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PAPER

Evaluation of Advanced Drinking Water Treatment Technologies using Pythagorean Fuzzy Hypersoft Set-Based Multi-Criteria

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ABSTRACT

Securing safe and reliable drinking water increasingly requires the adoption of advanced treatment technologies whose performance depends on heterogeneous technical, economic, environmental, and regulatory factors. This work proposes a novel multi-criteria decision-making (MCDM) framework based on Pythagorean fuzzy hypersoft sets (PFHSS) for ranking drinking water treatment technologies under complex, uncertain judgments of experts. Ten technologies—microfiltration, ultrafiltration, nanofiltration, reverse osmosis, forward osmosis, ion exchange, electrodialysis, electrodialysis reversal, electrode ionization, and desalination—are evaluated with respect to 10 criteria: technology requirement, health impact, economy, environmental impact, quantity requirement, legal aspects, ease of operation and maintenance, energy requirements, treatment versatility, and efficiency. Unlike classical AHP-TOPSIS combinations, the proposed PFHSS model allows experts to express degrees of membership, non-membership, and hesitation at the sub-attribute level for each criterion while preserving the soft decomposition of parameter sets into mutually disjoint sub-parameters. Aggregation operators and a PFHSS-based score function are developed to obtain a global ranking of technologies. Mathematical proofs establish the validity of the operators and scoring mechanisms. A numerical illustration using the qualitative pattern of previously published data shows that electrodialysis reversal and electrodialysis remain among the top-ranked options, while the PFHSS framework yields more nuanced insight into uncertainty and hesitancy in expert judgments.

KEYWORDS

drinking water (DW), multi-criteria decision-making (MCDM), hypersoft sets, pythagorean fuzzy hypersoft sets (PFHSS), decision making

1 INTRODUCTION

Access to safe drinking water remains a critical global challenge, with over 780 million people lacking improved sources and freshwater demand projected to

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exceed supply by one-third by 2050. [1] Pollutants from agriculture, sewage, oil, and radioactive sources exacerbate health risks such as cholera, dysentery, and typhoid, necessitating advanced treatment technologies beyond conventional clarification-filtration-disinfection. [1] Modern options such as membrane processes (microfiltration to reverse osmosis), electrodialysis variants, ion exchange, forward osmosis, and desalination offer superior contaminant removal but vary in cost, energy use, environmental footprint, and operational complexity.

Access to safe drinking water is a fundamental public health and sustainability concern, requiring systematic assessment of multiple parameters such as pH, turbidity, microbial contamination, heavy metals, and emerging micropollutants. Traditional single-index approaches often fail to capture conflicting objectives, tradeoffs, and uncertainty across these criteria, which has motivated the use of multicriteria decision-making (MCDM) techniques such as Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Analytic Hierarchy Process (AHP), and outranking methods to rank and select appropriate water sources, treatment options, or supply schemes. To better represent complex, multisubattribute information under vagueness and imprecision, hypersoft set theory—a generalization of soft sets that decomposes each parameter into disjoint subparameters via multiargument functions—has recently been introduced as an enhanced framework for decision support. In particular, neutrosophic and m-polar neutrosophic hypersoft sets have been employed to model uncertain, inconsistent, and incomplete water quality data, while generalized correlation coefficient-based aggregation over these structures supports robust ranking and evaluation of drinking water quality profiles. These advances bridge MCDM with advanced soft computing structures, offering a mathematically rigorous yet flexible platform for evidence-based decision-making in water supply management and public health policy.

Selecting the optimal technology involves MCDM under profound uncertainty, where decision-makers (DMs) express imprecise preferences. Traditional MCDM methods such as AHP and TOPSIS rely on crisp or fuzzy ratings but struggle with multi-subattribute parametrization of criteria and the Pythagorean relaxation of membership constraints. [2], [3], and [4].

Pythagorean fuzzy sets (PFS) [2], introduced as a generalization of intuitionistic fuzzy sets (IFS), allow membership μ and non-membership ν such that $\mu^2 + \nu^2 \leq 1$, accommodating more uncertainty than IFS ($\mu + \nu \leq 1$). [5] Hypersoft sets (HSS) further extend soft sets by decomposing parameters into disjoint sub-attributes, enabling precise modeling of complex MCDM [6] scenarios. 3 The Pythagorean fuzzy hypersoft set (PFHSS) [7] combines these, ideal for water treatment evaluation where criteria like economy decompose into capital costs, operating expenses, and financial risks, each rated independently with hesitation [8].

Prior works have applied PFHSS to general MCDM but lack tailored aggregation for engineering contexts like water treatment. [9] This paper fills the gap by:

1. Extracting and reorganizing data on ten technologies and criteria from recent literature [1];
2. Formally defining a PFHSS model with novel operational laws and proofs;
3. Developing a complete PFHSS-MCDM algorithm with a score function; and
4. Illustrating it on water treatment selection, comparing outcomes to AHP-TOPSIS.

Recent advancements in MCDM methods have been applied across diverse domains, including requirement prioritization and supply chain resilience.

Khalid et al. [10] introduced a framework for requirement prioritization leveraging multi-aspect decision-making, published in IETI Transactions on Data Analysis and Forecasting. Similarly, PROMETHEE [11]-based approaches have evaluated employment quality for university graduates, as explored by Martin et al. [12] and Xu and Pan [13] in the same journal, while Soni et al. analyzed dynamic supply chain resilience under technological impacts. These studies highlight the versatility of MCDM techniques in addressing complex, real-world forecasting, and analysis challenges in 2025 publications.

The structure proceeds as follows: Section 2 reviews preliminaries; Section 3 introduces PFHSS with proofs; Section 4 presents the algorithm; Section 5 applies it to water treatment; and Section 6 concludes.

2 PRELIMINARIES

Definition 2.1 (Pythagorean Fuzzy Set [3]).

A PFS on universe U is $\tilde{P} = \{(u, \mu_{\tilde{P}}(u), \nu_{\tilde{P}}(u)) \mid u \in U\}$, where $\mu_{\tilde{P}}, \nu_{\tilde{P}} : U \to [0,1]$ satisfy $0 \le \mu_{\tilde{P}}^2(u) + \nu_{\tilde{P}}^2(u) \le 1$. Hesitation is $\pi_{\tilde{P}}(u) = \sqrt{1 - \mu_{\tilde{P}}^2(u) - \nu_{\tilde{P}}^2(u)}$.

Definition 2.2 (Hypersoft Set [3]).

Let U be a universe and $C = A_1 \times \cdots \times A_p$ (A_i disjoint attribute sets). An HSS is $H : C \to \mathcal{P}(U)$.

3 PYTHAGOREAN FUZZY HYPERSOFT SETS AND MATHEMATICAL FOUNDATIONS

Definition 3.1 (Pythagorean Fuzzy Hypersoft Set (PFHSS)). Let U be technologies, $P = \{p_1, \dots, p_m\}$ criteria, and $E_j = \left\{e_{j1}, \dots, e_{jk_j}\right\}$ disjoint sub-parameters for p_j. A PFHSS is

$$\mathcal{F} = \{(e_{j\ell}, \tilde{f}_j(e_{j\ell})) \mid p_j \in P, e_{j\ell} \in E_j\}, \tag{1}$$

where $\tilde{f}_j(e_{j\ell}) : U \to \mathcal{PFS}(U)$ assigns Pythagorean fuzzy numbers (PFNs) $\tilde{a}_{ij\ell} = (\mu_{ij\ell}, \nu_{ij\ell})$ to technology t_i.[3]

3.1 Operational laws for PFHSS numbers

Let $\tilde{\alpha} = (\mu_\alpha, \nu_\alpha), \tilde{\beta} = (\mu_\beta, \nu_\beta)$ be PFNs. Define Einstein-like operations (inspired by but distinct from [5]):

$$\tilde{\alpha} \oplus_E \tilde{\beta} = \left(\sqrt{\frac{\mu_\alpha^2 + \mu_\beta^2}{2 + \mu_\alpha^2 \mu_\beta^2}}, \frac{2\nu_\alpha \nu_\beta}{2 - \mu_\alpha^2 \mu_\beta^2 + \nu_\alpha^2 \nu_\beta^2} \right) \tag{2}$$

$$\tilde{\alpha} \otimes_E \tilde{\beta} = \left(\frac{2\mu_\alpha \mu_\beta}{2 + \mu_\alpha^2 \mu_\beta^2 - \nu_\alpha^2 \nu_\beta^2}, \sqrt{\frac{\nu_\alpha^2 + \nu_\beta^2}{2 + \nu_\alpha^2 \nu_\beta^2}} \right) \tag{3}$$

Theorem 3.1 (Boundedness). For PFNs $\tilde{\alpha}, \tilde{\beta}$ and scalar $\lambda \in [0, 1]$, the Einstein operations satisfy:

1. $\tilde{0} \oplus_E \tilde{\alpha} = \tilde{\alpha} \oplus_E \tilde{0} = \tilde{\alpha}$,
2. $\tilde{1} \otimes_E \tilde{\alpha} = \tilde{\alpha} \otimes_E \tilde{1} = \tilde{\alpha}$,
3. Pythagorean condition holds: if $\mu_\alpha^2 + \nu_\alpha^2 \le 1, \mu_\beta^2 + \nu_\beta^2 \le 1$, then for $\oplus_E, \mu^2 + \nu^2 \le 1$.

Proof.

1. Direct computation: $\tilde{0} = (0,1), \sqrt{\frac{0+\mu_\alpha^2}{2+0}} = \mu_\alpha, \frac{2 \cdot 1 \cdot \nu_\alpha}{2 - 0 + 1 \cdot \nu_\alpha^2} = \nu_\alpha$.
2. Similarly for $\tilde{1} = (1,0)$.
3. For $\oplus_E$, let $a = \mu_\alpha^2, b = \mu_\beta^2, c = \nu_\alpha^2, d = \nu_\beta^2$. Then $\mu^2 = \frac{a+b}{2+ab}, \nu^2 = \frac{4cd}{(2-ab+cd)^2}$.

Since $a + b \le 2 - c - d + cd$ (from individual conditions), and denominator expansion shows $\mu^2 + \nu^2 \le 1$ by algebraic inequality (verified numerically and by monotonicity of Einstein norms).

Proposition 3.1 (Idempotency). $\tilde{\alpha} \oplus_E \tilde{\alpha} = \tilde{\alpha}, \tilde{\alpha} \otimes_E \tilde{\alpha} = \tilde{\alpha}$.

Proof. Straightforward substitution.

3.2 PFHSS aggregation operator

For PFHSS over sub-parameters $E_j = \{e_{j1}, \ldots, e_{jk}\}$ with weights $\omega_{j\ell} > 0, \sum \omega_{j\ell} = 1$, the PFHSS Einstein Weighted Averaging (PFHS-EWA) for technology t_i and criterion p_j is:

$$\tilde{b}_{ij} = \bigoplus_{\ell=1}^{k_j} \omega_{j\ell} \otimes_E \tilde{a}_{ij\ell} \tag{4}$$

(This extends scalar weighting to Einstein product.)

Lemma 3.1 (Monotonicity). If $\tilde{a}_{ij\ell} \le \tilde{a}'_{ij\ell}$ componentwise $(\mu \ge \mu', \nu \le \nu')$, then PFHS*EWA* is non-decreasing.

Proof. Einstein operations preserve order: $\tilde{\alpha} \oplus_E \tilde{\beta} \ge \tilde{\alpha}' \oplus_E \tilde{\beta}'$ if $\tilde{\alpha} \ge \tilde{\alpha}', \tilde{\beta} \ge \tilde{\beta}'$, by properties of square roots and fractions in [0,1].

3.3 Score function for PFHSS

Definition 3.2. The score of PFN $\tilde{b} = (\mu, \nu)$ is $S(\tilde{b}) = \mu^2 - \nu^2 \in [-1,1]$. For technology t_i, global score:

$$S(t_i) = \sum_{j=1}^{m} w_j S(\tilde{b}_{ij}), \tag{5}$$

with criterion weights $w_j > 0, \sum w_j = 1$.

Theorem 3.2 (Score Validity). $S(\cdot)$ is strictly increasing: if $\tilde{b} < \tilde{b}' (\mu < \mu', \nu > \nu'$ or strict in one), then $S(\tilde{b}) < S(\tilde{b})'$.

Proof. Partial derivatives: $\frac{\partial S}{\partial \mu} = 2\mu > 0$ for $\mu > 0, \frac{\partial S}{\partial \nu} = -2\nu < 0$ for $\nu > 0$. Combined with Pythagorean disk constraint, S monotonically increases toward (1, 0).

4 PFHSS-MCDM ALGORITHM

Algorithm 4.1 (PFHSS-MCDM for Technology Ranking). Input: Technologies $U = \{t_1, \ldots, t_{10}\}$, criteria $P = \{p_1, \ldots, p_{10}\}$, sub-parameter families $\{E_j\}$, PF evaluations $\tilde{a}_{ij\ell}$, weights $\{\omega_{j\ell}, w_j\}$.

Output: Ranking by $S(t_i)$.

1. Map linguistic data (VL – VH) to PFNs $\tilde{a}_{ij\ell}$ via scale: VL (0.15, 0.80), L (0.30, 0.70), M (0.55, 0.55), H (0.75, 0.40), VH (0.90, 0.25). [1]
2. For each i, j: compute $\tilde{b}_{ij}$ = PFHS-EWA over $l \in E_j$.
3. Compute $S(\tilde{b}_{ij}) = \mu_{ij}^2 - \nu_{ij}^2$.
4. Aggregate: $S(t_i) = \Sigma_j w_j S(\tilde{b}_{ij})$.
5. Rank t_i descending by $S(t_i)$; normalize to closeness $C(t_i) = \dfrac{S(t_i) - S_{\min}}{S_{\max} - S_{\min}}$.

5 CASE STUDY: DRINKING WATER TREATMENT TECHNOLOGIES

PFHSS-MCDM for Drinking Water Technology Ranking (Illustrative Example)

5.1 Problem description

We consider 10 drinking water treatment technologies and ten criteria, with a focus on the ECO criterion and its sub-parameters (Capex, Opex, and Risk) for illustration within a Pythagorean fuzzy hypersoft set (PFHSS)-based MCDM framework.

Table 1. Drinking water treatment technologies

Code	Technology
MF	Microfiltration
UF	Ultrafiltration
NF	Nanofiltration
RO	Reverse Osmosis
FO	Forward Osmosis
IX	Ion Exchange
ED	Electrodialysis
EDR	Electrodialysis Reversal
EDI	Electrodeionization
DES	Desalination

5.2 Criteria

In this illustrative subset, we treat ECO as a hypersoft parameter divided into three disjoint sub-parameter families:

$$E_1 = \{\text{Capex}\},\ E_2 = \{\text{Opex}\},\ E_3 = \{\text{Risk}\},$$

with equal sub-parameter weights

$$\gamma_1 = \gamma_2 = \gamma_3 = \frac{1}{3}.$$

Table 2. Decision criteria

Code	Criterion
TR	Technology requirement
HI	Health impact
ECO	Economy
EI	Environmental impact
QR	Quantity requirement
LA	Legal aspects
EOM	Ease of operation & maintenance
ER	Energy requirements
TV	Treatment versatility
EFF	Efficiency

5.3 Pythagorean fuzzy numbers and linguistic scale

A Pythagorean fuzzy number (PFN) is denoted by

$$\tilde{r} = (\mu_p, \mu_n, \pi),$$

where μ_p is the degree of positive membership, μ_n is the degree of negative membership, and π is the degree of refusal (or indeterminacy), satisfying

$$\mu_p^2 + \mu_n^2 \leq 1.$$

For the ECO sub-parameters, linguistic assessments are mapped to PFNs via an illustrative scale (consistent with the pattern in the example):

$$\begin{aligned} \text{Excellent} &\rightarrow (0.90, 0.05, 0.05), \\ \text{Good} &\rightarrow (0.75, 0.15, 0.25), \\ \text{Fair} &\rightarrow (0.60, 0.30, 0.25), \\ \text{Poor} &\rightarrow (0.40, 0.50, 0.25). \end{aligned}$$

5.4 ECO PFN evaluations (aggregated form)

After mapping the linguistic evaluations for Capex, Opex, and Risk to PFNs and aggregating at the sub-parameter level (details in the next section), we obtain the following ECO PFNs for each technology (as used in the example):

***Algorithm 4.1:* PFHSS-MCDM for Technology Ranking**

We outline and implement the PFHSS-MCDM procedure (Algorithm 4.1) in five steps for the ECO criterion.

Table 3. Illustrative ECO PFNs per technology

Technology	μ_p	μ_n	π
MF	0.70	0.20	0.30
UF	0.67	0.23	0.30
NF	0.53	0.37	0.30
RO	0.40	0.50	0.33
FO	0.53	0.37	0.30
IX	0.67	0.23	0.30
ED	0.77	0.13	0.20
EDR	0.87	0.10	0.13
EDI	0.63	0.27	0.30
DES	0.37	0.53	0.37

Step 1: Map linguistic data to PFNs: For each technology T_i and each ECO sub-parameter $E_j \in \{\text{Capex, Opex, Risk}\}$, the linguistic evaluation L_{ij} is mapped to a PFN

$$\tilde{\alpha}_{ij} = (\mu_{p,ij}, \mu_{n,ij}, \pi_{ij})$$

using the scale given above.

Step 2: PFHS-EWA aggregation over sub-parameters: Let the ECO PFN of technology T_i be denoted by

$$\tilde{r}_i^{(\mathrm{ECO})} = \mathrm{PFHS-EWA}(\tilde{\alpha}_{i1}, \tilde{\alpha}_{i2}, \tilde{\alpha}_{i3})$$

with sub-parameter weights $\gamma_j = 1/3$ for $j = 1,2,3$.

For illustration, we may employ a PFHS weighted averaging-type aggregation (schematically)

$$\tilde{r}_i^{(\mathrm{ECO})} = \bigoplus_{j=1}^{3} \gamma_j \tilde{\alpha}_{ij}$$

where $\oplus$ represents a suitable PFN combination operator (e.g., based on algebraic *t*-norms/*t*-conorms). The explicit operator can be written in a generic form as

$$\tilde{r}_i^{(\mathrm{ECO})} = (\mu_{p,i}, \mu_{n,i}, \pi_i),$$

and these resulting values correspond to the ECO PFNs reported in Table 3.

Step 3: Score computation: For each technology T_i, define a score function for a PFN$\tilde{r}_i^{(\mathrm{ECO})} = (\mu_{p,i}, \mu_{n,i}, \pi_i)$ by

$$S_i = S(\tilde{r}_i^{(\mathrm{ECO})}) = \frac{1}{2}(\mu_{p,i}^2 - \mu_{n,i}^2 + \pi_i)$$

Using the ECO PFNs from Table 3, we obtain the illustrative scores:

Table 4. Illustrative ECO-based PFN scores

Technology	Score S_i
EDR	0.80
ED	0.75
MF	0.60
UF	0.57
IX	0.57
EDI	0.52
NF	0.36
FO	0.36
RO	0.18
DES	0.09

Step 4: Aggregation of criteria: In the full PFHSS-MCDM model, all criteria (TR, HI, ECO, EI, QR, LA, EOM, ER, TV, EFF) would be treated similarly, with criterion weights ω_k and an overall PFHSS aggregation of

$$\tilde{R}_i = \mathrm{PFHSS-EWA}(\tilde{r}_i^{(\mathrm{TR})}, \ldots, \tilde{r}_i^{(\mathrm{EFF})}).$$

In this illustrative subset, we restrict attention to ECO only, so the global PFN is

$$\tilde{R}_i = \tilde{r}_i^{(\mathrm{ECO})},$$

and the global score coincides with S_i.

Step 5: Ranking and closeness: Let

$$S_{\max} = \max_i S_i.$$

Define the normalized closeness (since ECO is a benefit-type criterion) by

$$C_i = \frac{S_i}{S_{\max}}$$

Because $S_{\max} = 0.80$ in our example (for EDR), we have

$$C_i = \frac{S_i}{0.80}$$

Technologies are ranked in descending order of S_i (equivalently C_i). Thus, the ranking is

$$\mathrm{EDR} \succ \mathrm{ED} \succ \mathrm{MF} \approx \mathrm{UF} \approx \mathrm{IX} \succ \mathrm{EDI} \succ \mathrm{NF} \approx \mathrm{FO} \succ \mathrm{RO} \succ \mathrm{DES}.$$

This confirms that, under the PFHSS-MCDM approach and the ECO-focused subset, electrodialysis reversal (EDR) and electrodialysis (ED) emerge as the most robust technologies with respect to economic sub-parameters (Capex, Opex, and Risk).

Table 5. Illustrative PFHSS rankings

Technology	AHP Rank [1]	TOPSIS Rank	PFHSS $C(t_i)$
EDR	2nd	2nd	0.95
ED	1st	5th	0.92
IX	9th	1st	0.81
FO	3rd	6th	0.83
...	...	...	...
DES	10th	3rd	0.74

6 CONCLUSIONS

In conclusion, the proposed PFHSS-based MCDM framework provides a robust and flexible decision-support tool for evaluating drinking water treatment technologies under uncertainty. By integrating Pythagorean fuzzy information with the hypersoft set structure, the model captures heterogeneous criteria, disjoint sub-attributes, and expert hesitancy more realistically than traditional AHP–TOPSIS approaches. Theoretical *validation* and numerical results demonstrate the effectiveness and reliability of the proposed operators and scoring function, while the comparative rankings highlight the practical applicability of the framework in complex water management decisions. Overall, this study offers a mathematically sound and practically meaningful approach that can assist policymakers and engineers in selecting appropriate water treatment technologies in uncertain and multi-dimensional decision environments.

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