (0.7 ∣ 0.3, 0.8 ∣ 0.7)} | {(0.3 ∣ 0.4, 0.9 ∣ 0.6), (0.8 ∣ 0.6, 0.7 ∣ 0.4), (0.2 ∣ 0.5, 0.1 ∣ 0.5)} | {(0.1 ∣ 0.9, 0.3 ∣ 0.1), (0.6 ∣ 0.1, 0.5 ∣ 0.9), (0.6 ∣ 0.3, 0.8 ∣ 0.7)} |
| {(0.5 ∣ 0.7, 0.6 ∣ 0.3), (0.7 ∣ 0.7, 0.2 ∣ 0.3), (0.2 ∣ 0.4, 0.4 ∣ 0.6)} | {(0.2 ∣ 0.4, 0.8 ∣ 0.3), (0.9 ∣ 0.5, 0.5 ∣ 0.5), (0.4\|0.6, 0.5 ∣ 0.4)} | {(0.5 ∣ 0.8, 0.7 ∣ 0.2), (0.8 ∣ 0.2, 0.7 ∣ 0.8), (0.9 ∣ 0.4, 0.1 ∣ 0.6)} |
| {(0.7 ∣ 0.9, 0.8 ∣ 0.1), (0.8 ∣ 0.2, 0.6 ∣ 0.8), (0.1 ∣ 0.5, 0.3 ∣ 0.5)} | {(0.1 ∣ 0.9, 0.7 ∣ 0.9), (0.4 ∣ 0.2, 0.2 ∣ 0.8), (0.7 ∣ 0.9, 0.4 ∣ 0.1)} | {(0.9 ∣ 0.7, 0.8 ∣ 0.3), (0.9 ∣ 0.3, 0.3 ∣ 0.7), (0.2 ∣ 0.5, 0.3 ∣ 0.5)} |
| {(0.1 ∣ 0.8, 0.9 ∣ 0.2), (0.2 ∣ 0.1, 0.1 ∣ 0.9), (0.5 ∣ 0.2, 0.6 ∣ 0.8)} | {(0.6 ∣ 0.4, 0.5 ∣ 0.6), (0.3 ∣ 0.4, 0.1 ∣ 0.6), (0.2 ∣ 0.8, 0.3 ∣ 0.2)} | {(0.6 ∣ 0.6, 0.4 ∣ 0.4), (0.2 ∣ 0.4, 0.1 ∣ 0.6), (0.4 ∣ 0.8, 0.6 ∣ 0.2)} |
| {(0.7 ∣ 0.4, 0.3\|0.6), (0.8 ∣ 0.5, 0.9 ∣ 0.5), (0.9 ∣ 0.9, 0.8 ∣ 0.1)} | {(0.4 ∣ 0.9, 0.2 ∣ 0.1), (0.5 ∣ 0.9, 0.4 ∣ 0.1), (0.8 ∣ 0.7, 0.7 ∣ 0.3)} | {(0.2 ∣ 0.5, 0.3 ∣ 0.5), (0.4 ∣ 0.8, 0.7 ∣ 0.2), (0.5 ∣ 0.9, 0.3 ∣ 0.1)} |
| {(0.2 ∣ 0.1, 0.5 ∣ 0.9), (0.3 ∣ 0.4, 0.5 ∣ 0.6), (0.2 ∣ 0.8, 0.4 ∣ 0.2)} | {(0.6 ∣ 0.5, 0.8 ∣ 0.5), (0.3 ∣ 0.3, 0.2 ∣ 0.7), (0.9 ∣ 0.4, 0.3 ∣ 0.6)} | {(0.6 ∣ 0.4, 0.8 ∣ 0.6), (0.3 ∣ 0.5, 0.8 ∣ 0.5), (0.9 ∣ 0.6, 0.1 ∣ 0.4)} |

**Table 3** The PPFF score normalized the decision matrix

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
|---|---|---|---|---|---|---|
| $P_1$ | 1.0000 | 0.1759 | 0.7488 | 0.3166 | 0.4160 | 0.4718 |
| $P_2$ | 0.0000 | 0.4541 | 0.1366 | 0.4227 | 1.0000 | 0.3542 |
| $P_3$ | 0.9085 | 1.0000 | 1.0000 | 0.0000 | 0.0000 | 1.0000 |
| $P_4$ | 0.3062 | 0.0000 | 0.0000 | 0.5315 | 0.9566 | 0.6589 |
| $P_5$ | 0.5982 | 0.3898 | 0.0636 | 1.0000 | 0.9075 | 0.5132 |
| $P_6$ | 0.7114 | 0.5351 | 0.3542 | 0.4224 | 0.6256 | 0.0000 |

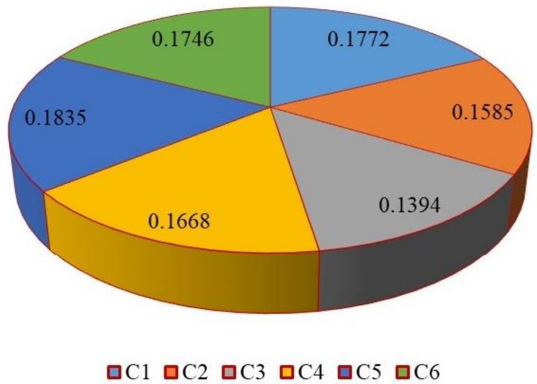


**Fig. 2** Criteria weights

### 6.2 Results of Alternative Values based on PPFF-COBRA

PPFFS was used to depict the uncertainty and probabilistic nature of expert judgments. Each criterion for each turbine option was assigned a degree of membership or non-membership. The COBRA technique was used to rank the options according to weighted criteria.

**Table 4** Normalized PPFF decision matrix

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
|---|---|---|---|---|---|---|
| $P_1$ | 1.0000 | 0.5464 | 0.8767 | 0.8053 | 0.7860 | 0.8147 |
| $P_2$ | 0.7246 | 0.6995 | 0.5762 | 0.7401 | 1.0000 | 0.7734 |
| $P_3$ | 0.9748 | 1.0000 | 1.0000 | 1.0000 | 0.6337 | 1.0000 |
| $P_4$ | 0.8089 | 0.4496 | 0.5091 | 0.6732 | 0.9841 | 0.8803 |
| $P_5$ | 0.8893 | 0.6642 | 0.4503 | 0.3853 | 0.9661 | 0.8292 |
| $P_6$ | 0.9205 | 0.7441 | 0.6830 | 0.7402 | 0.8628 | 0.6492 |

Equation (9) uses the PPFFS score matrix to normalize the decision matrix, as shown in Table 4. Equation (10) then calculates the weighted normalized result matrix as shown in Table 5. Equations (11-28) are used to determine the selection of a hydraulic tidal stream turbine. Table 6 shows the COBRA approach's results and the tidal stream turbines' evaluation. Fig. 3 shows that the lowest overall score was the best overall fit for the tidal turbine. The greatest possibilities for high production and established technology are SeaGen and Scotrenewables.

**Table 5** Weighted normalized PPFF decision matrix

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
|---|---|---|---|---|---|---|
| $P_1$ | 0.1771 | 0.0866 | 0.1222 | 0.1343 | 0.1442 | 0.1422 |
| $P_2$ | 0.1284 | 0.1108 | 0.0803 | 0.1234 | 0.1835 | 0.1350 |
| $P_3$ | 0.1727 | 0.1584 | 0.1394 | 0.1667 | 0.1163 | 0.1745 |
| $P_4$ | 0.1433 | 0.0710 | 0.0709 | 0.1122 | 0.1806 | 0.1537 |
| $P_5$ | 0.1575 | 0.1052 | 0.0753 | 0.0642 | 0.1773 | 0.1447 |
| $P_6$ | 0.1631 | 0.1179 | 0.0952 | 0.1234 | 0.1583 | 0.1133 |

**Table 6** The results of the PPFF-COBRA method

| | d(NIS) | d(PIS) | $d(AQ^+)$ | $d(AQ^-)$ | d(C) | Rank |
|---|---|---|---|---|---|---|
| $P_1$ | 0.0898 | 0.1187 | 0.0349 | 0.0270 | 0.0052 | 2 |
| $P_2$ | 0.0931 | 0.1204 | 0.0237 | 0.0344 | 0.0095 | 3 |
| $P_3$ | 0.1358 | 0.2879 | 0.0882 | 0.0438 | 0.0269 | 6 |
| $P_4$ | 0.0954 | 0.1334 | 0.0375 | 0.0527 | 0.0133 | 5 |
| $P_5$ | 0.1329 | 0.0937 | 0.0172 | 0.0608 | 0.0011 | 1 |
| $P_6$ | 0.0880 | 0.1130 | 0.0116 | 0.0307 | 0.0110 | 4 |

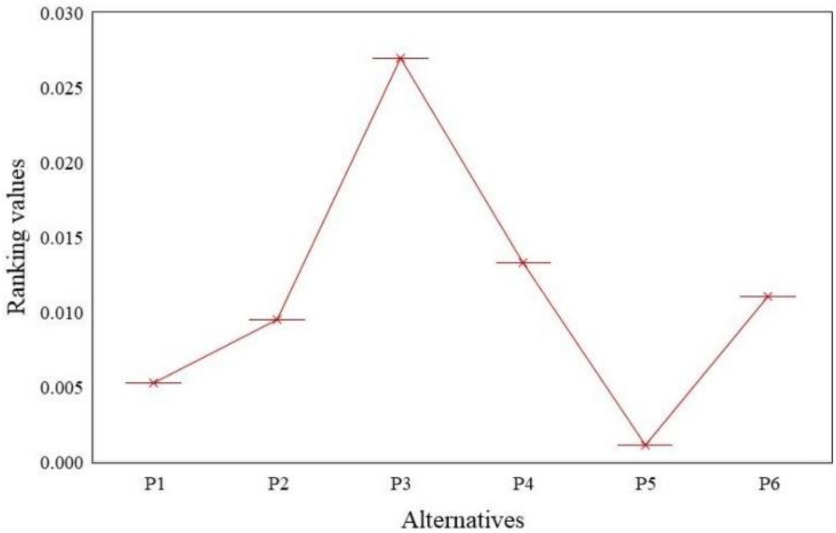


**Fig. 3** The proposed COBRA method ranking of the results

### 6.3 Comparative Analysis of Different Ranking Techniques

The integrated MCDM model utilized in this study effectively evaluated the different tidal turbine alternates for hydrokinetic energy conversion. The model integrates many MCDM approaches, including WASPAS, COPRAS, CODAS, MOORA, and EDAS.

Comparative research revealed that the COBRA technique provided rankings that were most consistent with WASPAS, CODAS, and MOORA. The consistency suggests that the ranking process is robust among several MCDM approaches as shown in Table 7.

Application of the proposed method to combine rankings from various MCDM approaches ensures robust and reliable results. The results demonstrate that SeaGen and Scotrenewables is the best substitute, followed by other turbine, with consistent rankings across different techniques as shown in Fig. 4. Despite the different techniques, the rank orders did not differ significantly, indicating that the best alternatives were consistently and reliably selected.

**Table 7** The comparison results are presented in a ranked order

| | WASPAS | CODAS | COPRAS | MOORA | EDAS | Proposed Method |
|---|---|---|---|---|---|---|
| $P_1$ | 0.4432 | -0.0990 | 0.8834 | 0.1090 | 0.3441 | 0.0052 |
| $P_2$ | 0.4179 | -0.0688 | 0.8552 | 0.1043 | 0.1970 | 0.0095 |
| $P_3$ | 0.5181 | 0.8122 | 0.9783 | 0.1235 | 0.5000 | 0.0269 |
| $P_4$ | 0.3937 | -0.2569 | 0.8368 | 0.1010 | 0.0901 | 0.0133 |
| $P_5$ | 0.3878 | -0.3240 | 1.0000 | 0.1216 | 0.5529 | 0.0011 |
| $P_6$ | 0.4252 | -0.0465 | 0.8693 | 0.1069 | 0.3541 | 0.0110 |

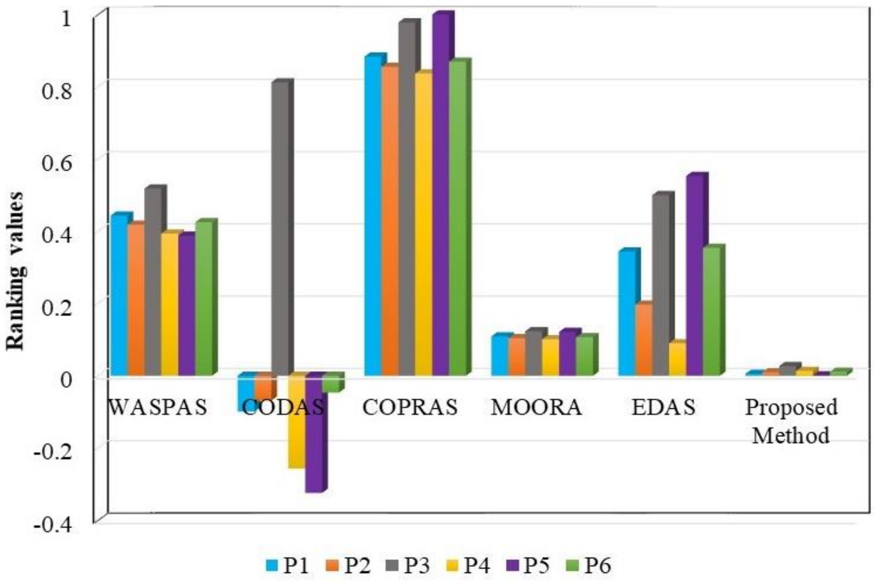


**Fig. 4** Comparative ranking of the results

### 6.4 Sensitivity Analysis

This study investigates the sensitivity of ranking alternatives in selecting tidal turbines for hydrokinetic power generation by changing the weights of the criteria. These weights are subjectively calculated by experts using PPFFSs-LOPCOW. Sensitivity analysis involves reassigning weights to the original seven criteria and testing two scenarios with multiple decision-makers.

**Case 1:** Weights of criteria are considered equal.

**Case 2:** In this case, the $j^{th}$ beneficial criterion is given equal weight and the others are assigned zero.

Figure 5 and Table 8 of the study demonstrate the resulting rankings for the two cases. Weight changes had a significant impact on the ranking of alternatives. The order of preferences for hydroelectric renewable energy is strongly dependent on the weights provided to the criteria.

This precision is needed to prioritize sustainability in the selection process for hydroelectric renewable energy sources. The study illustrates the robustness of the integrated MCDM model and its adaptability to various weighting scenarios, emphasizing the need for qualified judgment in criterion weighting.

**Table 8** The PSI-DNMA method's findings rank in the order of parameters

| | Ranking values | Ranking order | Optimal rank |
|---|---|---|---|
| Case 1 | 0.0037, 0.0123, 0.0191, 0.0171 0.0051, 0.0110 | $P_3 > P_4 > P_2 > P_6 > P_5 > P_1$ | $P_1$ |
| Case 2 | -0.0007, 0.0131, 0.122, 0.0233 0.0109, 0.0112 | $P_4 > P_2 > P_3 > P_6 > P_5 > P_1$ | $P_1$ |

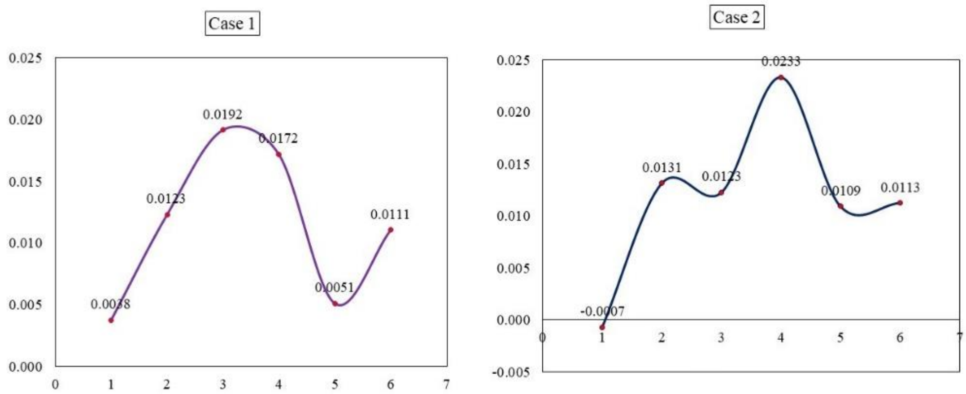


**Fig. 5** The solution is influenced by the parameter

The PFFS provided a robust framework to handle the inherent uncertainty in expert judgments. It allowed for a more nuanced representation of the experts' confidence levels compared to traditional fuzzy sets. Hydrokinetic energy harnessing technologies are pivotal in the sustainable energy landscape, as they offer a renewable and environmentally friendly alternative to traditional energy sources. These technologies capture the kinetic energy of moving water—whether from rivers, tidal currents, or ocean waves—to generate electricity. Tidal stream turbines operate similarly to underwater wind turbines. They are installed in tidal streams and ocean currents, capturing the energy from the movement of water.

The turbines can be horizontal or vertical axis designs, with blades that rotate as water flows past them. Tidal streams offer a predictable and reliable source of energy, as tidal patterns are well-understood and cyclical. MCDM methods, such as the newly proposed Picture probabilistic Fermatean fuzzy set based LOPCOW-COBRA method, are invaluable in addressing the complex trade-offs involved in turbine selection. These methods allow decision-makers to systematically evaluate and prioritize multiple criteria, incorporating both quantitative and qualitative factors.

LOPCOW is essential for tackling complex problems where traditional methods might fall short. Its structured approach helps in breaking down and analyzing intricate issues. By comparing outputs and weights at different levels, LOPCOW facilitates more informed decision-making. This is particularly important in fields such as economics, engineering, and data science, where results often have significant consequences. The approach helps in refining models and predictions by emphasizing detailed processing and comparison. This leads to more accurate and reliable outcomes. The unique feature of comparing outputs and weights allows for a deeper understanding of relationships and dependencies within the data. LOPCOW can integrate and process data from various sources, making it adaptable to different kinds of datasets and problems. This flexibility enhances its applicability and effectiveness.

Despite their low impact, hydrokinetic systems can still affect marine and riverine ecosystems. Concerns include the potential for fish and other aquatic organisms to be harmed by turbine blades, changes to sediment transport, and alterations to water flow patterns. The initial cost of hydrokinetic energy systems can be high due to the need for specialized materials and technologies. Additionally, maintenance in underwater environments is complex and costly. However, ongoing advancements and economies of scale are expected to reduce costs over time.

Sensitivity analysis showed that changes in criteria weights could significantly alter the rankings, highlighting the importance of accurate weight determination. Compared to traditional decision-making methods, the PFFS-based COBRA approach demonstrated superior performance in managing uncertainty and providing reliable rankings. The probabilistic aspect of the fuzzy sets offered a more flexible and realistic modeling of expert opinions.

The reliability of results depends on the quality and reliability of expert information. Consequently, this work develops an understanding model for factors and objectives before applying a multi-objective optimization method for genetic optimization of power coefficient, a primary indicator of tidal stream turbine hydraulic performance. As tidal power supply is abundant, hydraulic power generation is limited due to turbine conversion efficiency and production costs.

## 7. CONCLUSION

In this study, we introduced a novel hybrid MCDM technique capable of effectively solving practical decision-making (DM) situations. This research aims to present the concept of PPFFSs, which allows DM experts to provide beneficial and non-beneficial criteria for an alternative set using interval values. We have studied the basic operation rules, scoring, and accuracy functions for PPFFNs in comparison to FFSs and image probabilistic fuzzy sets. Next, we developed an extended LOPCOW-COBRA-based approach that uses the proposed functions to handle MCDM problems from a picture probabilistic Fermatean fuzzy perspective.

Finally, to show the model's utility and application, a case study of tidal turbines for hydrokinetic energy converter assessment has been considered on PPFFSs. For high output and proven technology, the best options are SeaGen and Scotrenewables (Orbital Marine Power). We suggested that basis operators are more useful because they reflect the interconnections of multiple criteria while reducing the detrimental influence of DM excessively high or low evaluation values on final selection decisions. Hydrokinetic systems are not weather-dependent and have lower initial capital costs than hydropower, photovoltaics, wave energy converters, and other renewable energy technologies. As a result, hydrokinetic devices are one of the most effective sources of renewable energy for isolated communities and small-scale needs. According to literature works, hydrokinetic technologies can be classified as turbine or non-turbine processes. These properties make our techniques well-suited for real-world MCDM problems. Also, a sensitivity analysis was performed to confirm the reliability of the obtained results. Finally, to illustrate their applicability and benefits, we compare the ones we developed with some existing models.

The significance of this research lies in its ability to provide a holistic evaluation of tidal stream turbine converters, addressing both environmental and technical dimensions of sustainability. A comprehensive distance-based approach provides a valuable tool for policymakers, engineers, and researchers involved in the development and implementation of sustainable wave energy technologies.

A high level of technical expertise may be required to properly implement the proposed method. This can be a barrier for organizations or individuals who lack the necessary skills. Implementing the LOPCOW-COBRA method can require significant computational resources, which can be challenging for small organizations with limited resources. Conduct thorough cost-benefit analyses to justify the initial investment and identify situations where the method's benefits outweigh the costs. Establish robust data quality assurance processes to ensure reliable and accurate input data.

Exploring the integration of tidal stream turbine systems with other renewable energy sources such as wind or solar power may provide new opportunities to improve overall energy sustainability and reliability. To better understand the economic feasibility and potential return on investment for tidal stream turbine technologies, further research is needed to conduct detailed economic analysis, including cost-benefit assessments and life cycle assessments. In addition, we will use these operators to introduce new MCDM models and explore various applications such as cluster analysis, medical diagnostics, computational imaging, and MCDM challenges. Future research could explore the integration of machine learning approaches with real-time data to further improve the decision-making process. It is possible to extend the approach to include more criteria or complex decision situations.

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