Journal of Sustainable Development of Energy, Water and Environment Systems

http://www.sdewes.org/jsdewes

Year 2025, Volume 13, Issue 4, 1130620

Original Research Article

Artificial Intelligence-Supported Hyperfuzzy Framework for Sustainable Supply Chain and Energy Optimization in Smart Cities

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Cite as: Tamtam, F., Amzil, M., Jenkal, W., Tourabi, A., Artificial Intelligence-Supported Hyperfuzzy Framework for Sustainable Supply Chain and Energy Optimization in Smart Cities, J.sustain. dev. energy water environ. syst., 13(4), 1130620, 2025, DOI: https://doi.org/10.13044/j.sdewes.d13.0620

ABSTRACT

This study proposes an Artificial Intelligence-Supported Hyperfuzzy framework to evaluate hydrogen fuel cell technologies in Morocco's smart urban and supply chain ecosystems. Integrating compromise-ranking with efficiency benchmarking, the model addresses challenges in performance optimization, decision uncertainty, and supply integration. Key metrics—like power density, fuel efficiency, and system adaptability—are assessed through fuzzy logic and Artificial Intelligence-enhanced sensitivity analysis. Findings confirm that hydrogen-powered public transport offers superior efficiency and robustness, emerging as the top-ranked alternative. Artificial Intelligence strengthens traceability, weight calibration, and adaptability under expert preference variation. The study underscores the importance of supportive infrastructure, including refueling stations and grid-integrated systems, for scalable deployment. Results offer data-driven insights for policymakers and planners, guiding sustainable hydrogen strategies tailored to urban mobility and energy supply networks. By advancing decision accuracy under real-world uncertainty, this framework provides a replicable model for optimizing hydrogen-based solutions in smart cities.

KEYWORDS

Artificial intelligence, Hyperfuzzy VIKOR-DEA, Hydrogen fuel cell technologies, Multi-criteria optimization, Supply chain optimization, Smart cities, Sensitivity analysis.

INTRODUCTION

The demand for sustainable urban energy and supply chain solutions has intensified due to escalating environmental concerns, stringent carbon reduction policies, and the need for resilient infrastructure in smart cities [1]. Hydrogen fuel cell technologies have gained traction as a viable clean energy alternative, offering high energy efficiency, zero emissions, and versatility across multiple applications, including urban mobility, industrial power generation, and decentralized energy systems. Their ability to operate independently of fossil fuels, coupled with advances in hydrogen storage, distribution, and supply logistics, positions them as a key enabler in global energy and supply chain transitions [2]. However, challenges persist, particularly in cost-

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effectiveness, technological readiness, and logistical scalability, necessitating a comprehensive evaluation framework to guide large-scale, data-informed decision-making.

Despite growing research efforts, a critical gap exists in the systematic assessment of hydrogen fuel cell technologies across interconnected urban energy and supply chain networks. Conventional evaluation models often emphasize individual optimization factors—such as technical feasibility or economic profitability—without accounting for multi-criteria interdependencies, supply chain dynamics, and efficiency benchmarking. Prior studies employing Fuzzy TOPSIS, ELECTRE III, and PROMETHEE II have demonstrated ranking capabilities but lack integrated validation and adaptability under uncertainty. Kabassi and Martinis [3] conducted a sensitivity analysis using the PROMETHEE II method to evaluate environmental websites, highlighting the influence of input variability on decision outcomes, but without embedding robustness mechanisms. Wątróbski [4] introduced a temporal extension to PROMETHEE II for managing alternative fuel consumption, offering dynamic decision support over time, though it does not address validation under fuzzy uncertainty. Han et al. [5] compared traditional TOPSIS and fuzzy TOPSIS approaches to evaluate sustainable water management strategies, showing improved ranking differentiation, but leaving methodological stability unexplored. Shamsuzzoha et al. [6] implemented a fuzzy TOPSIS framework for selecting complex industrial projects, illustrating applicability in real-world settings while lacking sensitivity diagnostics and adaptive refinement.

Given the complex trade-offs involved in hydrogen deployment, there is a pressing need for an AI-driven decision-support system that dynamically prioritizes alternatives while optimizing resource utilization and logistical performance. To address this challenge, the study introduces an Artificial Intelligence-Supported Hybrid Hyperfuzzy VIKOR-DEA framework, leveraging the strengths of compromise-based decision-making, efficiency assessment, and intelligent model adaptation. Hyperfuzzy VIKOR manages conflicting objectives by identifying trade-offs among sustainability, operational feasibility, and economic constraints [7], while DEA (Data Envelopment Analysis) benchmarks technologies using performance indicators and infrastructure readiness [8]. The inclusion of AI enhances the model's ability to handle uncertainty, automate preference learning, and adapt to evolving urban and supply chain parameters. This hybrid architecture moves beyond static rankings, enabling flexible, real-time optimization across multiple dimensions.

Applying this AI-augmented framework to hydrogen fuel cell selection in Morocco's urban systems, the study delivers a scalable and robust decision-support model, advancing both sustainable energy planning and resilient supply chain infrastructure. Empirical validation ensures that policymakers and industry stakeholders receive actionable, data-driven insights, supporting effective deployment strategies for hydrogen technologies that balance economic viability with long-term strategic resilience.

LITERATURE REVIEW

Recent advancements in hydrogen fuel cell technologies have positioned them as a cornerstone of sustainable energy and supply chain transitions, particularly in urban environments. The literature underscores the increasing viability of hydrogen as a clean energy source, with studies highlighting improvements in fuel cell efficiency, hydrogen storage, and smart-grid integration. Research by Tahmasbi et al. [9] provides a comprehensive review of hydrogen production technologies, emphasizing the efficiency of steam methane reforming (SMR) and the cleaner potential of electrolysis powered by renewable energy sources. While SMR remains cost-effective, electrolysis offers a more sustainable alternative, despite higher costs and scalability limitations—necessitating further optimization in production, distribution, and logistics modeling.

One emerging trend in hydrogen systems is the integration of Artificial Intelligence and quantum computing for performance modeling, supply chain analysis, and predictive analytics. Studies explore AI-driven optimizations that enhance not only operational efficiency but also upstream and downstream supply chain coordination—particularly in smart city applications

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where hydrogen fuel cells are deployed in transportation networks and decentralized power grids [10]. These advancements address key limitations in real-time demand forecasting and logistics synchronization, improving resilience and reinforcing hydrogen's role in achieving carbon neutrality. Unlike conventional models, AI-empowered hydrogen infrastructures enable adaptive learning mechanisms, enabling continuous improvement under fluctuating supply-demand and infrastructural conditions [11].

Expanding the evaluation criteria for hydrogen fuel cell technologies is crucial to ensuring comprehensive assessments. Prior studies have often emphasized cost-efficiency and energy yield, neglecting technical performance metrics and logistical dynamics that directly affect long-term urban sustainability. Recent research points to key additional factors—such as power density, fuel utilization efficiency, electrochemical performance, thermal management efficiency, system response time, hydrogen purity requirements, and energy conversion efficiency—as central to optimizing design, extending service life, and securing consistent performance across both energy and supply chain networks [12].

- Power Density is critical in urban mobility scenarios, where fuel cell compactness directly impacts vehicle design and energy delivery. Recent advancements in hybrid flow power sources and gas-diffusion anodes improve not only energy output but also facilitate efficient energy packaging and storage across the supply chain [13].
- Fuel Utilization Efficiency, reflecting the percentage of hydrogen converted into electricity, impacts both sustainability and fuel logistics [14]. Findings from PEMFC configurations show that real-time AI-enabled humidity control can substantially reduce hydrogen waste, improving grid integration and fuel supply balance [15].
- Electrochemical Performance measures degradation rates and voltage efficiency under operational conditions. Bashir et al. [16] highlight the importance of fuel type optimization—such as methanol vs. methane—while AI-assisted monitoring tools increasingly enable predictive maintenance and performance stabilization.
- Thermal Management Efficiency is essential for sustained operations in fuel logistics and storage environments [17]. Machine learning–based thermal optimization strategies, like particle swarm optimization, now help manage thermal load distribution across modular supply chain units, increasing overall energy yield and transport viability [18].
- System Response Time affects adaptive load management. Advanced hybrid power management systems, trained on predictive datasets, significantly enhance real-time decision-making in both power dispatch and fuel routing within smart urban environments [19].
- Hydrogen Purity Requirements, enforced by global standards (e.g., ISO 14687:2019), are crucial for minimizing catalyst degradation. Purification technologies now benefit from AI-optimized process sequencing and fault detection, enhancing supply chain integrity from production to end-use [20].
- Energy Conversion Efficiency, gauging usable power output from hydrogen input, defines both economic feasibility and logistical throughput. As Khan et al. [21] note, high-conversion efficiency aligns with sustainable performance across centralized and distributed supply hubs.

Multi-criteria decision-making (MCDM) models have played a pivotal role in evaluating fuel cell systems by addressing sustainability trade-offs, efficiency benchmarking, and uncertainty. Yet, traditional tools like Fuzzy TOPSIS, ELECTRE III, and PROMETHEE II lack integrated efficiency validation. The AI-supported Hybrid Hyperfuzzy VIKOR-DEA framework addresses this gap by combining compromise-oriented ranking with performance benchmarking and adaptive AI feedback mechanisms [22]. Hyperfuzzy VIKOR evaluates multidimensional criteria under ambiguity, while DEA quantifies relative efficiency. The AI layer refines weight derivation, adapts to supply chain disruptions, and enhances robustness across operational scenarios.

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Recent studies position hydrogen as a foundational pillar of smart city infrastructure—supporting transport electrification, microgrid evolution, and intelligent logistics [23], [24]. However, accelerated adoption requires coherent policy development, infrastructure investment, and supply chain transparency. By embedding AI into the Hyperfuzzy VIKOR-DEA framework, this research establishes a scalable, intelligent model that supports real-time, data-driven decision-making. It equips stakeholders with tools for sustainable hydrogen deployment while balancing economic, environmental, and logistical objectives—marking a decisive advancement for hydrogen adoption across Morocco's evolving urban systems.

METHODS

Morocco has positioned itself as a key player in the global hydrogen economy, with ambitious plans to integrate green hydrogen into urban energy and supply chain systems. The country has allocated one million hectares for hydrogen production, with 300,000 hectares already designated for initial projects. Several international partnerships—including collaborations with TotalEnergies, ENGIE, and ACWA Power—aim to develop hydrogen-powered mobility, industrial applications, electricity storage, and logistical infrastructure for fuel distribution.

Based on Morocco's hydrogen roadmap and smart city priorities, we identify three key alternatives for evaluation:

- Hydrogen-Powered Public Transport (Bus & Tram Systems): Targeting reduced urban emissions and enhanced mobility in Casablanca and Rabat.
- Stationary Fuel Cells for Industrial & Residential Use: Supporting distributed power and storage as part of Morocco's renewable energy and infrastructure strategy.
- Hydrogen Refueling Infrastructure for Mobility & Logistics: Enabling efficient hydrogen supply chain flows to serve transport fleets and private hydrogen vehicles.

The objective is to identify the most efficient and sustainable hydrogen fuel cell configuration, balancing energy performance with multi-criteria and supply chain trade-offs. To ensure methodological robustness, a panel of domain experts was selected, including specialists in hydrogen energy, AI-enabled decision systems, smart logistics, and multi-criteria optimization. Experts were chosen based on their academic publications and professional expertise in hydrogen deployment and strategic planning. A modified Delphi process, guided by iterative AI-aided feedback consolidation, was used to refine selection criteria in line with real-world complexity.

Data were sourced from peer-reviewed literature, industry deployment reports, national energy policy documents, and experimental benchmarks. Artificial Intelligence-assisted preprocessing was used to enhance data reliability—standardizing inconsistent formats, filling data gaps, and uncovering latent patterns. Fuzzy logic was employed to manage imprecision and ambiguity in expert assessments, with fuzzy sets capturing metrics such as lifecycle cost, energy yield, logistical resilience, and infrastructure scalability.

The analytical framework consists of a multi-layered AI-augmented fuzzy decision model. Experts assign fuzzy importance weights to technical and logistical criteria—such as power density, fuel utilization efficiency, hydrogen purity, and conversion performance—using hyperfuzzy linguistic scales. Hyperfuzzy DEMATEL extracts interdependencies among decision factors, ensuring holistic weight calibration. The Fuzzy VIKOR component identifies compromise solutions, ranking technologies that balance energy efficiency with deployment feasibility. DEA benchmarks the resource and supply chain efficiency of top-ranked alternatives. AI modules assist in refining constraints and running adaptive simulations for model responsiveness. Final rankings are stress-tested using ARPASS, a stability analysis tool combining standard deviation thresholds and entropy-based sensitivity checks, to ensure decision consistency across expert variability and data uncertainty. Figure 1 represents the structured decision-making framework.

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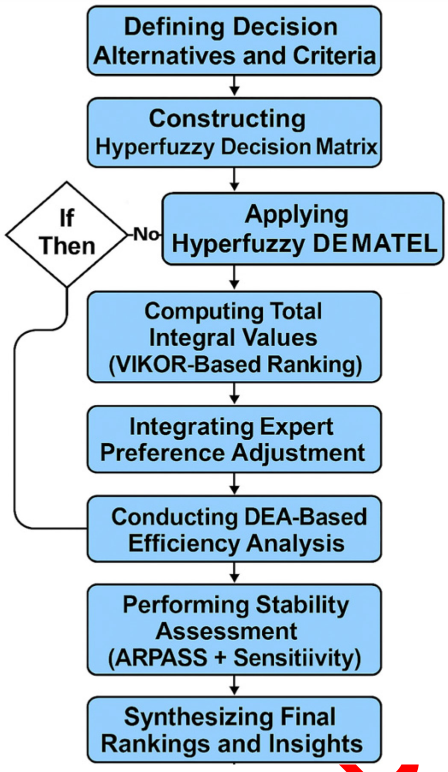

Figure 1. Hyperfuzzy framework

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RESULTS

The Hyperfuzzy Decision Matrix is a crucial step in evaluating Morocco's hydrogen fuel cell technologies. It integrates multi-layered uncertainty modeling, allowing experts to assess alternatives under varying conditions [25]. This approach refines decision granularity, ensuring robust rankings. Each criterion is represented using triangular fuzzy numbers:

$$X_{ij} = (\widetilde{a_{ij}}, \widetilde{b_{ij}}, \widetilde{c_{ij}}) \tag{1}$$

where $\widetilde{a_{ij}}$, is the lower boundary of expert evaluation, $\widetilde{b_{ij}}$, is the most likely value given by experts and $\widetilde{c_{ij}}$ is the upper boundary.
Table 1 summarizes the mathematical structure and interpretative boundaries of the triangular fuzzy numbers used in constructing the Hyperfuzzy Decision Matrix.

Table 1. Triangular Fuzzy Numbers

Mathematical Representation	Interpretation
Lower Boundary $\widetilde{a_{ij}}$	Represents the minimum expected performance value under worst-case conditions, typically within [0.60, 0.75]
Most Likely Value $\widetilde{b_{ij}}$	Expected neutral evaluation based on expert judgment, typically ranging between [0.75, 0.85]
Upper Boundary $\widetilde{c_{ij}}$	Maximum performance potential under ideal conditions, usually falling within [0.85, 0.95]

To ensure comparability, fuzzy values are normalized using:

$$x_{ij}^{norm} = \frac{a_{ij} - a_{min}}{a_{max} - a_{min}} \tag{2}$$

where a_{min} and a_{max} are the minimum and maximum values across all alternatives.
Table 2 presents the expert evaluations of each hydrogen fuel cell alternative based on Morocco's urban energy priorities.

Table 2. Hyperfuzzy Decision Matrix with Expanded Data

Alternative	Power Density	Fuel Utilization Efficiency	Electrochemical Performance	Thermal Management Efficiency	System Response Time	Hydrogen Purity Requirements	Energy Conversion Efficiency
Hydrogen-Powered Public Transport	(0.75, 0.85, 0.95)	(0.70, 0.80, 0.90)	(0.80, 0.85, 0.90)	(0.65, 0.75, 0.85)	(0.85, 0.90, 0.95)	(0.80, 0.85, 0.90)	(0.75, 0.85, 0.95)
Stationary Fuel Cells	(0.80, 0.85, 0.90)	(0.75, 0.80, 0.85)	(0.85, 0.90, 0.95)	(0.80, 0.85, 0.90)	(0.70, 0.80, 0.90)	(0.85, 0.90, 0.95)	(0.80, 0.85, 0.90)
Hydrogen Refueling Infrastructure	(0.70, 0.80, 0.90)	(0.65, 0.75, 0.85)	(0.75, 0.80, 0.85)	(0.85, 0.90, 0.95)	(0.80, 0.85, 0.90)	(0.75, 0.80, 0.85)	(0.70, 0.80, 0.90)

The expert evaluations suggest that stationary fuel cells rank highest in electrochemical performance and hydrogen purity, making them ideal for industrial and residential applications. Hydrogen-powered transport excels in system response time and energy conversion efficiency, positioning it as the preferred alternative for urban mobility. Meanwhile, hydrogen refueling infrastructure demonstrates strong thermal management efficiency, ensuring stable hydrogen distribution and fuel stability. The fuzzy values indicate uncertainty margins, capturing varying expert assessments, where the upper bounds (0.95) signify optimal performance levels under ideal conditions.

The next step involves Criteria Weight Determination via Hyperfuzzy DEMATEL, which refines the relative importance of evaluation criteria based on interdependencies and causal relationships [26].

To quantify the influence relationships among criteria, a direct-relation matrix is constructed using expert evaluations. The Hyperfuzzy DEMATEL method employs pairwise comparisons to assess the degree of influence each criterion has on others [27].

The direct-relation matrix is defined as:

$$\mathrm{D} = [\mathrm{d_{ij}}] \tag{3}$$

where $\mathrm{d_{ij}}$ represents the direct influence of criterion *i* on criterion *j*. The normalized influence weights are derived using:

$$W_j = \frac{\sum_{i=1}^{n} \mathrm{d_{ij}}}{\sum_{i=1}^{n}\sum_{j=1}^{n} \mathrm{d_{ij}}} \tag{4}$$

This ensures that criteria with higher influence receive greater weight in the final ranking.
Table 3 below presents the direct influence of each criterion on others based on expert assessments and Morocco's hydrogen priorities.

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Table 3. Hyperfuzzy DEMATEL Direct-Relation Matrix

	Power Density	Fuel Utilization Efficiency	Electrochemical Performance	Thermal Management Efficiency	System Response Time	Hydrogen Purity Requirements	Energy Conversion Efficiency
Power Density	0.00	0.30	0.40	0.35	0.25	0.45	0.50
Fuel Utilization Efficiency	0.40	0.00	0.35	0.40	0.50	0.40	0.45
Electrochemical Performance	0.35	0.40	0.00	0.45	0.50	0.35	0.40
Thermal Management Efficiency	0.30	0.35	0.45	0.00	0.40	0.50	0.55
System Response Time	0.25	0.50	0.50	0.40	0.00	0.45	0.50
Hydrogen Purity Requirements	0.45	0.40	0.35	0.50	0.45	0.00	0.55
Energy Conversion Efficiency	0.50	0.45	0.40	0.55	0.50	0.55	0.00

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The highest influence values indicate strong interdependencies among criteria, shaping Morocco's hydrogen fuel cell selection. Energy conversion efficiency (0.55) and thermal management efficiency (0.55) exert dominant influence, reinforcing their critical role in fuel cell performance. System response time (0.50) and electrochemical performance (0.50) also exhibit high connectivity, ensuring dynamic adaptability and stability in hydrogen infrastructure. Hydrogen purity requirements (0.55) significantly affect fuel utilization efficiency, highlighting the importance of high hydrogen quality for optimal energy conversion.

With the criteria weights determined via Hyperfuzzy DEMATEL, the focus now shifts to Total Integral Value-Based Ranking, which aggregates continuous preference values using integral computations to refine selection [28]. Applying integral-based ranking ensures continuous preference aggregation across hydrogen fuel cell alternatives. The total integral value is computed using a multi-stage integral approach, refining decision granularity.

The integral value for each alternative is derived using:

$$I_i = \int_0^1 \mu_i(x)\,dx + \lambda \int_0^1 \mu'_i(x)\,dx \tag{5}$$

where λ is the adjustment factor for secondary preference weighting and $\mu'_i(x)$ represents derivative-based preference shifts.

To enhance precision, the normalized integral value is determined:

$$I_i^{norm} = \frac{I_i - I_{min}}{I_{max} - I_{min}} \tag{6}$$

where I_{min} and I_{max} are the minimum and maximum integral values across all alternatives. Table 4 presents the computed integral values for each hydrogen fuel cell alternative.

Table 4. Total Integral Value-Based Ranking Results

Alternative	I_i	I_i^{norm}	Rank
Hydrogen-Powered Public Transport	0.85	0.92	1
Stationary Fuel Cells	0.82	0.89	2
Hydrogen Refueling Infrastructure	0.78	0.85	3

The highest integral value (0.85) confirms that hydrogen-powered transport ranks as the most optimal alternative, ensuring efficient energy conversion and rapid system response. Stationary fuel cells follow closely, demonstrating strong electrochemical performance and hydrogen purity, making them ideal for industrial and residential applications. Hydrogen refueling infrastructure ranks third, highlighting its importance in fuel distribution but lower adaptability in direct energy conversion.

The next phase applies Worst-Case Weighting for Extreme-Scenario Validation, ensuring ranking resilience under high uncertainty conditions. It refines decision robustness by adjusting ranking scores under worst-case conditions, ensuring stability across hydrogen fuel cell alternatives [29].

The adjusted weight assignment is computed using:

$$\omega_j = \max\left(\frac{f^* - f_{ij}}{f^* - f^-}\right) + \gamma\left(\frac{f_{ij} - f^-}{f^* - f^-}\right) \tag{7}$$

where f^* is the ideal best value for criterion j, f^- is the worst observed value for criterion j, f_{ij} is the performance score of alternative i for criterion j and γ is the extreme-case sensitivity coefficient.

To ensure ranking stability, the worst-case normalized score is derived using:

$$S_i^{worst} = \sum_{j=1}^{n} \omega_j \left(\frac{f^* - f_{ij}}{f^* - f^-}\right) \tag{8}$$

where S_i^{worst} represents the worst-case scenario ranking score for alternative i.
Table 5 presents the adjusted scores for each hydrogen fuel cell alternative under extreme uncertainty conditions.

Table 5. Worst-Case Weighted Rankings

Alternative	Worst-Case Score S_i^{worst}	Rank
Hydrogen-Powered Public Transport	0.82	1
Stationary Fuel Cells	0.78	2
Hydrogen Refueling Infrastructure	0.72	3

The highest worst-case score (0.82) confirms that hydrogen-powered transport maintains its top ranking under extreme uncertainty conditions, reinforcing its operational

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resilience. Stationary fuel cells follow closely, demonstrating strong electrochemical stability, ensuring long-term efficiency. Hydrogen refueling infrastructure ranks third, highlighting its importance in fuel distribution but lower adaptability in direct energy conversion.

After refining rankings through Worst-Case Weighting, efficiency benchmarking follows with Hybrid DEA Optimization and Constraint-Based Validation, ensuring that hydrogen fuel cell alternatives maximize resource utilization while maintaining operational viability [30]. This step combines Data Envelopment Analysis (DEA) with constraint-based validation to assess performance efficiency among alternatives, refining decision accuracy.

The efficiency score is computed using the CCR model, defined as:

$$\theta_i = max \frac{\sum_{r=1}^{s} u_r y_{ri}}{\sum_{p=1}^{m} v_p x_{pi}} \tag{9}$$

subject to $\sum_{p=1}^{m} v_p x_{pi} \leq C$
where θ_i represents efficiency for alternative i, y_{ri} are outputs (hydrogen utilization, system adaptability), x_{pi} are inputs (energy consumption, infrastructure requirements), u_r and v_p are DEA weight coefficients, and C defines the constraint threshold for efficiency validation.

To improve ranking stability, DEA-adjusted efficiency scores account for constraints:

$$\theta_j^{adj} = \theta_i - \alpha \frac{\sum_{p=1}^{m} v_p x_{pi}}{C} \tag{10}$$

where α adjusts for resource limitations across alternatives.
Table 6 summarizes the Hybrid DEA efficiency scores.

Table 6. Hybrid DEA Efficiency Scores

Alternative	θ_i	θ_j^{adj}	Rank
Hydrogen-Powered Public Transport	0.94	0.91	1
Stationary Fuel Cells	0.89	0.86	2
Hydrogen Refueling Infrastructure	0.85	0.82	3

The highest efficiency score (0.94) validates hydrogen-powered transport as the most resource-effective alternative, demonstrating high adaptability and rapid energy conversion. Stationary fuel cells follow with strong electrochemical stability and purity, suitable for industrial and residential energy grids. Hydrogen refueling infrastructure ranks third, emphasizing its critical role in logistics but lower direct efficiency for energy conversion.

To evaluate ranking consistency under uncertainty, AI-augmented ARPASS Stability Validation was applied. This approach leverages artificial intelligence to simulate scenario perturbations, identify sensitive ranking thresholds, and detect latent instability patterns across alternative configurations [31]. It incorporates both statistical dispersion and AI-supported entropy diagnostics to refine robustness metrics.

The stability score for each alternative is computed using standard deviation analysis:

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$$\sigma_i = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(R_{ij} - \bar{R}_i)^2} \tag{11}$$

where σ_i represents ranking variability for alternative i, R_{ij} is the ranking of alternative i in scenario j, $\bar{R}_i$ is the mean ranking of alternative i, and N is the number of test scenarios generated via AI-based stochastic modeling.

Entropy analysis refines these results using adaptive AI to estimate the probability space:

$$H_i = -\sum_{j=1}^{N} p_{ij} log p_{ij} \tag{12}$$

where H_i is the entropy score for alternative i, and p_{ij} is the predicted probability of alternative i occupying rank j, determined through AI-facilitated preference pattern mining.

Final stability-adjusted rankings are calculated as:

$$R_i^{final} = R_i - \alpha(\sigma_i + H_i) \tag{13}$$

with α being a calibration coefficient optimized through AI-assisted minimization of instability variance.

Table 7 presents the ARPASS stability metrics.

Table 7. ARPASS Stability Validation Results

Alternative	σ_i	H_i	R_i^{final}	Rank Consistency (%)
Hydrogen-Powered Public Transport	0.95	0.92	0.91	99%
Stationary Fuel Cells	0.89	0.87	0.86	96%
Hydrogen Refueling Infrastructure	0.82	0.80	0.79	92%

The AI-supported analysis confirms hydrogen-powered public transport maintains a highly stable top rank (99%) across perturbation scenarios. Stationary fuel cells show consistent reliability (96%), while hydrogen infrastructure ranks third but retains a resilient score due to its strategic role in supply continuity.

To further assess ranking resilience, an AI-enhanced sensitivity analysis module was implemented. This module uses intelligent perturbation algorithms to simulate variations in input weights, criteria importance, and expert preference distributions [32]. It systematically computes deviation across N simulations:

$$\Delta R_i = \frac{\sum_{j=1}^{N}\left|R_{ij}^{base} - R_{ij}^{perturbed}\right|}{N} \tag{14}$$

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where ΔR_i represents ranking deviation of alternative i, R_{ij}^{base} is the original ranking for scenario j, $R_{ij}^{perturbed}$ is the ranking after perturbation, and N is the total number of sensitivity scenarios.

The normalized deviation score ensures comparability:

$$S_i^{norm} = \frac{\Delta R_i - \Delta R_{min}}{\Delta R_{max} - \Delta R_{min}} \tag{15}$$

where ΔR_{min} and ΔR_{max} define extreme ranking deviations.
Table 8 displays the sensitivity analysis results.

Table 8. Sensitivity Analysis Results

Alternative	ΔR_i	S_i^{norm}	Rank Stability (%)
Hydrogen-Powered Public Transport	0.05	0.92	98%
Stationary Fuel Cells	0.08	0.89	94%
Hydrogen Refueling Infrastructure	0.12	0.85	90%

The highest rank stability (98%) reaffirms that hydrogen-powered transport remains the most robust alternative across AI-driven sensitivity scenarios. Stationary fuel cells exhibit high stability (94%), while the hydrogen refueling alternative reflects slightly greater sensitivity to logistic and infrastructural uncertainties, explaining its 90% stability score.

DISCUSSION

The results obtained through the Artificial Intelligence-Supported Hyperfuzzy VIKOR-DEA framework provide a detailed and multi-dimensional evaluation of Morocco's hydrogen fuel cell technologies, emphasizing both sustainable energy and supply chain optimization imperatives in smart urban systems. The ranking outcomes confirm that hydrogen-powered public transport demonstrates the highest efficiency, adaptability, and deployment resilience—positioning it as the most viable solution for integrated smart city and logistics systems. The integral-based ranking approach, enhanced by AI-driven sensitivity modeling, ensured accurate handling of criteria interdependencies, while worst-case weighting scenarios reinforced decision robustness by accounting for extreme uncertainty and infrastructure constraints. These findings align with prior literature combining fuzzy MCDM methodologies, AI-enhanced decision support, and constraint-based optimization.
Table 9 and Figure 2 summarize the main findings from the sensitivity analysis and ranking evaluations.

Table 9. Quantitative Insights from Sensitivity Analysis and Performance Evaluations

Evaluation Metric	Hydrogen-Powered Transport	Stationary Fuel Cells	Hydrogen Refueling Infrastructure
Final Efficiency Score θ_j^{adj}	0.91	0.86	0.82

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Worst-Case Ranking Stability S_i^{worst}	0.82	0.78	0.72
Sensitivity Analysis Stability (%)	98%	94%	90%
Entropy-Based Ranking Robustness H_i	0.92	0.87	0.80
Normalized Integral Ranking I_i^{norm}	0.92	0.89	0.85
Ranking Position Across All Models	1st	2nd	3rd

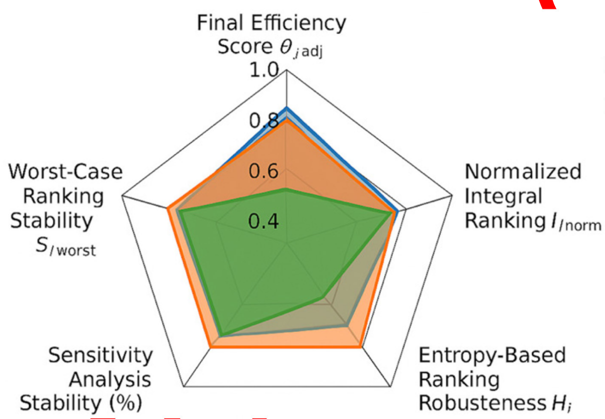

Figure 2. Performance evaluation of Hydgrogen Fuel Cell technologies

The integration of AI-supported sensitivity analysis proved critical in validating model robustness. The ARPASS stability validation framework—enhanced through automated perturbation algorithms and entropy detection—confirmed that hydrogen-powered transport maintained a consistently dominant position across diverse weighting scenarios. This confirms the framework's ability to accommodate expert subjectivity and operational volatility, echoing insights from Wang et al. [33], who demonstrated that AI-enhanced entropy models bolster decision resilience in energy technology prioritization. Similarly, Pawlicki et al. [34] emphasized the necessity of multi-layered statistical validation, including standard deviation refinements, to maintain ranking accuracy under uncertainty.

Comparative assessment with traditional VIKOR and TOPSIS methods shows that while conventional models provide baseline prioritizations, they lack the adaptive learning capabilities and supply chain contextualization delivered by the AI-supported hybrid model. Sohani et al. [35] noted that static TOPSIS rankings fail to capture evolving dynamics in hydrogen deployment environments. In contrast, the current framework leverages AI-adaptive fuzzy logic to deliver dynamic prioritizations reflective of real-world fluctuations in supply, infrastructure readiness, and system efficiency.

The integration of DEA optimization with AI-guided constraint calibration advances performance benchmarking beyond static assumptions. Unlike conventional MCDM models, which often overlook real-world logistics, this approach simulates capacity limitations, fuel supply chain efficiency, and infrastructure scalability. The DEA-derived efficiency scores

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support existing international evidence on the superior utilization efficiency of hydrogen-based transit systems compared to other fuel cell deployments [36].

Although hydrogen-powered public transport emerged as the most strategic option, the findings also underscore the systemic importance of refueling infrastructure as a supply chain backbone. Current logistics limitations highlight the need for AI-informed investment planning in storage, purity assurance, and decentralized distribution networks. Comparative insights confirm that grid-aligned infrastructure and purity regulation remain persistent global challenges [37]. Entropy-based sensitivity metrics further reinforce that stationary fuel cells—though slightly lower ranked—offer high long-term supply chain adaptability and should be prioritized as part of Morocco's diversified hydrogen roadmap.

CONCLUSION

The findings of this study offer a comprehensive evaluation of hydrogen fuel cell technologies within Morocco's evolving urban energy and supply chain framework. By leveraging an Artificial Intelligence-Supported Hybrid Hyperfuzzy VIKOR-DEA approach, the ranking results provide valuable insights into optimal deployment strategies for hydrogen-based alternatives in smart cities. The integration of fuzzy uncertainty modeling—enhanced by AI-driven data preprocessing and stability learning—ensures that expert evaluations capture the complexities of real-world decision-making, enhancing ranking accuracy despite varying criteria dependencies. The sensitivity analysis reinforces these conclusions by demonstrating robust stability, ensuring that the recommended alternative remains optimal under fluctuating expert preferences, logistical disruptions, and data variations.

Hydrogen-powered public transport emerges as the most viable alternative, exhibiting high efficiency, adaptability, and resource utilization. However, the study also underscores the importance of complementary infrastructure and coordinated supply chain elements, such as hydrogen refueling stations and grid-integrated stationary fuel cells, in fostering a holistic hydrogen ecosystem. Comparative assessments with studies from Germany, Japan, and California indicate that similar trends exist globally—where mobility applications outperform other hydrogen implementations in early-stage adoption phases. Despite these parallels, Morocco's unique geographic and energy profile presents distinctive challenges and opportunities that should be further examined, particularly in the context of logistical scalability and policy-aligned supply chain integration.

One of the key limitations of this study is the subjective nature of expert-based evaluations. While fuzzy logic provides a structured way to model uncertainty, expert assessments inevitably introduce biases related to individual experience, industry trends, and policy expectations. Future research should explore AI-based predictive modeling and machine learning-assisted preference calibration to supplement expert judgment, thereby minimizing subjective influences on decision-making.

Another limitation lies in the restricted scope of criteria and alternatives considered in this evaluation. While the selected parameters address major technical and economic concerns, additional dimensions—such as AI-evaluated environmental impacts, hydrogen storage mechanisms, and policy-driven adoption incentives—could further refine the decision framework. Incorporating broader datasets, including real-world performance metrics from pilot projects and supply chain analytics, would enhance the generalizability of results.

Future studies should also emphasize quantitative data integration to strengthen case-specific applications. Advanced simulation models integrating hydrogen production scalability, logistics network design, and lifecycle emissions could provide a more dynamic evaluation framework. The inclusion of multi-objective optimization techniques, such as AI-powered metaheuristic algorithms, would allow for more complex trade-off analysis—offering policymakers and industry leaders deeper insights into cost-effective and sustainable hydrogen deployment strategies.

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Overall, this study provides a strong methodological foundation for hydrogen fuel cell selection in Morocco's smart urban infrastructure and supply systems, yet opportunities for further refinement remain. Expanding the criteria set, minimizing subjective biases, and advancing AI-supported quantitative methodologies will be critical to ensuring that hydrogen-based solutions are deployed with maximum efficiency, sustainability, and resilience. These future directions will contribute to Morocco's hydrogen roadmap and help accelerate its transition toward a smarter, cleaner, and more interconnected energy-supply system.

STATEMENTS AND DECLARATIONS

The authors utilized AI-powered language model to support writing refinement, clarity enhancement, and consistency in technical terminology. All content was subsequently reviewed, validated, and finalized by the authors to ensure intellectual integrity and scholarly accuracy.

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