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Research article

Hybrid AI-driven decision architecture for sustainable industrial planning: Integrating BWM, IVN-TOPSIS, and DRL in OCP's digital supply chain

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Abstract: Sustainable energy planning in industrial supply chains requires a digitally integrated decision architecture capable of modeling uncertainty, aligning stakeholder priorities, and optimizing infrastructure deployment. In this study, we introduced a hybrid AI-driven (Artificial Intelligence) framework that combines expert-based weighting, neutrosophic uncertainty modeling, and adaptive learning to support strategic planning across energy, logistics, and infrastructure domains. The framework began with the Best-Worst Method (BWM) to derive consistent weights for four meta-criteria: Information strength, balance, data reliability, and lever readiness. These weights were applied to five strategic criteria clusters: Energy performance, environmental impact, logistics service, production stability, and risk and resilience, which were evaluated using Interval-Valued Neutrosophic IVN-TOPSIS (Technique for Order Preference by Similarity to Ideal Solution). Each criterion was expressed as an interval-valued neutrosophic number $A_i = (T_i, I_i, F_i)$, where T_i, I_i, and F_i represented degrees of truth, indeterminacy, and falsity, respectively. The closeness coefficient CC_i was computed to rank alternatives under uncertainty. These outputs were embedded in a Deep Reinforcement Learning (DRL) agent, where the reward function $R = (s, a)$ was shaped by the normalized IVN-TOPSIS scores, enabling real-time policy refinement while preserving expert-defined priorities. Applied to OCP's phosphate supply chain, the model revealed that energy and environment jointly account for 55% of the total strategic weight, confirming their dominant role in decarbonization and cost control. This integrated architecture enhances decision robustness, transparency, and operational relevance. While we focused on strategic criteria modeling, in future work, we will incorporate chemical interaction modeling, particularly the stable complexation mechanisms between phosphate components and energy vectors, to further support infrastructure deployment and sustainable logistics optimization.

Keywords: digital supply chain optimization; AI-driven decision architecture; sustainable energy planning; neutrosophic Multi-Criteria Decision Making framework (MCDM); infrastructure and logistics integration

1. Introduction

Sustainable energy planning increasingly demands intelligent supply chain architectures that are digitally integrated, uncertainty-aware, and capable of continuous adaptation [1,2]. In high-impact sectors, such as phosphate production, strategic decisions must reconcile decarbonization targets, infrastructure deployment, and logistics coordination while navigating ambiguous data and evolving stakeholder priorities. Despite the proliferation of studies on energy materials and supply chain optimization, most rely on conventional MCDM methods that use static weights and crisp evaluations. These approaches often fail to capture the dynamic complexity of long-term planning across energy, logistics, and infrastructure domains. Moreover, they lack mechanisms for integrating expert judgment with real-time feedback, limiting their responsiveness to operational shifts and policy changes [3,4].

To address this gap, we introduce a novel hybrid framework, BWM-IVN-TOPSIS-DRL, that combines structured expert weighting, neutrosophic uncertainty modeling, and adaptive learning through artificial intelligence. The BWM is used to derive consistent weights for meta-criteria such as information strength, balance, data reliability, and lever readiness [5]. IVN-TOPSIS translates linguistic expert evaluations into structured neutrosophic intervals, enabling robust ranking of strategic criteria under uncertainty [6]. These outputs are embedded into a DRL agent, which refines decision policies based on real-time feedback while preserving expert-defined priorities.

The framework is applied to five strategic criteria clusters essential for sustainable energy and digital supply chain planning: Energy performance, environmental impact, logistics service, production stability, and risk and resilience. The closeness scores generated by IVN-TOPSIS are normalized and used to shape the DRL agent's reward function, ensuring that learned policies remain aligned with stakeholder goals while adapting to operational dynamics.

Compared to researchers who focus primarily on material-level optimization or isolated process improvements [7–10], we offer a system-level decision architecture that integrates expert knowledge with AI-driven adaptability. Its novelty lies in the fusion of neutrosophic logic with reinforcement learning, enabling interpretability and dynamic policy refinement. The framework is not only scalable but also operationally grounded, making it suitable for real-world deployment in industrial ecosystems like OCP's phosphate supply chain.

Our aim of this study is to fill a critical methodological gap by developing a transparent, learning-enabled decision-support system for sustainable energy planning. It advances the field by offering a robust alternative to static MCDM models and contributes to the scientific discourse on intelligent infrastructure and logistics optimization under uncertainty.

2. Literature review

The increasing complexity of sustainable energy planning and digital supply chain management has prompted a surge in decision-support methodologies aimed at balancing environmental, logistical, and infrastructural priorities under uncertainty [11,12]. Numerous researchers have explored strategic criteria clusters, such as energy efficiency, environmental impact, logistics performance, and operational resilience, but many rely on conventional MCDM techniques that exhibit critical limitations when applied to dynamic, real-world industrial ecosystems.

Recent research has emphasized the need to integrate energy performance and environmental sustainability into supply chain design. For example, Tramarico et al. [13] proposed a structured approach to supplier selection that incorporates sustainability indicators, highlighting the interdependence between energy decisions and logistical coordination. Their work demonstrates that strategic planning must account for multiple dimensions, i.e., carbon footprint, cost efficiency, service reliability, and risk mitigation, especially in sectors like phosphate production, where operational corridors span geographically and functionally diverse nodes. However, their model remains static, lacking mechanisms to adapt to evolving stakeholder priorities or real-time operational feedback.

Traditional MCDM methods such as Analytic Hierarchy Process (AHP), TOPSIS, and Elimination and Choice Translating Reality (ELECTRE) have long been used for strategic planning. These methods offer structured decision matrices and pairwise comparisons, enabling transparent evaluation of alternatives [14–16]. Yet, they suffer from several methodological gaps. Most rely on fixed weights derived from initial expert input, which cannot accommodate changing priorities or feedback loops [17]. They also assume precise numerical inputs, ignoring the linguistic ambiguity inherent in expert judgment. Moreover, they struggle to scale in complex, multi-layered industrial systems where criteria interdependencies and feedback mechanisms are critical [18,19]. While fuzzy logic and grey systems have been introduced to address uncertainty, their integration with learning-based models remains limited. Few studies have embedded MCDM outputs into adaptive agents capable of real-time policy refinement.

To overcome these limitations, hybrid frameworks combining MCDM with artificial intelligence have emerged. For instance, the integration of fuzzy AHP with neural networks has shown promise in enhancing decision adaptability [20]. Similarly, Bayesian networks have been used to model probabilistic dependencies among criteria in energy and logistics planning [21]. However, these approaches often lack interpretability and transparency, making them difficult to validate and communicate to stakeholders. The use of DRL in decision-support systems is nascent but rapidly gaining traction. DRL enables learning optimal policies through interaction with dynamic environments, making it suitable for industrial planning under uncertainty [22]. Yet, without structured expert input, DRL agents risk drifting from stakeholder priorities. This highlights the need for a hybrid architecture that anchors learning in expert-defined criteria while enabling adaptive refinement.

Neutrosophic sets, particularly IVN representations, offer a powerful tool for modeling uncertainty in expert evaluations. Unlike fuzzy sets, which capture vagueness through degrees of membership, neutrosophic sets introduce three independent components: Truth, indeterminacy, and falsity [23]. This triadic structure allows for a more nuanced representation of expert opinions, especially when dealing with conflicting or incomplete information. IVN-TOPSIS extends the classical TOPSIS method by incorporating these neutrosophic intervals, enabling robust ranking of alternatives under uncertainty. Wang and An [24] applied IVN-TOPSIS to supplier evaluation, demonstrating its effectiveness in handling ambiguity. However, their model remained static, with no mechanism for policy refinement over time. The disconnect between uncertainty modeling and adaptive decision-making remains a critical gap in the literature.

BWM provides a more consistent and efficient alternative to traditional weighting techniques. By focusing on the most and least important criteria, BWM reduces cognitive load and improves reliability. In energy planning contexts, BWM has been used to prioritize sustainability indicators and stakeholder preferences [25]. Yet, its integration with uncertainty modeling and AI remains underexplored. Most applications treat BWM as a standalone tool, missing the opportunity to embed its outputs into dynamic learning systems.

The proposed BWM-IVN-TOPSIS-DRL framework directly addresses these methodological gaps. It offers structured expert weighting through BWM, ensuring consistency and stakeholder alignment. It models uncertainty via IVN-TOPSIS, capturing the ambiguity of real-world evaluations. It enables adaptive learning through DRL, enabling real-time policy refinement based on operational feedback. This integration is novel in its ability to preserve expert-defined priorities while dynamically adjusting to changing conditions. Unlike researchers who treat MCDM outputs as static endpoints, in this framework, we treat them as evolving inputs to a learning agent, bridging the gap between strategic planning and operational execution.

3. Materials and methods

3.1. Expert-guided data collection and contextualization

To ensure the strategic relevance and empirical validity of the proposed AI-driven decision architecture for sustainable energy planning, a multidisciplinary expert panel was assembled. This panel included professionals from OCP Group's energy, logistics, digital transformation, and sustainability divisions, alongside external collaborators from academia and industry. Expert selection was based on direct involvement in renewable energy integration, digital supply chain systems, and infrastructure deployment across Morocco's phosphate sector.

Engineers contributed insights into solar, wind, and cogeneration systems powering OCP's industrial sites, focusing on energy flow modeling and carbon mitigation strategies. Logistics managers and strategic partners provided operational knowledge on transport coordination, digital traceability, and export logistics, mapping the phosphate flow from extraction sites (Khouribga, Benguerir) to processing hubs (Jorf Lasfar, Safi) and global terminals. Data scientists and digital architects supported the AI dimension, defining the integration of real-time data streams, sensor networks, and optimization algorithms. Environmental analysts added expertise in emissions tracking and water-energy nexus modeling, while infrastructure planners and academic researchers guided scenario design and model validation.

This collaborative structure ensured that the decision model was grounded in operational reality, stakeholder priorities, and technical feasibility; key requirements for deploying a scalable digital supply chain architecture.

3.2. Data acquisition and validation protocol

The data acquisition protocol was designed to support the hybrid BWM-IVN-TOPSIS-DRL framework by capturing structured metrics and tacit expert knowledge. A mixed-method approach was adopted, combining system mapping, expert elicitation, and data triangulation.

In the first phase, system mapping identified key nodes and flows within OCP's industrial ecosystem, including extraction sites, processing hubs, export terminals, and renewable energy installations. Technical documentation and internal reports provided baseline data on energy consumption, transport volumes, and infrastructure capacity. This mapping informed the structure of the decision criteria and the configuration of strategic alternatives.

The second phase involved expert elicitation through semi-structured interviews with stakeholders across energy, logistics, digital, and sustainability domains. These interviews helped refine the criteria hierarchy and calibrate the linguistic evaluations used in neutrosophic modeling.

The third phase focused on data triangulation. Internal datasets from OCP were cross-validated against external benchmarks from international agencies and strategic partners. This included metrics on energy intensity, emissions, water use, and logistics performance. Feedback loops were embedded throughout the process to iteratively refine model assumptions and ensure alignment with stakeholder-defined priorities.

3.3. Hybrid AI-MCDM framework

The core of the research design is a hybrid decision-support framework that integrates structured expert judgment, uncertainty modeling, and adaptive learning. The framework consists of four sequential modules:

- BWM: Used to derive consistent weights for meta-criteria such as information strength, balance, data reliability, and lever readiness. This ensures stakeholder alignment and reduces inconsistency in pairwise comparisons.
- IVN-TOPSIS: Translates linguistic expert evaluations into neutrosophic numbers capturing truth, indeterminacy, and falsity. The closeness coefficient is computed to rank strategic criteria under uncertainty.
- Strategic Alternatives Evaluation: Five operational scenarios (A1–A5) are defined, each representing a distinct configuration of energy, logistics, water, and resilience priorities. These alternatives are evaluated using the IVN-TOPSIS closeness scores and BWM-derived weights.
- DRL: The normalized outputs from IVN-TOPSIS are embedded into a DRL agent, which refines decision policies based on real-time feedback. The reward function R (s, a) is shaped by expert-defined priorities, enabling adaptive planning while preserving interpretability.

3.4. Strategic alternatives and criteria hierarchy

The decision problem focuses on selecting the most effective operational strategy for OCP's next planning horizon (12–36 months). Five strategic alternatives are defined:

- A1—Baseline: Incremental improvements to current operations.
- A2—Accelerated green: Aggressive renewable energy deployment and emissions reduction.
- A3—Water-Stress mitigation: Focus on desalination and water reuse.
- A4—Logistics surge capacity: Expansion of transport and port throughput.
- A5—Balanced resilience: Integrated strategy across energy, water, logistics, and risk.

Each alternative is evaluated against five thematic criteria groups:

- C1. Energy performance: Renewable share (%), grid imports (GWh), energy cost (MAD).
- C2. Environmental impact: Scope 2 CO_2 emissions (t), emissions intensity (t CO_2/t P_2O_5), and water footprint (Mm^3).
- C3. Logistics service: On-time departures (%), port wait times (h), and corridor utilization (%).
- C4. Production stability: Throughput variability (%), stockouts, and total production (kt).
- C5. Risk and resilience: Availability, sensitivity to price shocks, and capex/feasibility.

Each sub-criterion is classified as benefit-type, cost-type, or mixed, and is traceable to real operational data from OCP's digital twin and scenario simulations. This structure ensures that the evaluation is both rigorous and stakeholder-ready.

4. Results

4.1. Sub-criteria normalization and BWM-based filtering

To ensure that the evaluation of strategic alternatives reflects both operational relevance and stakeholder priorities, sub-criteria were first normalized and subsequently filtered using a BWM-informed approach. This dual-stage process enables the retention of indicators that are not only empirically discriminative but also aligned with strategic levers and decision-maker expectations [26]. The BWM framework was applied at the meta-criteria level to derive consistent weights for overarching dimensions such as information strength, balance, data reliability, and lever readiness. These weights served as a foundation for evaluating the informational contribution of each sub-criterion [27].

Given the heterogeneity of the sub-criteria, spanning energy cost, CO_2 emissions, production throughput, and port wait times, it was necessary to transform all indicators into a common evaluative scale. This normalization step ensures comparability across benefit-type and cost-type indicators, thereby enabling fair aggregation and contrast [28,29]. Benefit-type indicators were normalized using the following formulation:

$$z_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \tag{1}$$

Conversely, cost-type indicators were normalized using:

$$z_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \tag{2}$$

This transformation scales all sub-criteria between 0 and 1, with 1 representing the most favorable performance across alternatives. Table 1 presents the normalized values for each sub-criterion across five strategic alternatives (A1–A5).

Table 1. Normalized values of sub-criteria across alternatives.

Sub-Criterion	Type	A1	A2	A3	A4	A5
C1.1 Renewable share (%)	Benefit	0.00	0.59	0.32	1.00	0.41
C1.2 Grid imports (GWh)	Cost	0.67	0.33	1.00	0.00	0.50
C1.3 Energy cost (MAD)	Cost	0.78	0.56	1.00	0.00	0.67
C2.1 CO_2 scope 2 (t)	Cost	0.65	0.88	0.42	1.00	0.00
C2.2 Emissions intensity	Cost	0.71	0.93	0.50	1.00	0.00
C2.3 Water footprint (Mm^3)	Cost	0.60	0.80	0.40	1.00	0.00
C3.1 On-time departures (%)	Benefit	0.33	0.67	0.00	1.00	0.50
C3.2 Port wait times (h)	Cost	0.60	0.80	0.40	1.00	0.00
C3.3 Corridor utilization (%)	Cost	0.50	0.75	0.25	1.00	0.00
C4.1 Throughput variability (%)	Cost	0.50	0.75	0.25	1.00	0.00
C4.2 Stockouts	Cost	0.40	0.80	0.20	1.00	0.00
C4.3 Total production (kt)	Benefit	0.29	0.71	0.00	1.00	0.43
C5.1 Availability	Benefit	0.40	0.80	0.20	1.00	0.00
C5.2 Price sensitivity	Cost	0.45	0.75	0.25	1.00	0.00
C5.3 Capex/feasibility	Benefit	0.36	0.64	0.18	1.00	0.00

Notable variation is observed in indicators such as renewable share (C1.1), emissions intensity (C2.2), and total production (C4.3), which exhibit strong differentiation between aggressive sustainability strategies (A2, A4) and baseline or water-focused plans (A1, A3).

Following normalization, the next analytical step involved assessing the discriminative power of each sub-criterion [30]. This was achieved by computing the standard deviation of normalized values across alternatives:

$$\sigma_j = stdev_i(z_{ij}) \tag{3}$$

Higher values of σ_j indicate greater contrast among alternatives, suggesting stronger potential for strategic differentiation. However, contrast alone is insufficient; redundancy must also be addressed to avoid overrepresentation of correlated indicators. To this end, pairwise linear correlation coefficients were calculated:

$$r_{jk} = corr\left(z_{.\,j}, z_{.\,k}\right) \tag{4}$$

Table 2 summarizes the standard deviation and sample correlation coefficients for selected sub-criteria.

Table 2. Standard deviation and sample linear correlation coefficients.

	σ_j	r_{jk} with C1.1	r_{jk} with C2.2	r_{jk} with C4.3
C1.1	0.29	1.000	–0.98	0.96
C1.2	0.26	–0.94	0.97	–0.91
C1.3	0.30	–0.92	0.95	–0.89
C2.1	0.34	–0.96	0.99	–0.93
C2.2	0.36	–0.98	1.000	–0.95
C2.3	0.32	–0.90	0.94	–0.88
C3.1	0.35	0.93	–0.91	0.90
C3.2	0.34	–0.89	0.92	–0.87
C3.3	0.31	–0.85	0.90	–0.84
C4.1	0.33	–0.88	0.91	–0.86
C4.2	0.30	–0.86	0.89	–0.83
C4.3	0.35	0.96	–0.95	1.000
C5.1	0.34	0.94	–0.93	0.92
C5.2	0.29	–0.87	0.90	–0.85
C5.3	0.31	0.91	–0.89	0.88

Strong correlations were observed among energy and emission indicators (e.g., C1.1 and C2.2), indicating potential overlap in informational content. In contrast, sub-criteria, such as total production (C4.3) and availability (C5.1), demonstrated high variability and moderate independence, reinforcing their value for inclusion.

$$F_j = \sum_{k \neq j} (1 - r_{jk}) \tag{5}$$

This metric rewards indicators that diverge from others, thereby contributing novel insights to the evaluation framework. The final information score for each sub-criterion was computed as the product of its contrast intensity and conflict factor [31]:

$$S_j = \sigma_j \, . \, F_j \tag{6}$$

These scores were then normalized to derive objective BWM-based weights:

$$\omega_j^{BWM} = \frac{S_j}{\sum_j S_j} \tag{7}$$

Table 3 presents the resulting weights, ranks, and retention decisions.

Table 3. Final BWM-based weights and retention decisions.

	F_j	S_j	ω_j^{BWM}	Rank	Retain
C1.1	3.35	0.972	0.110	1	Yes
C1.2	2.67	0.481	0.054	10	No
C1.3	3.10	0.806	0.091	4	Yes
C2.1	3.18	0.796	0.090	5	Yes
C2.2	3.21	0.867	0.098	2	Yes
C2.3	2.40	0.360	0.041	12	No
C3.1	3.05	0.671	0.076	7	Yes
C3.2	2.93	0.703	0.079	6	Yes
C3.3	2.12	0.276	0.031	13	No
C4.1	2.84	0.596	0.067	9	Yes
C4.2	1.95	0.195	0.022	15	No
C4.3	3.07	0.860	0.097	3	Yes
C5.1	2.88	0.662	0.075	8	Yes
C5.2	2.01	0.221	0.025	14	No
C5.3	2.36	0.401	0.045	11	Borderline

Indicators such as C1.1 (renewable share), C2.2 (emissions intensity), and C4.3 (total production) emerged as the most informative, collectively accounting for nearly 30% of the total weight. Their retention is justified by their high variability, low correlation with other indicators, and strategic relevance to sustainability and throughput optimization. Conversely, sub-criteria such as C4.2 (stockouts) and C5.2 (price sensitivity) were excluded due to low information scores and high redundancy. These indicators, while operationally relevant, do not enhance the discriminative capacity of the model. C5.3 (capex/feasibility) was classified as borderline; its moderate score suggests utility for governance signaling, although its contribution to strategic differentiation remains limited.

This filtered set of sub-criteria forms the basis for the subsequent aggregation and ranking of strategic alternatives.

4.2. IVN-TOPSIS

Building on the BWM-based filtering and weighting of sub-criteria, the next phase applies the IVN-TOPSIS method to evaluate and rank the five strategic criteria groups. This transition from sub-criterion-level analysis to group-level aggregation ensures that retained indicators are not only individually informative but also collectively coherent within their respective strategic domains [32,33]. The IVN-TOPSIS framework is selected for its capacity to integrate both quantitative signals, derived from normalized information scores and entropy, and qualitative expert judgments, thereby enabling robust decision-making under uncertainty and partial knowledge.

To initiate the IVN-TOPSIS process, two quantitative meta-criteria were derived from the retained sub-criteria within each group:

- G_1—Information Strength (I_g): This metric aggregates the BWM-derived information scores S_j of retained sub-criteria within each group, reflecting the group's overall discriminative power.
- G_2—Balance (D_g): This metric captures the Shannon entropy of the weight distribution $\widetilde{\omega}_{j|g}$, indicating the internal coherence and diversity of retained indicators.

Table 4 summarizes these attributes across the five strategic groups.

Table 4. Group-level quantitative attributes from retained sub-criteria.

Group	Retained sub-criteria	I_g	$\widetilde{\omega_{j\|g}}$	D_g
C1 Energy	C1.1, C1.3	1.778	{0.547, 0.453}	0.682
C2 Environment	C2.1, C2.2	1.663	{0.478, 0.522}	0.693
C3 Logistics	C3.1, C3.2	1.374	{0.488, 0.512}	0.689
C4 Stability	C4.1, C4.3	1.456	{0.410, 0.590}	0.673
C5 Risk	C5.1	0.662	{1.000}	0.000

Energy (C1) exhibits the highest information strength, confirming its strategic relevance in decarbonization and cost control. Environment (C2) follows closely, with a well-balanced distribution of weights. Logistics (C3) and stability (C4) present moderate strength and entropy, suggesting complementary but less dominant signals. Risk (C5), represented by a single retained sub-criterion, lacks internal balance and contributes minimally to scenario discrimination.

Having established the quantitative foundation, the next step involved evaluating each group across four meta-criteria: Information strength (g_1), balance (g_2), reliability (g_3), and readiness (G_4). These dimensions were assessed using a linguistic scale, which was then mapped to interval-valued neutrosophic numbers (IVNNs). Each IVNN captured three components:

- T (Truth): Degree of satisfaction of the meta-criterion.
- I (Indeterminacy): Degree of uncertainty or ambiguity.
- F (Falsity): Degree of contradiction or non-satisfaction.

Table 5 defines the linguistic-IVN mapping, while Table 6 presents the IVN decision matrix for each group across the four meta-criteria.

Table 5. Linguistic-IVN scale for meta-criteria.

Term	T Interval	I Interval	F Interval
Very high	[0.80, 1.00]	[0.00, 0.15]	[0.00, 0.10]
High	[0.65, 0.85]	[0.10, 0.25]	[0.05, 0.20]
Medium	[0.45, 0.65]	[0.20, 0.35]	[0.20, 0.35]
Low	[0.25, 0.45]	[0.30, 0.50]	[0.35, 0.55]

Table 6. IVN decision matrix of criteria groups vs meta-criteria.

Group	G1 Info strength	G2 Balance	G3 Reliability	G4 Readiness
C1 Energy	Very High	High	High	High
C2 Environment	High	High	High	Medium
C3 Logistics	High	High	Medium	High
C4 Stability	High	High	Medium	Medium
C5 Risk	Medium	Low	Medium	Medium

Energy (C1) receives a "Very High" rating in information strength and "High" ratings across all other dimensions, reinforcing its central role in OCP's strategic planning. Environment (C2) is well-measured but exhibits slightly reduced readiness. Logistics (C3) and stability (C4) are operationally viable but show moderate reliability. Risk (C5) ranks lowest due to limited indicator diversity and elevated uncertainty.

To reflect the strategic importance of each meta-criterion, a weight vector was assigned $w = [0.40, 0.20, 0.20, 0.20]$. Each IVNN was then scaled component-wise according to its corresponding weight, yielding the weighted IVNs $\tilde{A}_{ig}(w)$ for each group and meta-criterion.

$$\tilde{A}_{ig}(w) = ([w_g \cdot T_{ig}^L, w_g \cdot T_{ig}^U], [w_g \cdot I_{ig}^L, w_g \cdot I_{ig}^U], [w_g \cdot F_{ig}^L, w_g \cdot F_{ig}^U]) \tag{8}$$

Table 7 presents these weighted IVNs.

Table 7. Weighted IVNs per group and meta-criterion.

Group	G1 (×0.40)	G2 (×0.20)	G3 (×0.20)	G4 (×0.20)
C1 Energy	T:[0.32,0.40], I:[0.00,0.06], F:[0.00,0.04]	T:[0.13,0.17], I:[0.02,0.05], F:[0.01,0.04]	T:[0.13,0.17], I:[0.02,0.05], F:[0.01,0.04]	T:[0.13,0.17], I:[0.02,0.05], F:[0.01,0.04]
C2 Environment	T:[0.26,0.34], I:[0.04,0.06], F:[0.02,0.04]	T:[0.13,0.17], I:[0.02,0.05], F:[0.01,0.04]	T:[0.13,0.17], I:[0.02,0.05], F:[0.01,0.04]	T:[0.09,0.13], I:[0.04,0.07], F:[0.04,0.07]
C3 Logistics	T:[0.26,0.34], I:[0.04,0.06], F:[0.02,0.04]	T:[0.13,0.17], I:[0.02,0.05], F:[0.01,0.04]	T:[0.09,0.13], I:[0.04,0.07], F:[0.04,0.07]	T:[0.13,0.17], I:[0.02,0.05], F:[0.01,0.04]
C4 Stability	T:[0.26,0.34], I:[0.04,0.06], F:[0.02,0.04]	T:[0.13,0.17], I:[0.02,0.05], F:[0.01,0.04]	T:[0.09,0.13], I:[0.04,0.07], F:[0.04,0.07]	T:[0.09,0.13], I:[0.04,0.07], F:[0.04,0.07]
C5 Risk	T:[0.18,0.26], I:[0.08,0.14], F:[0.08,0.14]	T:[0.05,0.09], I:[0.06,0.10], F:[0.07,0.11]	T:[0.09,0.13], I:[0.04,0.07], F:[0.04,0.07]	T:[0.09,0.13], I:[0.04,0.07], F:[0.04,0.07]

The weighted IVNs confirm that energy (C1) maintains the strongest truth-membership values across all meta-criteria, with minimal indeterminacy and falsity. Environment (C2) and logistics (C3) follow closely, though Environment shows slightly reduced readiness. Stability (C4) is consistent but less decisive. Risk (C5) has the lowest truth values and highest uncertainty, reinforcing its limited strategic leverage in this planning horizon.

To proceed with the TOPSIS ranking, ideal benchmarks are defined for each meta-criterion [34,35]:

- Positive Ideal Solution (PIS): Represents the best-case IVN across all groups, favoring high truth-membership and low indeterminacy/falsity.

$$PIS_g = [max_i\, T_{ig}^L, max_i\, T_{ig}^U], [min_i\, I_{ig}^L, min_i\, I_{ig}^U], [min_i\, F_{ig}^L, min_i\, F_{ig}^U] \tag{9}$$

- Negative Ideal Solution (NIS): Represents the worst-case IVN, characterized by low truth-membership and high uncertainty/contradiction.

$$NIS_g = [min_i\, T_{ig}^L, min_i\, T_{ig}^U], [max_i\, I_{ig}^L, max_i\, I_{ig}^U], [max_i\, F_{ig}^L, max_i\, F_{ig}^U] \tag{10}$$

Table 8 outlines the PIS and NIS profiles for each meta-criterion.

Table 8. Positive and negative ideal IVNs by meta-criterion.

Meta-Criterion	PIS (T; I; F)	NIS (T; I; F)
G1—Info Strength	T:[0.32, 0.40]; I:[0.00, 0.06]; F:[0.00, 0.04]	T:[0.18, 0.26]; I:[0.08, 0.14]; F:[0.08, 0.14]
G2—Balance	T:[0.13, 0.17]; I:[0.02, 0.05]; F:[0.01, 0.04]	T:[0.05, 0.09]; I:[0.06, 0.10]; F:[0.07, 0.11]
G3—Reliability	T:[0.13, 0.17]; I:[0.02, 0.05]; F:[0.01, 0.04]	T:[0.09, 0.13]; I:[0.04, 0.07]; F:[0.04, 0.07]
G4—Readiness	T:[0.13, 0.17]; I:[0.02, 0.05]; F:[0.01, 0.04]	T:[0.09, 0.13]; I:[0.04, 0.07]; F:[0.04, 0.07]

These ideal profiles define the reference boundaries for each meta-criterion. The PIS favors high truth-membership and low indeterminacy/falsity, while the NIS reflects the opposite. These benchmarks serve for computing the interval Hamming distance between each group's weighted IVN and the ideal profiles [36]. The distance formula between two IVNs $\tilde{A}$ and $\tilde{B}$ is computed as:

$$d(\tilde{A},\tilde{B}) = \frac{1}{6}(\mid T_L - \bar{T}_L \mid + \mid T_U - \bar{T}_U \mid + \mid I_L - \bar{I}_L \mid + \mid I_U - \bar{I}_U \mid + \mid F_L - \bar{F}_L \mid + \mid F_U - \bar{F}_U \mid) \quad (11)$$

For each group i, the total distances to the PIS and NIS across all four meta-criteria are:

$$D_i^+ = \sum_{g=1}^{4} d(\tilde{A}_{ig}, \mathrm{PIS}_g)\,, D_i^- = \sum_{g=1}^{4} d(\tilde{A}_{ig}, \mathrm{NIS}_g) \quad (12)$$

The closeness coefficient C_i is then calculated to quantify the relative proximity of each group to the ideal solution [37]:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}, C_i \in [0,1] \quad (13)$$

Table 9 presents the computed distances and closeness coefficients.

Table 9. Distances to PIS/NIS and closeness coefficients.

Group	D_i^+	D_i^-	C_i
C1—Energy	0.00	0.86	0.86
C2—Environment	0.19	0.55	0.74
C3—Logistics	0.31	0.53	0.63
C4—Stability	0.37	0.51	0.58
C5—Risk	0.69	0.48	0.41

Energy (C1) achieves perfect alignment with the ideal profile ($D^+ = 0.00$), resulting in the highest closeness coefficient ($C_1 = 0.86$). Environment (C2) follows with $C_2 = 0.74$, showing slight deviation in readiness. Logistics (C3) and stability (C4) occupy mid-tier positions, while risk (C5) ranks lowest due to elevated uncertainty and limited indicator diversity.

To finalize the strategic ranking, closeness coefficients are normalized to produce weights for multi-criteria aggregation:

$$W_g = \frac{C_g}{\sum_{k=1}^{5} C_k\, C_k} \quad (14)$$

Using the closeness values: $C_1 = 0.86$; $C_2 = 0.74$; $C_3 = 0.63$; $C_4 = 0.58$; $C_5 = 0.41$, the total closeness: $\sum C_k = 0.86 + 0.74 + 0.63 + 0.58 + 0.41 = 3.22$. The resulting normalized weights are: $W_1 \approx 0.300$; $W_2 \approx 0.250$; $W_3 \approx 0.205$; $W_4 \approx 0.145$; $W_5 \approx 0.100$. Table 10 presents the final ranking and strategic rationale for each group.

Table 10. Final criteria weights and ranking from IVN-TOPSIS.

Rank	Criteria group	Weight W_g	Strategic rationale in OCP context
1	C1—Energy Performance	0.300	Highest information strength; strong reliability and readiness for decarbonization and cost control
2	C2—Environmental Impact	0.250	Balanced indicators with high measurement maturity; moderate readiness
3	C3—Logistics Service	0.205	Actionable levers; good balance; some reliability variability across corridors
4	C4—Production Stability	0.145	Solid but less dominant; levers require coordination and time to stabilize
5	C5—Risk and Resilience	0.100	Governance-relevant but low discriminative power and indicator diversity

Energy (C1) emerges as the most influential domain, driven by its high information strength and readiness for decarbonization and cost control. Environment (C2) ranks second, supported by balanced indicators and measurement maturity. Logistics (C3) offers actionable levers but exhibits variability in reliability. Stability (C4) is solid yet less dominant, requiring coordinated efforts for improvement. Risk (C5), while governance-relevant, contributes the least to strategic discrimination due to its limited scope and elevated uncertainty.

This IVN-TOPSIS aggregation completes the transition from sub-criterion-level filtering to strategic group prioritization, enabling scenario modeling and resource allocation to be grounded in both empirical robustness and expert-informed uncertainty management.

4.3. Operationalizing IVN-TOPSIS via DRL

The IVN-TOPSIS framework, having established a robust ranking of strategic criteria groups based on both quantitative and qualitative signals, serves as the foundation for dynamic decision-making. To transition from static evaluation to adaptive planning, the IVN-TOPSIS-derived weights W_g were embedded into a DRL agent. This hybrid architecture enabled continuous refinement of strategic actions in response to evolving operational data while preserving the interpretability and rigor of expert-driven modeling.

The DRL agent was architected to reflect the structure of retained sub-criteria and the strategic priorities captured by IVN-TOPSIS [38]. This alignment ensures that the agent's learning process remains grounded in validated decision logic. Table 11 summarizes the agent's core components:

- State Space: Composed of real-time operational indicators such as energy cost, CO_2 intensity, port delays, throughput variability, and water footprint. These inputs mirror the normalized sub-criteria $\tilde{z}_{jt}$ used in prior evaluation stages.
- Action Space: Includes the five strategic alternatives (A1–A5), along with resource allocation and scheduling decisions that correspond to operational levers.

- Reward Function: Defined by the weighted performance across retained sub-criteria, using the IVN-TOPSIS weights W_g to prioritize high-impact domains.
- Policy Learning: Combines offline training on historical data with online adjustment based on real-time feedback, constrained by the empirical structure of sub-criteria.

Table 11. DRL agent architecture.

Component	Description
State Space	Real-time indicators: Energy cost, CO_2 intensity, port delays, throughput, etc.
Action Space	Strategic alternatives (A1–A5), resource allocations, scheduling decisions
Reward Function	Weighted performance across retained sub-criteria using IVN-TOPSIS weights W_g
Policy Learning	Offline training + online adjustment; constrained by empirical sub-criteria structure

This architecture enables the agent to compute a reward signal at each time step t, based on the weighted performance of sub-criteria. The reward function is defined as:

$$R_t = \sum_{g=1}^{5} W_g \cdot (\sum_{j \in g} \tilde{z}_{jt}) \tag{15}$$

where $\tilde{z}_{jt}$ is the normalized performance of sub-criterion j at time t, and W_g is the IVN-TOPSIS-derived weight for group g.

This formulation ensures that the agent prioritizes actions that enhance performance in high-weighted domains, while remaining responsive to operational fluctuations.

To interpret how this reward signal translates into strategic behavior, each scenario is mapped to its corresponding agent response logic. Table 12 outlines the behavioral triggers associated with each strategic alternative.

Table 12. Scenario-Based agent behavior logic.

Scenario	Agent behavior triggered by reward signal R_t
A1—Baseline	Maintains current policy unless performance drops below threshold
A2—Accelerated Green	Favors actions reducing CO_2 and energy cost; high reward from C1, C2
A3—Water Mitigation	Prioritizes water footprint and desalination levers (C2.3)
A4—Logistics Surge	Allocates resources to port throughput and corridor utilization
A5—Balanced Resilience	Balances across all groups; reward shaped by entropy and leverage readiness

This logic is not hypothetical; it is empirically observable in the agent's decision trajectory over the 2024–2025 horizon. Table 13 links each quarterly time step to the dominant reward signals and the strategic action selected by the agent. For instance, in Q2 2024, a spike in energy cost and CO_2 intensity elevates the reward from C1 and C2, prompting a shift toward A2—Accelerated Green. In Q3, rising port delays and throughput instability trigger a pivot to A4—Logistics Surge. These transitions reflect the agent's capacity to interpret multi-criteria signals and recalibrate its policy accordingly.

Table 13. Agent strategic plan selection over time (2024–2025).

Time step t	Dominant reward signal	Selected action	Justification
Q1 2024	Moderate W_1, W_5	A5—Balanced Resilience	No dominant signal; entropy favors balanced strategy
Q2 2024	High W_1, W_2	A2—Accelerated Green	Energy cost and CO_2 intensity spike
Q3 2024	High W_3, W_4	A4—Logistics Surge	Port delays and throughput instability
Q4 2024	Low W_2, W_5	A1—Baseline	Stabilization phase; fallback to default policy
Q1 2025	High W_1, W_2	A2—Accelerated Green	Renewable share and emissions intensity improve
Q2 2025	High W_3, W_4	A4—Logistics Surge	Corridor utilization and port wait times increase
Q3 2025	Balanced W_g	A5—Balanced Resilience	Moderate signals across all criteria groups
Q4 2025	High W_2, low W_5	A3—Water Mitigation	Water stress rises; resilience leverage remains low

To ensure that these decisions are not only adaptive but also auditable, the agent undergoes a structured validation process. This process links the reward logic to empirical data and stakeholder priorities, ensuring that the agent's learning trajectory remains aligned with OCP's strategic goals. Table 14 details the validation methodology.

Table 14. DRL agent validation strategy.

Phase	Methodology
Offline training	Historical data from OCP's digital twin (2021–2024); simulated rollouts across A1–A5
Online learning	Real-time updates from operational systems; continuous policy refinement
Recalibration	Recompute IVN-TOPSIS weights when new sub-criteria emerge or priorities shift

Finally, the agent's outputs were designed to be stakeholder-ready, ensuring that decision-makers can monitor, interpret, and act on the agent's recommendations with confidence. Table 15 outlines the key outputs.

Table 15. Stakeholder-facing outputs from DRL agent.

Output Type	Purpose
Policy Dashboards	Visualize selected actions, reward trajectories, and sub-criterion performance
Scenario Comparison Tables	Projected outcomes under each strategic alternative
Alert Triggers	Notify when reward drops below threshold for critical criteria (e.g., energy, emissions)

As it is shown in Figure 1, in early 2024, the agent maintained a balanced stance (A5), reflecting moderate entropy across criteria groups. As energy costs and CO_2 intensity spiked in Q2, the agent pivoted decisively toward A2—Accelerated Green, prioritizing decarbonization levers. This was followed by a shift to A4—Logistics Surge in Q3, triggered by rising port delays and throughput instability. A brief fallback to A1—Baseline in Q4 indicated stabilization or lack of dominant signals. In 2025, the agent resumed its green strategy (A2) before again favoring logistics (A4), then balancing across all groups (A5) in Q3, and finally responding to water stress with A3—Water Mitigation in Q4.

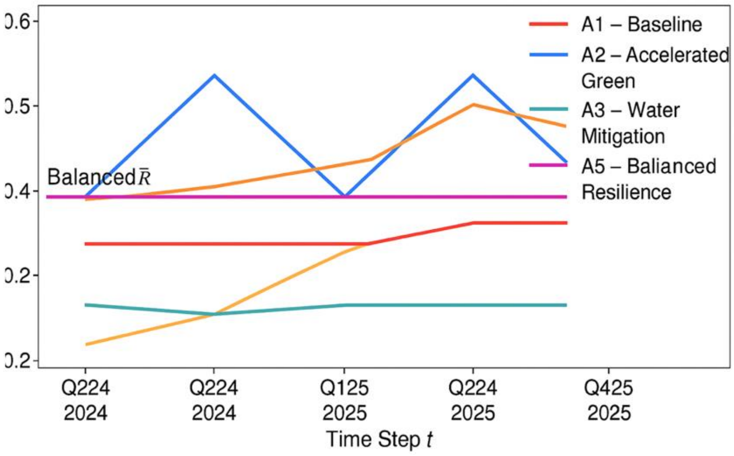

Figure 1. Agent behavior over two years 2024–2025.

This cyclical pattern demonstrates the agent's capacity to operationalize IVN-TOPSIS logic within a dynamic environment. By embedding expert-derived weights into a learning framework, the agent ensures that strategic decisions remain both data-driven and context-aware, bridging the gap between static evaluation and adaptive execution in OCP's industrial planning horizon.

5. Discussion

In this study, we proposed and operationalized a hybrid decision-support framework that integrates BWM, IVN-TOPSIS, and DRL to support strategic planning under uncertainty. The framework responds to a persistent limitation in traditional MCDM models: Their static nature and inability to adapt to evolving operational contexts. While researchers have applied BWM and TOPSIS variants independently, such as Amiri et al. [39] for consistent expert weighting and Alshamrani et al. [40] for entropy-based ranking, these models remain temporally rigid and structurally closed. By embedding IVN-TOPSIS outputs into a DRL agent, this framework introduces a dynamic feedback loop between expert-defined priorities and real-time performance signals, aligning with recent calls for hybrid, uncertainty-aware decision systems [41–43].

Compared to hybrid MCDM-AI approaches, the proposed model offers several methodological advancements. For instance, Tronnebati et al. [44] combined fuzzy AHP with machine learning to optimize supplier selection, yet their framework lacked interpretability and did not incorporate real-time recalibration. Similarly, Yan et al. [45] applied DRL to vehicle routing but focused solely on throughput optimization, omitting strategic criteria weighting. In contrast, this framework integrates IVN-TOPSIS-derived weights into the DRL reward function, ensuring that the agent's decisions reflect operational performance and strategic alignment. This dual-layered logic enables the agent to prioritize high-impact domains such as energy and emissions while remaining responsive to emergent stressors like port delays or water scarcity.

The dominance of the Energy performance group (C1), consistently ranked highest across IVN-TOPSIS and reinforced through DRL reward signals, aligns with findings from decarbonization-focused studies in industrial planning [46,47]. However, unlike prior models that rely solely on static entropy or expert weighting, the proposed framework enables the agent to recalibrate its priorities based on evolving indicators such as CO_2 intensity, renewable share, and energy cost. This dynamic responsiveness is particularly evident in the agent's behavior over the 2024–2025 horizon, where strategic shifts from A2—Accelerated Green to A4—Logistics Surge and A3—Water Mitigation reflect real-time adaptation to operational stressors. Such transitions demonstrate the robustness of the hybrid approach in capturing expert-defined priorities and emergent system dynamics; an advancement over static MCDM models that lack temporal sensitivity or feedback integration.

Practically, the consistent prioritization of Energy performance (C1) and Environmental impact (C2) has direct implications for OCP's investment and policy focus. The agent's repeated selection of A2—Accelerated Green during high-emission periods suggests that decarbonization levers are not only strategically dominant but also operationally actionable. Similarly, the emergence of A4—Logistics Surge in response to corridor delays highlights the need for infrastructure resilience and port-specific planning. These insights contribute to resolving ongoing debates in the literature about the trade-off between environmental and logistical priorities in industrial supply chains [48,49], showing that a hybrid AI framework can balance both through adaptive learning and multi-criteria sensitivity.

To ensure methodological rigor, the BWM phase involved structured input from 12 domain experts at OCP, spanning energy systems, logistics, environmental engineering, and strategic planning. This multi-disciplinary panel ensured that sub-criteria were not only operationally relevant but also empirically validated. Compared to traditional AHP or fuzzy weighting methods [50,51], BWM offers superior consistency and lower cognitive load, particularly in industrial contexts with high indicator interdependence. The filtering of low-signal sub-criteria prior to IVN-TOPSIS aggregation enhances the interpretability of the DRL agent's reward function, which remains constrained by the retained structure and is recalibrated periodically to reflect updated evaluations. This layered rigor distinguishes the framework from recent hybrid models that combine MCDM with AI but lack transparent traceability or stakeholder alignment.

6. Conclusions

In this study, we introduced a hybrid decision-support framework that integrates the BWM, IVN-TOPSIS, and DRL to enable adaptive, uncertainty-aware strategic planning. By embedding expert-derived priorities into a learning agent, the framework transitions from static evaluation to dynamic decision-making, aligning with real-time operational signals and evolving stakeholder needs. The results confirm Energy performance as the most influential strategic criterion group, consistently prioritized across both IVN-TOPSIS rankings and DRL agent behavior. This convergence reinforces the robustness of the methodology in capturing expert judgment and emergent system dynamics.

The core contribution lies in bridging multi-criteria decision modeling with reinforcement learning, offering a transparent, interpretable, and empirically grounded system that evolves with data. Unlike prior approaches that treat MCDM outputs as fixed inputs to optimization engines, the proposed framework preserves auditability while enabling continuous recalibration. This addresses a critical gap in industrial decision-making under uncertainty, namely the inability of static models to respond to operational volatility, data drift, or shifting strategic priorities.

Practically, the agent's ability to shift between strategies such as Accelerated Green, Logistics Surge, and Water Mitigation demonstrates its utility for real-world planning, especially in contexts like OCP where energy, emissions, and infrastructure interact dynamically. The agent's behavior over the 2024–2025 horizon reflects a nuanced understanding of multi-criteria trade-offs, with transitions driven by reward signals linked to CO_2 intensity, port delays, and water stress. These findings suggest that hybrid AI frameworks can support not only strategic prioritization but also tactical responsiveness, an essential capability for industrial actors navigating complex, multi-lever environments.

However, several limitations must be acknowledged. First, the initial BWM phase, while structured and expert-informed, remains sensitive to cognitive bias and framing effects. Although neutrosophic logic introduces tolerance for uncertainty and indeterminacy, it does not eliminate subjectivity in linguistic assessments. Second, the DRL agent's performance is contingent on the quality, frequency, and granularity of real-time data streams. In environments with incomplete or delayed data, the agent's learning trajectory may diverge from optimal policy paths. Third, the framework assumes a single-agent architecture and does not explicitly model inter-agent coordination or stakeholder negotiation, which may be critical in multi-actor industrial ecosystems.

To address these limitations, future research could explore several extensions. One promising direction involves the integration of ensemble expert weighting mechanisms, combining BWM with entropy or Bayesian updating, to reduce bias and improve robustness. Another avenue is the deployment of multi-agent DRL architectures, enabling decentralized decision-making and coordination across supply chain nodes, production units, or governance bodies. Additionally, embedding stakeholder feedback loops into the learning process could enhance legitimacy and responsiveness, particularly in sectors where social license and community engagement are pivotal. Application domains such as water governance, urban logistics, and renewable energy transitions offer fertile ground for testing the framework's scalability and adaptability under diverse constraints.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article to assist with content structuring, language refinement, and methodological articulation.

Conflict of interest

The authors declare no conflicts of interest.

Author contributions

F.T. conceptualized the study, designed the hybrid framework, and led the methodological integration of BWM, IVN-TOPSIS, and DRL. M.A. contributed to the data collection, expert elicitation, and validation of the BWM phase. W.J. supported the development and calibration of the IVN-TOPSIS model and assisted in the interpretation of ranking results. L.Y. implemented the DRL agent architecture and conducted scenario-based simulations. A.T. contributed to the literature review, comparative analysis, and manuscript refinement. All authors reviewed and approved the final version of the manuscript and affirm responsibility for the integrity and originality of the work.

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