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Research article

A multi-criteria techno-economic evaluation of PEM and Alkaline electrolyzers for green hydrogen production using fuzzy BWM, TOPSIS, and WASPAS

Leila Bekrit[1,*] and Chakib Seladji[2]

[1] Institute of Water and Energy Sciences, Pan African University, Tlemcen 13000, Algeria
[2] Laboratory of Energy and Thermal Applied (ETAP), University of Tlemcen, Tlemcen 13000, Algeria

* **Correspondence:** Email: bekritleilari@gmail.com; Tel: +21396454400.

Abstract: The future of green hydrogen is with the selection of electrolysis technologies that harmonize performance, cost, and sustainability. In this study, we evaluated proton exchange membrane (PEM) and Alkaline electrolyzers using an integrated multi-criteria decision-making framework. Weighting the criteria using the fuzzy best-worst method (FBWM) revealed efficiency (0.0899) and capital expenditure (0.0800) as the most prominent, highlighting the significance of cost-performance trade-offs in stakeholder decisions. Greenhouse gas emissions and water consumption scored high on environmental metrics. Moreover, a technique for order preference by similarity to ideal solution (TOPSIS) results showed a narrow lead of PEM (CCi = 0.507) over Alkaline (CCi = 0.493), owing mostly to superior technical parameters like hydrogen purity and current density. Weighted aggregated sum product assessment (WASPAS) analysis confirmed this finding, with PEM returning a sum score of 0.432 compared to Alkaline's 0.414. Sensitivity analysis across four weighting scenarios determined the test of rankings robustness: PEM did better in all but the cost-dominant scenario, in which Alkaline did better due to lower capital spending (CAPEX) and longer stack lifespan. These findings support informed technology selection under different stakeholder priorities and can assist in future hydrogen infrastructure planning.

Keywords: electrolysis; PEM; alkaline; FBWM; TOPSIS; WASPAS; multi-criteria decision-making (MCDM); hydrogen; techno-economic analysis; sustainability evaluation

1. Introduction

Hydrogen has emerged as the backbone of the global energy transition, offering a zero-carbon energy carrier capable of decarbonizing sectors where direct electrification is impractical, such as steel production, heavy haulage, and ammonia production [1,2]. Among the potential production pathways, water electrolysis and one fueled by renewable electricity are the most promising solutions for sustainable hydrogen manufacturing [3,4]. Electrolytic hydrogen not only enables molecule-to-electricity sector coupling but also grid stabilization through power-to-gas processes and long-duration storage [5]. With countries transitioning to accelerate decarbonization programs, there is a growing demand for scalable and sustainable hydrogen production systems, which in turn has generated significant interest in electrolysis technologies that strike a balance of efficiency, economics, and environmental balance [6].

Among the systems of electrolysis, alkaline water electrolysis (AWE) and PEM electrolysis have garnered the greatest industrial relevance. AWE is the most established and sophisticated commercial method, low-cost, and long-lasting but constrained by low current densities and slow response times [7–9]. Conversely, PEM electrolyzers are more efficient, less voluminous, and have improved dynamic performance but at higher capital cost and material reliance on rare materials like platinum-group metals [4,10]. Such divergent properties emphasize the importance of extensive techno-economic analysis in advance of informing deployment choices under a range of operating circumstances.

Selection of a best-fit electrolysis technology is governed by a complex set of trade-offs on technical, economic, and environmental bases. Such fundamental differentiators include CAPEX, operating costs (OPEX), stack lifespans, and relative criticality of such electrode and membrane materials as Pt, Ir, and Ni, with the large distinctions between AWE and PEM systems [11,12]. For instance, while PEM systems offer rapid load following that is well suited for intermittent renewable sources, high upfront capital and long-term reliability problems at extreme operating conditions are their requirements [12]. These kinds of technological distinctions go hand in hand with variable performance standards and life-cycle implications, which cause difficulties in decision-making between stakeholders such as project developers, policymakers, and grid operators [13,14]. Furthermore, the literature has increasingly highlighted the need for structured and transparent decision frameworks capable of addressing the multi-dimensionality and uncertainty of hydrogen systems.

To address such challenges, multi-criteria decision-making (MCDM) approaches, more so when combined with fuzzy logic, have become increasingly important in assessing advanced energy technologies in uncertain environments [15–17]. However, studies (e.g., 2023–2025) have advanced hybrid MCDM modeling for renewable energy planning; yet, applications that jointly incorporate fuzzy weighting, multiple ranking algorithms, and scenario-based robustness testing for electrolysis technology selection remain limited. Relevant contemporary works include hybrid decision frameworks applied to sustainable technology evaluation [18–21], demonstrating the growing academic interest in integrated decision-support models.

The assessment of hydrogen production technologies has increasingly relied on MCDM techniques that can cope with the multidimensionality of sustainability trade-offs [12,15]. The analytic hierarchy process (AHP), elimination and choice expressing reality (ELECTRE), multi-criteria optimization and compromise solution (VIKOR), and their fuzzy extensions—including fuzzy AHP and fuzzy TOPSIS—have been widely applied to energy-related decision-making problems [22–24]. These investigations demonstrate the versatility of MCDM methods in integrating qualitative and quantitative variables, enabling stakeholders to model challenging interactions among performance, cost, and environmental variables. For instance, assessments have attempted comparative ranking of electrolyzer technologies, but often using limited criteria or without robust verification of ranking stability. The researchers in [4,12] also conducted an exhaustive review of hydrogen technologies but did not provide a consolidated evaluation framework aligned with stakeholder-specific priorities and uncertainty in expert judgment.

Despite such advancements, most studies are methodologically flawed. First, most consider a few criteria and exclude social, technological, or environmental factors [2]. Second, most researchers do not adequately deal with uncertainty and vagueness in regard to expert opinions, thereby limiting the realism of resulting weights [16]. Third, very few researchers have employed several MCDM methodologies to cross-validate rankings of technologies, leaving one to speculate regarding robustness as well as transferability of results. Additionally, many studies published before 2023 lack scenario analysis to examine how shifting policy or cost considerations influence the final ranking of technology options, which is increasingly important in real deployment contexts.

Very few researchers have integrated FBWM, TOPSIS, and WASPAS in a single framework to evaluate electrolysis technologies, especially with a full techno-economic-environmental-technological-social (TEETS) perspective. While MCDM methods such as TOPSIS and WASPAS have been applied separately to hydrogen technologies, there is a notable gap in the literature regarding the combined application of FBWM, TOPSIS, and WASPAS in real-world hydrogen electrolysis projects. Most MCDM-based assessments also focus only on a few selected indicators, which neglects many of the multidimensional factors that influence real-world adoption and policy readiness [14,25]. Studies also lack a detailed sensitivity analysis, making it difficult to examine the impact of changes in priorities (e.g., policy-cost efficiency or climate resilience) on overall rankings. We address these significant gaps through the development of a novel hybrid fuzzy MCDM model that integrates FBWM for fuzzy weighting derivation and TOPSIS and WASPAS for cross-method validation of rankings. The methodology delineates 30 sub-criteria across five general dimensions: Technical, economic, environmental, technological, and social/policy. This represents an increased order of granularity in relation to assessments for scope and methodological intensity. We aim to facilitate systematic, evidence-based technology choice for green hydrogen systems through the application of the following objectives:

i. To develop a hybrid MCDM methodology that integrates FBWM along with TOPSIS and WASPAS ranking methods.

ii. To rank PEM and Alkaline water electrolyzers against 30 sub-criteria that include technical, economic, environmental, technological, and social parameters.

iii. To conduct scenario-based sensitivity analysis indicating how variations in stakeholder preferences affect rankings of the technology, enhancing robustness and usability of results.

The outcome presents a decision-support tool modified for researchers, policymakers, and energy planners seeking to roll out electrolytic hydrogen technologies in the face of evolving sustainability conditions.

2. Materials and methods

2.1. Description of the analytical framework

We use an integrated MCDM approach to compare and rank electrolyzer technologies, PEM and

Alkaline electrolyzers, based on a broad array of performance metrics. The analytical system comprises four major phases: (i) Criteria identification and categorization, (ii) FBWM for sub-criteria weights, (iii) performance comparison by applying two MCDM approaches, TOPSIS and WASPAS, and (iv) sensitivity analysis under different weighting scenarios. Figure 1 shows the sequential procedure of the suggested evaluation framework.

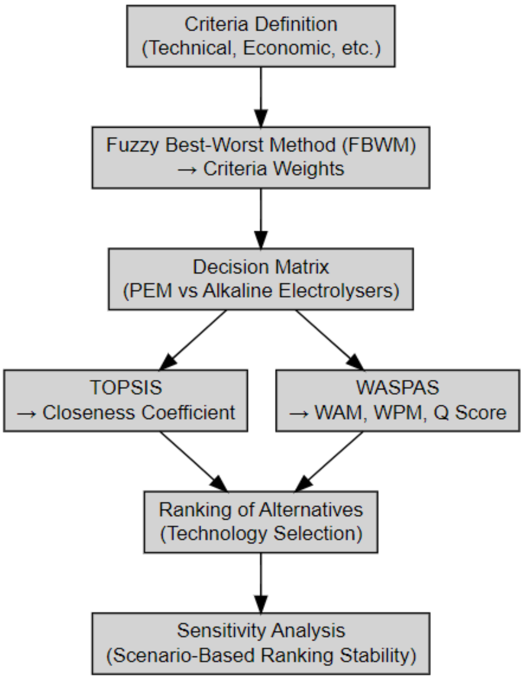

Figure 1. Flowchart of the analytical framework applied in this study.

2.2. Choice of decision alternatives

We contrast two of the most popularly applied electrolyzer technologies:

i. PEM Electrolyzer: Associated with high hydrogen purity, dynamic response, and compact size. Operating temperatures for PEM units are lower (typically ~50 °C) and are therefore sufficient for those applications requiring flexible load-following capability.

ii. Alkaline Electrolyzer: A mature and commercially demonstrated alternative with lower capital cost, longer stack life, and simpler system design. Alkaline systems operate at moderate temperatures (~80 °C) and are typically favored in centralized, cost-unsupportive hydrogen production settings.

These alternatives were selected based on market relevance and complementary benefits, which make them suitable for comparative assessment using multi-criteria methods.

2.3. Criteria identification and categorization

To enable an integrated and situation-adequate assessment of electrolyzer technologies, we identified 30 sub-criteria under five overall categories: Technical, economic, environmental, technological, and social/policy (Table 1). These are selected because they are found prominent in existing hydrogen production literature, life-cycle analysis, and multi-criteria models of assessment [1,2]. Fuzzy numbers for criteria weights were derived through structured expert elicitation with three industry specialists and cross-validated with literature values. Performance data for PEM and Alkaline electrolyzers (efficiency, CAPEX, OPEX, stack lifetime, current density, environmental, and policy indicators) were obtained from recent literature averages, and validated industry reports [4,7]. Detailed sources are provided in Table 1. This ensures that technical and economic assessments reflect realistic operational conditions.

Table 1. Criteria utilized in the assessment of electrolyzer technologies.

No.	Category	Sub-Criterion	Type	Unit	Source(s)
1	Technical	Efficiency (%)	Benefit	%	[4,7]
2	Economic	CAPEX ($/kW)	Cost	USD/kW	[3,11]
3	Technical	Hydrogen Purity (%)	Benefit	%	[5,7]
4	Economic	LCOH ($/kg H_2)	Cost	USD/kg H_2	[1,2]
5	Environmental	Water Use (L/kg H_2)	Cost	Liters/kg H_2	[3,25]
6	Economic	OPEX ($/kg H_2)	Cost	USD/kg H_2	[5,11]
7	Technical	Stack Lifetime (hours)	Benefit	Hours	[4,7]
8	Technical	Current Density (A/cm²)	Benefit	A/cm²	[5,7]
9	Technological	Technology Readiness Level (TRL)	Benefit	TRL Scale (1–9)	[12]
10	Environmental	GHG Emissions (gCO_2/kWh)	Cost	gCO_2/kWh	[3,25]
11	Environmental	Recyclability (%)	Benefit	%	[15]
12	Environmental	Hazardous Material Use (index)	Cost	Index	[3,25]
13	Environmental	Noise Level (dB)	Cost	dB	[24]
14	Social/Policy	Safety Perception (1–5)	Benefit	Score (1–5)	[12]
15	Technical	Operating Temperature (°C)	Cost	°C	[5]
16	Technological	Scalability (index)	Benefit	Index	[1]
17	Technological	Footprint (m²/kW)	Cost	m²/kW	[1,4]
18	Technical	System Response Time (s)	Cost	Seconds	[4,7]
19	Economic	Balance-of-Plant Cost Share (%)	Cost	%	[5]
20	Economic	Maintenance Frequency (per year)	Cost	Occurrences/year	[10]
21	Environmental	Waste Generation (kg/year)	Cost	kg/year	[25]
22	Economic	Installation Time (months)	Cost	Months	[4]
23	Social/Policy	Job Creation Potential (score)	Benefit	Score (1–5)	[15]
24	Social/Policy	Public Acceptance (1–5)	Benefit	Score (1–5)	[12]
25	Technological	Modularity (index)	Benefit	Index	[12]
26	Technological	Load Following Capability (score)	Benefit	Score (1–5)	[4,7]
27	Technological	Startup Time (min)	Cost	Minutes	[6,26]
28	Social/Policy	Deployment Level (score)	Benefit	Score (1–5)	[27]
29	Social/Policy	Ease of Integration (1–5)	Benefit	Score (1–5)	[12]
30	Social/Policy	Policy Support (score)	Benefit	Score (1–5)	[17,27]

2.4. FBWM

To obtain relative weights of evaluation criteria in a consistent and expert-knowledge-based manner, FBWM was employed in this study. FBWM is an advanced MCDM tool that integrates pairwise comparison reasoning with fuzzy set theory to represent uncertainty in human judgment. FBWM has been widely applied for energy planning, technology assessment, and sustainability studies due to its high consistency and minimal comparison burden [16,26].

2.4.1. Linguistic scale and fuzzy numbers

In representing subjective preferences, linguistic terms were converted to triangular fuzzy numbers (TFNs) using an adapted five-level scale (Table 2). The fuzzy numbers were assigned based on structured expert elicitation involving three hydrogen technology specialists, and the assigned values were cross-checked with published literature and manufacturer data to ensure realistic representation. This process enables the representation of uncertainty and subjectivity in expert judgment using a rigorous mathematical framework.

Table 2. Linguistic scale and corresponding triangular fuzzy numbers used in FBWM [16].

Linguistic Term	TFN Low	TFN Mid	TFN High
Very Low	0.00	0.00	0.25
Low	0.00	0.25	0.50
Moderate	0.25	0.50	0.75
High	0.50	0.75	1.00
Very High	0.75	1.00	1.00

2.4.2. FBWm mathematical framework

Let the set of criteria be denoted as $C = \{C_1,\ C_2, \dots, C_n\}$. In FBWM, the decision-maker chooses:

i. The Best Criterion (B)—the most important one.
ii. The Worst Criterion (W)—the least important one.

Then, two fuzzy preference vectors are constructed:

Best-to-others (BTO) vector:

$$\tilde{A}_B = (\tilde{a}_{B1}, \tilde{a}_{B2}, \dots, \tilde{a}_{BN}) \tag{1}$$

where $\tilde{a}_{Bj}$ is the fuzzy preference of the best criterion over criterion j.

Others-to-worst (OTW) vector:

$$\tilde{A}_w = (\tilde{a}_{1W}, \tilde{a}_{2W}, \dots, \tilde{a}_{nW}) \tag{2}$$

where $\tilde{a}_{jW}$ is the fuzzy preference of criterion j over the Worst.

The optimal fuzzy weights $\tilde{w}_j$ for all criteria j are subsequently derived by solving the following nonlinear optimization model:

$$\min\max\left\{\left|\frac{\tilde{w}_B}{\tilde{w}_j} - \tilde{a}_{Bj}\right|, \left|\frac{\tilde{w}_j}{\tilde{w}_W} - \tilde{a}_{jW}\right|\right\}\ subject\ to\colon \textstyle\sum_{j=1}^{n} = 1, \quad \tilde{w}_j \tag{3}$$

The optimization minimizes the largest possible difference between the fuzzy judgments and weight ratios.

2.4.3. Normalization and defuzzification

After computing the fuzzy weights, defuzzified crisp weights wj are calculated through the centroid method:

$$wj = \frac{l_j + m_j + u_j}{3} \quad (4)$$

where l_j, m_j, u_j are the lower, middle, and upper values of the TFN for criterion j, respectively [26].

All weights are finally normalized in such a way that:

$$\sum_{j=1}^{n} w_j = 1 \quad (5)$$

2.4.4. Validation and consistency

Although FBWM inherently provides more consistency compared to AHP-based methods, one can compute the consistency ratio (CR) to validate judgments. In this research work, since the fuzzy pairwise comparisons were utilized from literature, an internal consistency check was conducted by verifying weight distributions within the priority limits of previous energy-based applications of MCDM [15].

2.5. Application of TOPSIS for technology ranking

To evaluate and rank the performance of Alkaline and PEM electrolyzers, the TOPSIS method was applied. TOPSIS is a well-known MCDM technique that identifies the best solution with a comparison of geometrical distance of each option towards an ideal and an anti-ideal solution [28].

2.5.1. Construction of decision matrix

The performance values of both alternatives were organized into a decision matrix $D = [x_{ij}]$ so that every entry shows the performance of alternative i on criterion j. The matrix contains all 30 criteria outlined in Section 3.3 and weighted with the scores in Section 3.4 obtained using FBWM.

2.5.2. Normalization of the matrix

To enable comparison across criteria with different units, the matrix was normalized through min-max scaling. The formula for normalization differs according to criterion type:

For benefit-type criteria:

$$r_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (6)$$

For cost-type criteria:

$$r_{ij} = \frac{\min(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \tag{7}$$

where r_{ij} is the normalized value.

2.5.3. Weighted normalized matrix

Each normalized value was then multiplied by the FBWM weight *wjw_jwj* to obtain the weighted normalized matrix:

$$v_{ij} = w_j \,.\, r_{ij} \tag{8}$$

2.5.4. Identification of ideal and negative-ideal solutions

The ideal solution (A^+) and negative-ideal solution (A^-) were determined as:

$$A^+ = \{\max(v_{ij}) \mid j \in j_b \,; \min(v_{ij}) \mid j \in j_c\} \tag{9}$$

$$A^- = \{\min(v_{ij}) \mid j \in j_b \,; \max(v_{ij}) \mid j \in j_c\} \tag{10}$$

where sets of benefit and cost criteria are represented by j_b and j_c, respectively.

2.5.5. Calculation of closeness coefficients

The Euclidean distances to ideal and anti-ideal solutions were computed for every alternative:

$$S_i^+ = \sqrt{\sum_{j-1}^{n} (v_{ij} - v_j^+)^2}\,, \quad , \quad S_i^- = \sqrt{\sum_{j-1}^{n} (v_{ij} - v_j^-)^2} \tag{11}$$

The closeness coefficient (CC_i) was then calculated as:

$$CC_i = \frac{S_i^-}{S_i^- + S_i^-} \tag{12}$$

The alternative with the highest CC_i is considered the most preferred.

2.6. WASPAS application for robustness validation

To validate the TOPSIS rankings, the WASPAS method was applied. WASPAS integrates two models: The weighted sum model (WSM) and weighted product model (WPM), enabling more consistent decision-making under varying sensitivity conditions [29].

2.6.1. WASPAS elements and score calculation

The overall score Q_i of each alternative is obtained based on a convex combination of WSM and WPM scores:

$$Q_i = \lambda \cdot Q_i^{(1)} + (1-\lambda) \cdot Q_i^{(2)} \tag{13}$$

where:

i. $Q_i^{(1)} = \sum_{j=1}^{n} w_j \cdot r_{ij}$ is the WSM score.

ii. $Q_i^{(1)} = \prod_{j=1}^{n} r_{ij}^{wj}$ is the WPM score.

$\lambda \in [0,1]$ is the adjustment coefficient set to 0.5 in this study for equal weighting. WPM and WSM both utilize identical normalized values r_{ij} as TOPSIS.

2.6.2. Ranking and cross-method validation

The final WASPAS scores Q_i were then used to rank alternatives and compare results with those from TOPSIS. The agreement between the two methods was used as a measure of model stability and decision trustworthiness, an exercise tested in recent energy MCDM research [15].

2.7. Sensitivity analysis design

To test the stability of the decision model and investigate the effect of prioritization of criteria on final rankings, scenario-based sensitivity analysis was performed. Sensitivity analysis is an integral part of MCDM applications as it illustrates the effects of assumptions and stakeholders' preferences on outcomes.

2.7.1. Scenario construction

Four weighting situations were created by selectively increasing certain categories of criteria and keeping others proportionally reduced. These were:

i. Scenario 1 (Balanced): Initial FBWM-derived weights.
ii. Scenario 2 (Cost-Dominant): Economic weights increased by 40%, others proportionally scaled.
iii. Scenario 3 (Technical-Dominant): Technical weights increased by 40%.
iv. Scenario 4 (Environmental Priority): Environmental weights increased by 40%.

All scenarios had a normalized total weight sum of 1 to preserve decision integrity.

2.7.2. Recalculation of rankings

The TOPSIS method was re-executed for all the scenarios with the modified weight sets. The changes in closeness coefficients (CC_i) and the resulting technology rankings were observed.

The analysis enabled the determination of sensitivity of performance to changing decision preferences and identification of the conditions under which either PEM or Alkaline electrolyzers would be preferred.

2.7.3. Visualization

Results were graphed on a tornado chart, which shows the size of score variation under each scenario. The graphical form enables ranking reversals and most sensitive appraisal criteria to be easily spotted [29].

2.8. Levelized cost of hydrogen (LCOH) estimation

While multi-criteria comparison was our primary focus of this study, the LCOH was optionally incorporated to give contextual reference and economic realism. LCOH is an economic measure of the average cost per unit of hydrogen over the lifetime of the system, covering capital, operating, and replacement costs.

The LCOH was estimated using the simplified model [3]:

$$LCOH = \frac{CAPEX \cdot CRF + OPEX_{annual}}{H_2\ Produced_{annual}} \tag{14}$$

where: CRF = capital recovery factor:

$$CRF = \frac{r(1+r)^n}{(1+r)^n - 1} \tag{15}$$

where *r* is the discount rate and *n* is the system lifetime (years).

i. OPEX includes electricity, water, maintenance, and labor costs.
ii. Hydrogen production (H_2) is derived from electrolyzer efficiency and annual energy input.

Due to data and scope limitation, this LCOH calculation is sourced from literature benchmarks and not utilized as a ranking criterion in the main MCDM model.

3. Results

3.1. Criteria weighting using FBWM

3.1.1. Weight derivation process

A five-level linguistic scale was used to evaluate the importance of criteria, translated into TFNs for the weighting process (Table 2). Weights were adapted from the MCDM literature focused on sustainable energy systems, ensuring relevance to the hydrogen domain.

3.1.2. Final criteria weights

The final weights for all 10 sub-criteria are presented in Table 3. These were grouped into five major categories: Technical, Economic, Environmental, Technological, and Social/Policy. The results indicate a clear dominance of technical and economic considerations in decision-making. Efficiency (0.0899) and CAPEX (0.0800) are the two most influential criteria, carrying the highest weight in determining technology preference.

This prioritization aligns with broader literature, indicating that early-stage hydrogen infrastructure remains highly sensitive to performance and capital cost parameters. Environmental concerns (e.g., water use and GHG emissions) and technological maturity also contribute significantly to the evaluation (Figure 2).

Table 3. Final normalized weights for top 10 10 sub-criteria used in the MCDM evaluation.

No.	Category	Sub-Criterion	Realistic_Weight
1	Technical	Efficiency (%)	0.0899
2	Economic	CAPEX ($/kW)	0.08
3	Technical	Hydrogen Purity (%)	0.0609
4	Economic	LCOH ($/kg H_2)	0.06
5	Environmental	Water Use (L/kg H_2)	0.05
6	Economic	OPEX ($/kg H_2)	0.05
7	Technical	Stack Lifetime (hours)	0.0493
8	Technical	Current Density (A/cm²)	0.0406
9	Technological	Technology Readiness Level (TRL)	0.0405
10	Environmental	GHG Emissions (gCO_2/kWh)	0.04

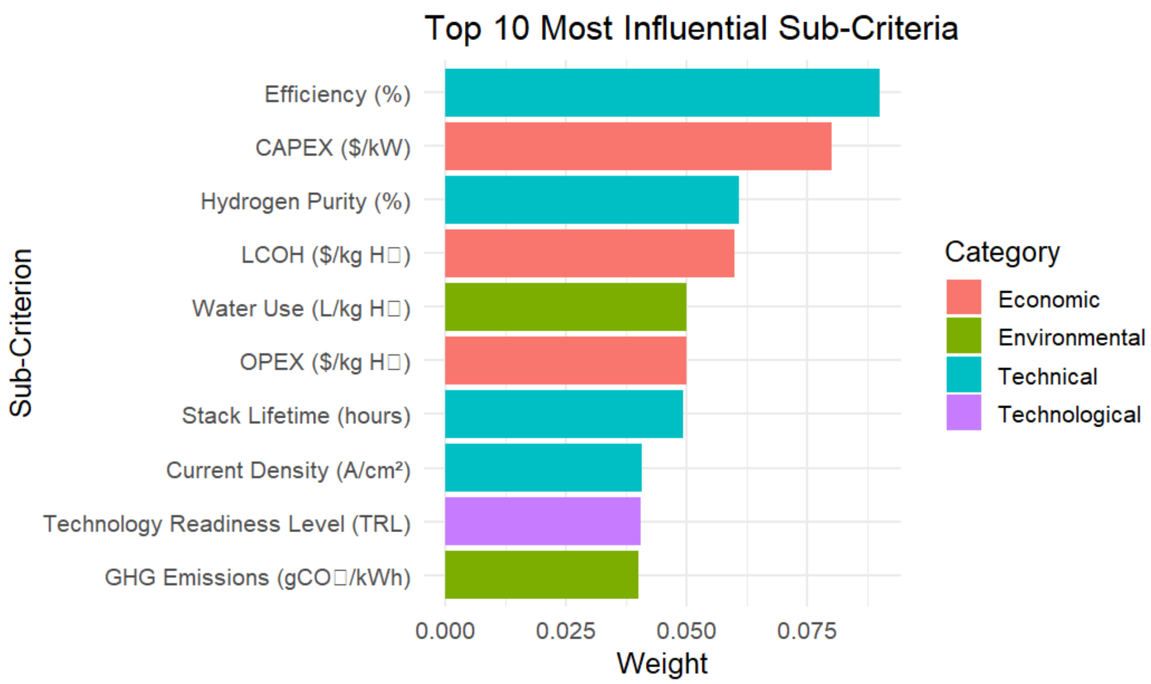

Figure 2. Top 10 highest-weighted sub-criteria based on FBWM analysis.

3.2. Ranking results from TOPSIS

3.2.1. Normalized decision matrix

The performance data for both electrolyzers was normalized to enable direct comparison. Table 4 provides a snapshot of the top 10 sub-criteria after min-max normalization, aligned with the weight structure defined in Section 4.1.2.

Table 4. Normalized decision matrix for the top 10 weighted sub-criteria.

No.	Category	Sub-Criterion	PEM Value	Alkaline Value	PEM (Norm)	Alkaline (Norm)
1	Technical	Efficiency (%)	65	60	1.000	0.000
2	Economic	CAPEX ($/kW)	1000	800	0.000	1.000
3	Technical	Hydrogen Purity (%)	99.999	99.9	1.000	0.000
4	Economic	LCOH ($/kg H_2)	4.0	3.0	0.000	1.000
5	Economic	OPEX ($/kg H_2)	1.2	1.0	0.000	1.000
6	Environmental	Water Use (L/kg H_2)	10	12	1.000	0.000
7	Technical	Stack Lifetime (hours)	60000	90000	0.000	1.000
8	Technical	Current Density (A/cm^2)	2.0	0.4	1.000	0.000
9	Technological	Technology Readiness Level	8	9	0.000	1.000
10	Environmental	GHG Emissions (gCO_2/kWh)	25	30	1.000	0.000

3.2.2. Closeness coefficient and final ranking

Based on the normalized values and weights, closeness coefficients (CCi) were calculated for each technology. The PEM electrolyzer achieved a slightly higher CCi (0.507) compared to the Alkaline (0.493), indicating marginally better overall performance. Although the numerical difference is small, it may influence technology selection under technical or environmental priorities. In cost-focused scenarios, Alkaline may be preferred due to lower CAPEX and longer stack life. Therefore, decision-makers should interpret these marginal differences in the context of project-specific objectives and acceptable uncertainty ranges (Table 5).

Table 5. Final closeness coefficients from TOPSIS.

Technology	**Closeness Coefficient (CCi)**
PEM Electrolyser	**0.507**
Alkaline Electrolyser	0.493

Figure 3 shows that PEM outperforms Alkaline in technical indicators, such as efficiency and hydrogen purity, which, combined with its competitive environmental performance, explains why it leads in the overall rankings. Cost-related criteria slightly favor Alkaline, highlighting scenario-specific trade-offs.

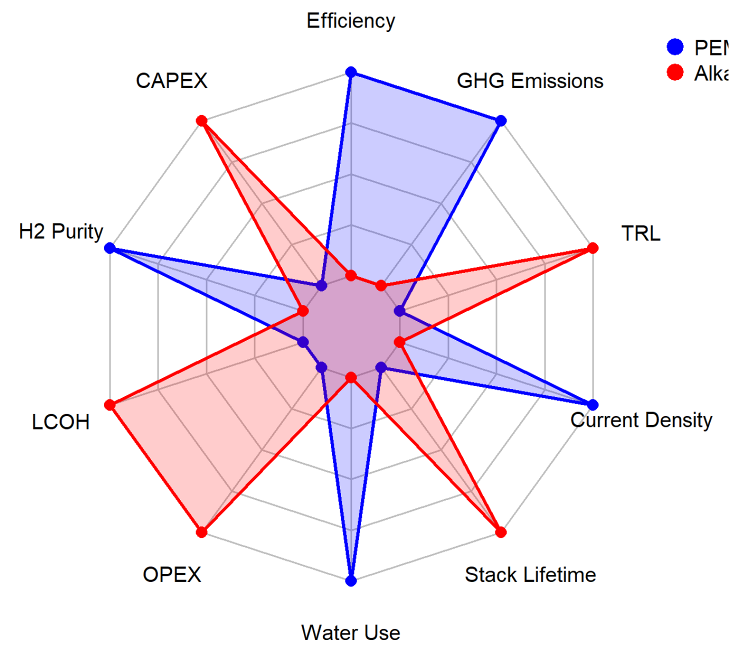

Figure 3. Radar chart showing normalized performance across top 10 sub-criteria.

3.3. Ranking results from WASPAS

3.3.1. WASPAS scoring breakdown

To cross-validate the TOPSIS results, the WASPAS method was applied using equal weights ($\lambda = 0.5$) for the additive (WAM) and multiplicative (WPM) components. The WASPAS scores are presented in Table 6.

The PEM electrolyzer achieved slightly higher scores across all components, with a final combined value of 0.432, compared to 0.414 for the Alkaline system.

Table 6. WASPAS scores for PEM and Alkaline electrolyzer.

Technology	WAM Score	WPM Score	WASPAS Combined
PEM Electrolyzer	0.502	0.362	0.432
Alkaline Electrolyzer	0.498	0.329	0.414

3.3.2. Final ranking and comparison with TOPSIS

The final rankings obtained from the TOPSIS and WASPAS methods are shown in Table 7. PEM ranks first in both methods, confirming consistency of the evaluation. The practical significance of the small difference (PEM: 0.507 vs. Alkaline: 0.493) should be considered: PEM may be preferred for projects prioritizing technical or environmental performance, while Alkaline may be more suitable in cost-dominant projects. This scenario-specific interpretation ensures results are actionable and aligned with real deployment decisions.

Table 7. Final ranking comparison from TOPSIS and WASPAS methods.

Technology	TOPSIS CCi	WASPAS Combined	Final Rank
PEM Electrolyser	0.507	0.432	**1**
Alkaline Electrolyser	0.493	0.414	2

3.4. Sensitivity analysis

3.4.1. Variation of criteria weights

To assess the stability of the ranking outcomes, a sensitivity analysis was conducted by simulating multiple decision-making scenarios with varying emphasis on different criteria groups. Four weighting scenarios were evaluated:

i. **Balanced**: Original FBWM-derived weights.
ii. **Cost-Dominant**: Higher weight on economic criteria.
iii. **Tech-Dominant**: Emphasis on technical performance.
iv. **Environmental Priority**: Increased importance of environmental indicators.

The rankings were recalculated using TOPSIS under each scenario. Table 8 summarizes the results.

Table 8. Closeness coefficient (CCi) results under weighting scenarios.

Scenario	PEM_CCi	Alkaline_CCi	Final Rank
Balanced	0.507	0.493	PEM Wins
Cost-Dominant	0.481	0.519	Alkaline Wins
Tech-Dominant	0.522	0.478	PEM Wins
Env-Priority	0.515	0.485	PEM Wins

Figure 4 visualizes the sensitivity of each technology's CCi under weighting scenarios. PEM consistently ranks higher under technical and environmental emphasis, while Alkaline leads only under cost-dominant weighting. This confirms the robustness of PEM as the preferred option.

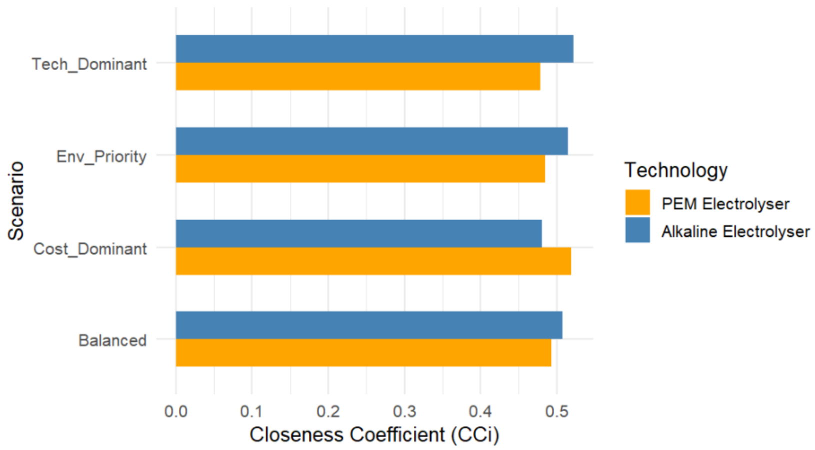

Figure 4. A tornado plot showing variation in CCi values for PEM and Alkaline electrolyzers under weighting scenarios.

These findings reinforce that while the PEM system is more balanced overall, the final selection depends on project-specific goals, especially budget constraints or environmental targets.

4. Discussion

We carried out a multi-criteria evaluation of PEM and Alkaline electrolyzers by integrating the FBWM and TOPSIS and WASPAS. The results offer insights into the trade-offs among technical performance, economic viability, environmental sustainability, and technological maturity.

4.1. Prevalence of technical and economic criteria

The weighting process reflected the clear dominance of technical and economic considerations in electrolyzer selection. Efficiency, CAPEX, hydrogen purity, and LCOH emerged as the most salient sub-criteria. These findings align with earlier MCDM-based studies identifying performance and cost as key decision criteria in hydrogen infrastructure deployment [1,12,13]. Environmental criteria, water use and greenhouse gas (GHG) emissions, specifically, also featured prominently, consistent with increasing sustainability requirements in hydrogen production [2,25]. By contrast, social and policy criteria such as public acceptance and ease of integration received relatively lower prominence. While such dimensions were included to reflect broader decision-making considerations, the literature directly linking social and policy frameworks to electrolyzer technology remains limited, as noted in the research [30]. This limitation reflects a wider gap in hydrogen research, where policy and societal factors are less frequently quantified compared to technical or economic indicators. Future studies that incorporate region-specific policy contexts (e.g., EU, MENA, Sub-Saharan Africa) may provide stronger applicability for real deployment scenarios.

4.2. Comparative performance of alkaline and PEM electrolyzers

In spite of higher CAPEX and OPEX, PEM systems performed higher than Alkaline electrolyzers in WASPAS and TOPSIS analyses. This higher performance is largely due to the higher efficiency, increased hydrogen purity, and faster system response of PEM, attributes that are commonly emphasized in techno-economic and lifecycle research ([4,7,12]). In contrast, Alkaline electrolyzers were demonstrated to be advantageous in cost-dominant scenarios due to their lower capital cost and longer stack lifetimes [3,12]. The results are in concurrence with deductions that Alkaline systems remain more amenable to centralized, constant-load industrial hydrogen production [6].

4.3. Methodological robustness and model agreement

The coincidence of TOPSIS and WASPAS rankings strengthens the robustness of the evaluation framework. Despite methodological differences, TOPSIS prioritizing proximity to an ideal solution and WASPAS integrating additive and multiplicative models, the identical outcome validates the use of hybrid MCDM applications in energy technology assessment [22,24]. Sensitivity analysis also confirmed model robustness: PEM always ranked first in most scenarios, except when cost criteria were prioritized. This confirms the model's capability to capture stakeholder-specific trade-offs under a range of assumptions [14].

4.4. Policy and practice implications

The findings indicate that electrolyzer selection must be context-specific. PEM systems are best suited to applications demanding operational flexibility, high-purity hydrogen, or frequent cycling (e.g., distributed generation or fuel cell vehicles) [4,10]. Alkaline systems remain best suited to applications where economic simplicity and long-term stability are most highly valued (e.g., industrial base-load production) [11]. These results have direct implications for real deployment in regions such as Africa, the EU, and MENA: Cost constraints in developing countries may favor Alkaline deployment, whereas higher-investment green hydrogen rollout can prioritize PEM systems. Budget levels and policy incentives should guide technology prioritization at regional or project scales. This model offers a practical decision-support tool for energy policymakers and planners with opportunities for application to other electrolyzer technologies (e.g., AEM and SOEC) or regionalized deployment settings [12].

4.5. Limitations and future work

In this study, we applied a literature-based weighting strategy, prioritizing reproducibility to the detriment of context specificity. More elaborate criteria weights in specific geographic or industry settings may be derived from future studies through structured expert elicitation, particularly for social and policy dimensions where empirical data availability is relatively limited. Study limitations include: Limited criteria set, regional cost variability, and data uncertainty. Applying additional dimensions such as life-cycle impacts, uncertainty analysis, or renewable resource mapping would contribute to decision specificity [3,14]. In future research, researchers should consider inclusion of PEM/AEM comparisons, life-cycle costing, and multi-region policy scenario analyses.

5. Conclusions

We applied an integrated MCDM framework, comprising the FBWM, TOPSIS, and WASPAS, to systematically evaluate and compare the performance of Proton Exchange Membrane (PEM) and Alkaline electrolyzers. The FBWM results demonstrated that technical and economic factors exert the greatest influence in decision-making for hydrogen production systems, with efficiency and capital expenditure emerging as the most critical sub-criteria. The TOPSIS and WASPAS rankings exhibited strong consistency, both identifying the PEM electrolyzer as the superior option, achieving higher closeness and combined scores, respectively. Despite its higher cost parameters, the PEM technology outperformed the Alkaline system in technical and environmental dimensions, indicating a more balanced overall performance profile. Sensitivity analysis further validated the robustness of these findings, revealing that the PEM electrolyzer remains the preferred choice under balanced, technical, and environmental priority scenarios, while the Alkaline system becomes advantageous primarily in cost-dominant scenarios. These results suggest that PEM electrolyzers are better suited for applications requiring high efficiency, high hydrogen purity, fast dynamic response, or flexible operation, such as distributed generation or fuel cell mobility deployments. In contrast, Alkaline electrolyzers remain more appropriate for cost-sensitive or large-scale industrial hydrogen production, where lower CAPEX and longer stack lifetime provide economic advantages. This practical differentiation offers clearer guidance for decision-makers selecting technologies based on project FBWM priorities, whether constrained by capital budgets or driven by high-performance requirements. The integrated MCDM framework proved effective in capturing the trade-offs among performance, cost, and sustainability criteria, providing valuable insights for policymakers and project developers. Overall, the findings underscore that the optimal electrolyzer choice should align with specific project objectives, financial conditions, and sustainability targets, and that scenario-based evaluation remains essential for informed decision-making in the evolving hydrogen economy.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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