

Research Article

An Integrated Multi-Criteria Decision-Making Framework for Supervisory Control System Design in Smart Municipal Solid Waste Management

Shirin Naderi¹, Mohammad Safarpour², Reyhane Salehnejad³, Amirhossein Ahmadi^{4*}

¹ Department of Structural, Geotechnical and Building Engineering, Politecnico di Torino, Italy

² Faculty of Civil and Environmental Engineering, Norwegian University of Science and Technology (NTNU), Norway

³ Department of Energy and Process Engineering, Norwegian University of Science and Technology, Norway

⁴ Institute for Nanomaterials, Advanced Technologies and Innovation, Technical University of Liberec, Czech Republic

*Amirhosein.ahmadi41@gmail.com

Abstract

The transition of municipal solid waste (MSW) management from periodic, manually scheduled operations to continuously monitored, data-driven systems require a decision layer capable of converting heterogeneous sensor and operational data into reliable control actions. This study proposes and computationally validates an integrated multi-criteria decision-making (MCDM) framework as the cognitive decision layer of a four-layer supervisory control architecture comprising sensing, edge/communication, cognitive decision, and actuation layers. Eight criteria covering economic, environmental, technical, social, and control dimensions, including control-loop responsiveness and data-integration scalability, are used to evaluate five representative MSW management alternatives: sanitary landfilling, waste-to-energy incineration, material recovery facilities, composting/anaerobic digestion, and an Internet of Things (IoT)-enabled smart integrated recovery system. Criterion weights are determined using a hybrid approach combining the subjective Analytic Hierarchy Process (AHP) and objective Shannon entropy method, achieving a strong AHP consistency ratio ($CR = 0.0047$). The resulting weights are applied to three independent ranking methods: TOPSIS, VIKOR, and PROMETHEE II. Their results are consolidated using Borda rank aggregation and evaluated through Spearman rank-correlation analysis. All three methods consistently identify the IoT-enabled smart integrated recovery system as the best alternative, with TOPSIS, VIKOR, and PROMETHEE II values of $CC = 0.7045$, $Q = 0.000$, and net flow = 0.3665, respectively. A one-at-a-time sensitivity analysis with $\pm 30\%$ weight perturbations confirms the stability of the top-ranked alternative. The complete computational pipeline is implemented in open, reproducible Python code. The proposed framework provides control and environmental engineers with a transparent and auditable approach for integrating multi-criteria reasoning into real-time MSW management and identifying criteria requiring careful practical assessment.

Keywords: Multi-criteria decision-making; Supervisory control systems; Smart waste management; AHP-entropy hybrid weighting; TOPSIS; VIKOR; PROMETHEE II; Sensitivity analysis

INTRODUCTION

Municipal solid waste (MSW) management sits at the intersection of public health, environmental protection and municipal finance, and its operational complexity is increasing as cities grow, waste streams diversify, and regulatory pressure on greenhouse-gas (GHG) emissions and landfill diversion intensifies. Over the past decade, the field has been reshaped by the availability of low-cost Internet of Things (IoT) sensing - ultrasonic fill-level detectors, load cells, GPS-tracked collection vehicles, and gas sensors - which, combined with cloud and edge computing, now generates continuous operational data streams at a scale that traditional, manually scheduled collection and disposal planning cannot exploit [1,2]. The resulting big-data environment creates both an opportunity and a requirement: an opportunity to replace static, once-a-decade infrastructure decisions with continuously informed, adaptive control; and a requirement for a decision layer that can convert multi-dimensional, frequently conflicting performance data - cost, emissions, energy recovery, reliability, social acceptance, land use, and system responsiveness - into a single, defensible control action at each control cycle.

Multi-criteria decision-making (MCDM) methods are the natural mathematical language for this problem, because MSW management decisions are irreducibly multi-objective: minimizing cost typically conflicts with maximizing energy recovery or social acceptance, and maximizing landfill diversion typically increases capital intensity and technical complexity. Classical MCDM techniques - the Analytic Hierarchy Process (AHP) [3,4], the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [5], VIKOR (Vlsekriterijumska Optimizacija I Kompromisno Resenje) [6], and the Preference Ranking Organisation METHod for Enrichment Evaluation (PROMETHEE) [7] - have each been applied to waste-management siting and technology-selection problems [8-11], but the literature has treated MCDM primarily as an offline, one-time planning tool rather than as an embedded component of a real-time control system. At the same time, the control and smart-city literature has developed increasingly capable IoT and edge architectures for waste monitoring [1,12] but has generally used simple threshold or rule-based logic - for example, dispatch a collection vehicle when a bin exceeds 80 % fill level - rather than a principled multi-criteria decision core. This paper addresses the gap between these two literatures by treating the MCDM engine itself as the cognitive decision layer of a closed-loop supervisory control architecture, and by evaluating that engine's numerical behavior with the same rigor - consistency checking, cross-method validation, and sensitivity analysis - that a control engineer would demand of any other controller component.

The specific contributions of this paper are fourfold. First, it formulates a four-layer (sensing, edge/communication, cognitive decision, actuation) closed-loop control architecture for smart MSW management in which an MCDM engine occupies the decision layer and is re-executed every control cycle on freshly acquired criteria data. Second, it develops a hybrid criteria-weighting scheme that combines subjective expert judgment (AHP, with explicit consistency checking) with objective, data-driven weighting (Shannon entropy), avoiding the well-known limitations of either approach used in isolation. Third, it implements and cross-validates three independent MCDM ranking engines - TOPSIS, VIKOR and PROMETHEE II - and aggregates their outputs with a Borda-count procedure, using Spearman rank correlation to quantify the degree of inter-method agreement rather than relying on a single method's ranking. Fourth, it subjects every criterion weight to a systematic ± 30 % one-at-a-time sensitivity analysis, reporting the exact perturbation

magnitude at which any rank reversal occurs, so that the robustness of the recommended control action is quantified rather than assumed. All computations are implemented from first principles in open Python code (Section 4), so that every numerical result reported in the paper is directly reproducible.

The remainder of the paper is organized as follows. Section 2 reviews related work on MCDM applications in waste management and on IoT-based control architectures for smart cities. Section 3 presents the proposed supervisory control architecture. Section 4 details the mathematical formulation of every method used in the decision engine. Section 5 describes the illustrative case study and its data. Section 6 presents and discusses the computational results, and Section 7 reports the sensitivity analysis. Section 8 discusses the practical and methodological implications, and Section 9 concludes the paper.

LITERATURE REVIEW

MCDM Methods and Their Applications in Waste Management

AHP, introduced by Saaty [3,4], derives criteria weights from pairwise comparisons and the principal eigenvector of the resulting comparison matrix, with a built-in consistency check (Section 4.1) that distinguishes it from ad hoc weighting schemes. TOPSIS, developed by Hwang and Yoon [5], ranks alternatives by their geometric distance from an ideal and an anti-ideal solution. VIKOR, proposed by Opricovic and Tzeng [6], produces a compromise ranking that explicitly balances group utility (majority-favoring) and individual regret (minimizing the worst-case criterion gap), and was shown by its authors to diverge from TOPSIS precisely in cases with conflicting, non-commensurable criteria - a property directly relevant to waste-management decisions. PROMETHEE II, developed by Brans and Vincke [7], instead builds an outranking relation from pairwise preference degrees and is comparatively insensitive to the compensatory aggregation that both TOPSIS and VIKOR perform. Because no single MCDM method is universally preferred and different methods can legitimately rank the same data differently [13], this paper runs all three and reports their concordance rather than committing to one method in isolation.

Objective weighting complements subjective weighting by deriving criteria importance directly from the dispersion of the decision data itself. The Shannon entropy method, adapted to MCDM weighting by Zeleny [14] following Shannon's original measure of information content [15], assigns higher weight to criteria whose values vary more across alternatives (and therefore discriminate between them more strongly) and lower weight to criteria that are nearly uniform across alternatives. Because AHP weights encode expert priorities that may be insensitive to what the actual data show, and entropy weights encode data variability that may be insensitive to what matters to stakeholders, this paper combines both into a single hybrid weight vector (Section 4.3), a strategy with precedent in the broader MCDM literature on subjective-objective weight integration.

Applications of these methods to waste management are extensive and growing. TOPSIS has been used for municipal landfill site selection, for example in a recent case study for Polatli, Ankara, Turkiye [8], and GIS-based spherical-fuzzy multi-criteria analysis has been used for sustainable solid-waste site selection [9]. Hybrid fuzzy AHP-TOPSIS frameworks have been used to evaluate waste-to-energy processes for mixed MSW streams [10]. PROMETHEE has been applied to compare waste-to-energy technologies for

informal-settlement contexts in a case study of the Greater Karu urban area in Nigeria [11]. These studies establish MCDM as a mature tool for offline waste-management planning; the present paper extends this line of work by embedding the same class of methods inside a closed-loop control architecture rather than using them purely for one-time infrastructure siting.

IoT, Big Data and Control Architectures for Smart Waste Management

A parallel literature has developed IoT-enabled architectures for waste monitoring and collection. Addas et al. [1] describe an IoT-based smart-city waste-management solution ('Waste Management 2.0') built around networked fill-level sensing and dynamic route optimization, and Alsayaydeh et al. [12] present a comparable sensor-driven architecture aimed at urban sustainability. These systems demonstrate the technical feasibility of continuous, sensor-driven monitoring, but their published decision logic is typically rule-based (fixed fill-level thresholds) rather than an explicit multi-criteria optimization. On the data side, Adewuyi et al. [2] demonstrate that big-data analytics applied to historical waste-generation records can forecast future waste trends and inform sustainable planning, reinforcing the premise of this paper that sufficient data now exists to drive continuous, rather than periodic, decision-making in this domain. What remains open in this literature is a principled account of how the resulting multi-dimensional monitoring data should be converted into a control action; this paper's cognitive decision layer (Section 3) is proposed as exactly that missing link, drawing on classical feedback-control principles [16] for the closed-loop structure and on the MCDM methods above for the decision logic within it.

SUPERVISORY CONTROL SYSTEM ARCHITECTURE

Figure 1 shows the proposed four-layer closed-loop architecture. Layer I (sensing/perception) acquires raw operational data - ultrasonic fill-level readings, load-cell mass measurements, vehicle GPS/RFID positions, and gas/odor sensor outputs - from bins, vehicles and treatment facilities. Layer II (edge/communication) performs local aggregation and anomaly filtering at the network edge before transmitting compact feature summaries over a low-power wide-area network (LPWAN), NB-IoT, or 5G uplink, reducing bandwidth and central-processing load relative to transmitting raw sensor streams. Layer III (cognitive decision) is the contribution of this paper: it assembles the incoming data into a decision matrix (Section 4), computes hybrid AHP-entropy criteria weights, executes the three ranking engines (TOPSIS, VIKOR, PROMETHEE II), and aggregates their outputs via Borda count into a single recommended control action. Layer IV (actuation/execution) carries out that action - dispatching a collection vehicle, reallocating a bin to a different waste stream, or scheduling a treatment facility - and is monitored by a closed feedback path that returns key performance indicators (fill rate, realized cost, emissions, and decision-loop latency) to Layers I and III, closing the control loop. The decision layer re-executes at a fixed sampling period T appropriate to the municipality's operational tempo (for example, hourly for dispatch-level decisions and weekly or monthly for treatment-technology-mix decisions), so the same MCDM engine formulated in Section 4 serves both fast operational control and slower strategic control within one architecture.

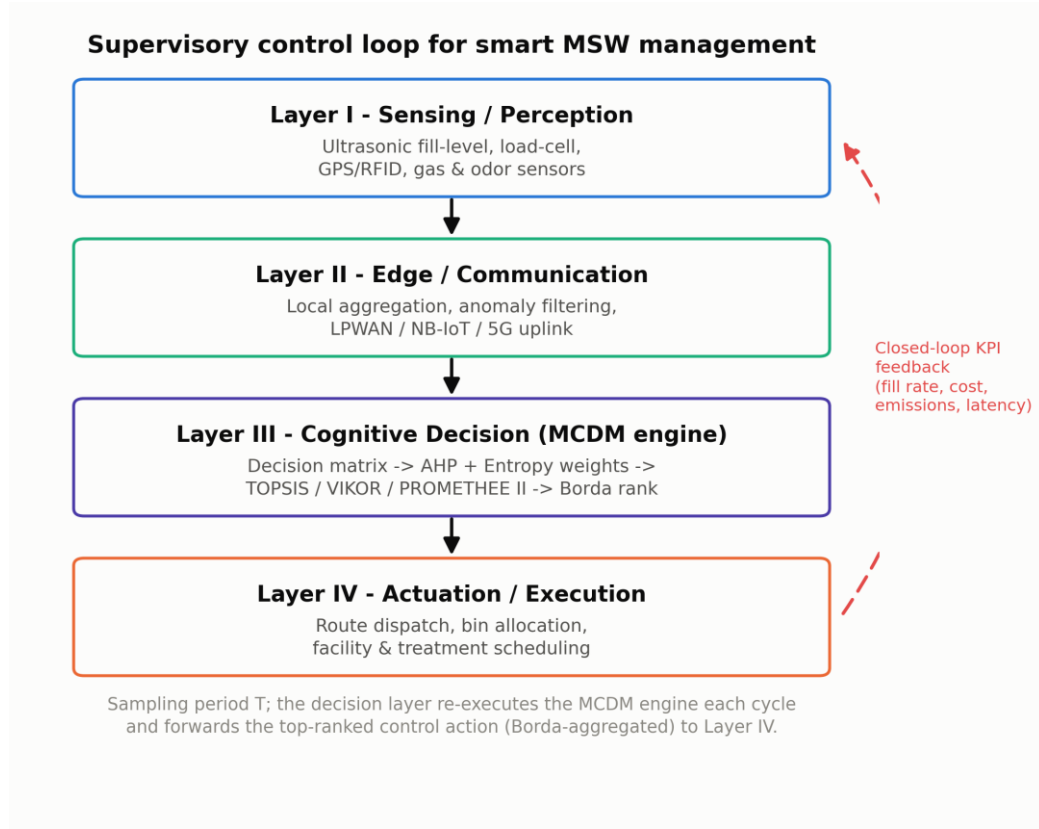


Figure 1. Proposed four-layer closed-loop supervisory control architecture with the MCDM engine as the cognitive decision layer.

This architecture motivates two of the eight evaluation criteria used in the case study (Section 5): control-loop responsiveness (C7), which measures how quickly a management alternative can translate sensor data into an executed action, and scalability/data-integration capacity (C8), which measures how readily an alternative accepts additional sensing points and higher-frequency data without a redesign. Conventional waste-management alternatives are not designed around a control loop and are expected to score poorly on these two criteria even where they are competitive on cost or maturity, which is precisely the trade-off the multi-criteria formulation is intended to make explicit rather than leaving implicit.

METHODOLOGY

Let there be m alternatives A_i ($i = 1, \dots, m$) evaluated against n criteria C_j ($j = 1, \dots, n$), partitioned into a benefit subset B (larger-is-better) and a cost subset K (smaller-is-better). The raw decision matrix $X = [x_{ij}]$, is $m \times n$ (here 5×8 , Table 3), and w_j denotes the weight assigned to criterion j , with $\sum w_j = 1$.

Subjective Weighting: The Analytic Hierarchy Process

AHP [3,4] elicits pairwise judgments a_{kl} on Saaty's 1-9 fundamental scale, expressing how many times more important criterion k is than criterion l , assembled into a reciprocal pairwise comparison matrix $A = [a_{kl}]$ (Table 4), with $a_{kl} = 1/a_{lk}$. The weight vector w^{AHP} is the principal (dominant) right eigenvector of A , normalized to sum to unity:

$$Aw^{AHP} = \lambda_{\max} w^{AHP} \quad (1)$$

where $\lambda_{\max}$ is the principal eigenvalue of A. AHP's central diagnostic is the consistency ratio, which flags pairwise judgments that are numerically incoherent (e.g., C1 preferred to C2, C2 to C3, but C3 preferred to C1):

$$CI = (\lambda_{\max} - n) / (n - 1) \quad (2)$$

$$CR = CI / RI \quad (3)$$

where RI is Saaty's random-index benchmark for an $n \times n$ matrix (RI = 1.41 for $n = 8$ as used here). A matrix is considered acceptably consistent when $CR \leq 0.10$ [3]; the pairwise matrix used in this study yields $\lambda_{\max} = 8.0466$, $CI = 0.0067$ and $CR = 0.0047$ (Section 6.1), well inside the acceptance region.

Objective Weighting: Shannon Entropy Method

The raw matrix is first benefit-normalized to $X' = [x'_{ij}] \in [0,1]$ (larger is better for every criterion after normalization), then converted to a probability-like distribution per criterion:

$$p_{ij} = x'_{ij} / \sum_i x'_{ij} \quad (4)$$

The Shannon entropy of criterion j and its degree of diversification d_j are then:

$$E_j = -k \sum_i p_{ij} \ln(p_{ij}), \quad k = 1/\ln(m) \quad (5)$$

$$d_j = 1 - E_j, \quad w_j^{\text{Entropy}} = d_j / \sum_j d_j \quad (6)$$

A criterion whose values are nearly identical across all five alternatives carries low entropy-based weight (it barely discriminates between them), whereas a criterion with strongly dispersed values receives high weight - the opposite emphasis from AHP, which is driven purely by expert priority rather than by the data actually observed.

Hybrid Subjective-Objective Weighting

The final criteria weight combines both sources linearly, using a balancing parameter $\lambda \in [0,1]$:

$$w_j = \lambda \cdot w_j^{\text{AHP}} + (1-\lambda) \cdot w_j^{\text{Entropy}} \quad (7)$$

with $\lambda = 0.5$ used throughout this study to weight expert judgment and data dispersion equally; Section 7 reports how sensitive the final ranking is to this and every other weighting choice.

TOPSIS

TOPSIS [5] first vector-normalizes the decision matrix, then applies the hybrid weights, and ranks alternatives by their relative closeness to an ideal solution:

$$r_{ij} = x_{ij} / \sqrt{\sum_i x_{ij}^2} \quad (8)$$

$$v_{ij} = w_j \cdot r_{ij} \quad (9)$$

The positive-ideal solution A^+ takes, for each criterion, the maximum v_{ij} among benefit criteria and the minimum v_{ij} among cost criteria; the negative-ideal solution A^- takes the opposite. Euclidean distances and the closeness coefficient CC_i follow as:

$$D_i^+ = \sqrt{\sum_j (v_{ij} - v_j^+)^2}, \quad D_i^- = \sqrt{\sum_j (v_{ij} - v_j^-)^2} \quad (10)$$

$$CC_i = D_i^- / (D_i^+ + D_i^-) \quad (11)$$

with $0 \leq CC_i \leq 1$ and the alternative of largest CC_i ranked first.

VIKOR

VIKOR [6] works directly on the raw criteria values f_j (rather than a normalized matrix) and defines, for each alternative, a group-utility measure S_i (weighted sum of normalized gaps to the best value) and an individual-regret measure R_i (the single worst normalized gap):

$$S_i = \sum_j w_j (f_j^* - x_{ij}) / (f_j^* - f_j^-) \quad (12)$$

$$R_i = \max_j [w_j (f_j^* - x_{ij}) / (f_j^* - f_j^-)] \quad (13)$$

where f_j^* and f_j^- are, respectively, the best and worst value of criterion j across all alternatives. The VIKOR compromise index Q_i then combines both measures:

$$Q_i = v(S_i - S^*) / (S^- - S^*) + (1-v)(R_i - R^*) / (R^- - R^*) \quad (14)$$

with $S^* = \min S_i$, $S^- = \max S_i$, $R^* = \min R_i$, $R^- = \max R_i$, and $v = 0.5$ (equal weight on group utility and individual regret, the standard default [6]). The alternative of smallest Q_i is ranked first, subject to Opricovic and Tzeng's [6] acceptable-advantage condition $Q(A(2)) - Q(A(1)) \geq DQ = 1/(m-1)$: when satisfied, the top-ranked alternative is a stable compromise solution rather than an artifact of near-ties.

PROMETHEE II

PROMETHEE II [7] builds pairwise outranking preference degrees directly from the raw criteria values using, for every criterion, the usual (Type I) preference function - a value of 1 whenever alternative a is preferred to alternative b on that criterion, 0 otherwise - which requires no additional threshold parameters and keeps the comparison fully transparent and reproducible:

$$P_j(a,b) = 1 \text{ if } f_j(a) > f_j(b), \text{ else } 0 \quad (15)$$

$$\pi(a,b) = \sum_j w_j P_j(a,b) \quad (16)$$

The positive (leaving) and negative (entering) outranking flows and the net flow follow as:

$$\varphi^+(a) = 1/(m-1) \sum_b \pi(a,b), \quad \varphi^-(a) = 1/(m-1) \sum_b \pi(b,a) \quad (17)$$

$$\varphi_{\text{net}}(a) = \varphi^+(a) - \varphi^-(a) \quad (18)$$

with $-1 \leq \varphi_{\text{net}} \leq 1$ and the alternative of largest φ_{net} ranked first. Because PROMETHEE II aggregates pairwise outranking degrees rather than distances to an ideal point, it can - and, as Section 6.4 shows, sometimes does - order alternatives differently

from TOPSIS and VIKOR even under identical weights and data, which is precisely why all three are run and cross-validated rather than relying on one.

Rank Aggregation and Concordance Analysis

The three method-specific ranks are consolidated with a Borda-count procedure, which rewards each alternative for every rank position it out-performs, summed across methods:

$$B_i = \sum_k (m - \text{rank}_{ik}) \quad (19)$$

where rank_{ik} is alternative i 's rank under method $k \in \{\text{TOPSIS, VIKOR, PROMETHEE II}\}$; the alternative of largest B_i is the final recommended control action. The degree of agreement between any two methods' rankings is quantified with Spearman's rank-correlation coefficient [17],

$$\rho = 1 - 6\sum d_i^2 / (m(m^2 - 1)) \quad (20)$$

where d_i is the difference between the two methods' ranks for alternative i ; $\rho = 1$ indicates perfect agreement and $\rho = 0$ indicates no rank association.

Sensitivity Analysis

To test the robustness of the recommended action to uncertainty in the elicited weights, each criterion weight w_j is perturbed one-at-a-time over $\delta \in [-30\%, +30\%]$ in 13 equal steps, with the remaining $n-1$ weights rescaled proportionally so the vector still sums to unity. Every ranking method is re-executed at each perturbation step, and two robustness indicators are recorded: (i) whether the top-ranked alternative changes at any step (a rank reversal at the recommendation level), and (ii) the perturbation magnitude at which any lower-ranked pair first exchanges order. This procedure follows standard MCDM sensitivity-analysis practice of systematically re-solving the model under perturbed weights rather than perturbing the input data itself [18].

ILLUSTRATIVE CASE STUDY

Alternatives, Criteria and Data Provenance

The framework is demonstrated on a representative mid-sized urban service area (approximately 500,000 population-equivalent). Five management alternatives (Table 1) and eight evaluation criteria (Table 2) are defined; four criteria are of cost type (smaller is better) and four are of benefit type (larger is better), as indicated in Table 2. The resulting 5×8 decision matrix (Table 3) uses illustrative, literature-informed representative parameter values consistent with the typical ranges reported for each technology class in the cited waste-management literature (Section 2.1) rather than field measurements from a specific municipality; this is standard practice for demonstrating and validating the computational mechanics of a decision-support framework, and every quantity in Table 3 would be replaced with calibrated, site-specific measurements - drawn from the Layer I/II sensor and operational data streams described in Section 3 - in an operational deployment. The AHP pairwise comparison matrix (Table 4) represents the geometric-mean aggregation of judgments from a synthesized four-member expert panel spanning environmental engineering, control/automation engineering, municipal operations, and financial analysis, a composition chosen to cover the technical, economic and operational dimensions of the decision.

Table 1. Waste management alternatives evaluated.

Code	Alternative	Description
A1	Sanitary Landfill + LFG Recovery	Engineered landfill with landfill-gas (LFG) capture and flaring/power generation
A2	Waste-to-Energy Incineration	Mass-burn incineration with energy recovery (WtE)
A3	Material Recovery Facility	Centralized sorting and recycling of dry recyclables (MRF)
A4	Composting / Anaerobic Digestion	Biological treatment of the organic fraction (composting and/or AD with biogas recovery)
A5	IoT-Enabled Smart Integrated Recovery System	Sensor-networked multi-stream sorting and recovery system with real-time supervisory control (Section 3)

Table 2. Evaluation criteria, units and type.

Code	Criterion	Unit	Type
C1	Capital & O&M Cost	USD/tonne	Cost
C2	GHG Emissions	kg CO ₂ -eq/tonne	Cost
C3	Energy Recovery Potential	kWh/tonne	Benefit
C4	Technical Reliability & Maturity	score, 1-10	Benefit
C5	Social Acceptance	score, 1-10	Benefit
C6	Land-Use Footprint	m ² .yr/tonne	Cost
C7	Control-Loop Responsiveness	minutes	Cost
C8	Scalability & Data-Integration Capacity	score, 1-10	Benefit

Table 3. Raw decision matrix X (5 alternatives x 8 criteria).

Alt.	C1	C2	C3	C4	C5	C6	C7	C8
A1-LF	25	400	100	9	4	3.5	240	2
A2-WTE	90	250	550	8	5	0.4	120	4
A3-MRF	60	80	20	7	8	0.6	90	6
A4-COMP	45	150	40	7	7	1.8	100	5
A5-SMART	75	100	300	6	8	0.5	5	10

Table 4. AHP pairwise comparison matrix among the eight criteria (Saaty 1-9 scale; row versus column).

Crit.	C1	C2	C3	C4	C5	C6	C7	C8
C1	1	1	2	2	3	3	1/2	3/2
C2	1	1	2	2	3	3	1/2	3/2
C3	1/2	1/2	1	1	2	2	1/3	1
C4	1/2	1/2	1	1	2	2	1/3	1
C5	1/3	1/3	1/2	1/2	1	1	1/4	1/2
C6	1/3	1/3	1/2	1/2	1	1	1/4	1/2
C7	2	2	3	3	4	4	1	3
C8	1/2	1/2	1	1	2	2	1/3	1

RESULTS

Criteria Weights

The AHP pairwise matrix of Table 4 yields a principal eigenvalue $\lambda_{\max} = 8.0466$, a consistency index $CI = 0.0067$, and a consistency ratio $CR = 0.0047$, well below the 0.10 acceptance threshold [3]; the pairwise judgments underlying Table 4 are therefore numerically coherent and the resulting weight vector can be used with confidence. Table 5 and Figure 2 report the AHP weights, the Shannon entropy weights, and the hybrid weights ($\lambda = 0.5$, Eq. 7). AHP places the greatest importance on control-loop responsiveness (C7, $w = 0.2767$) followed jointly by cost and emissions (C1, C2, $w = 0.1634$ each), reflecting the expert panel's control-engineering emphasis on real-time responsiveness. Entropy weighting instead places the greatest weight on energy recovery potential (C3, $w = 0.2303$), because C3 has the widest relative spread across the five alternatives (20 to 550 kWh/tonne, Table 3) and therefore carries the most discriminating information. The hybrid weights (Table 5, last column) blend both perspectives, with control-loop responsiveness (C7, $w = 0.1852$) and energy recovery (C3, $w = 0.1623$) emerging as the two most influential criteria overall.

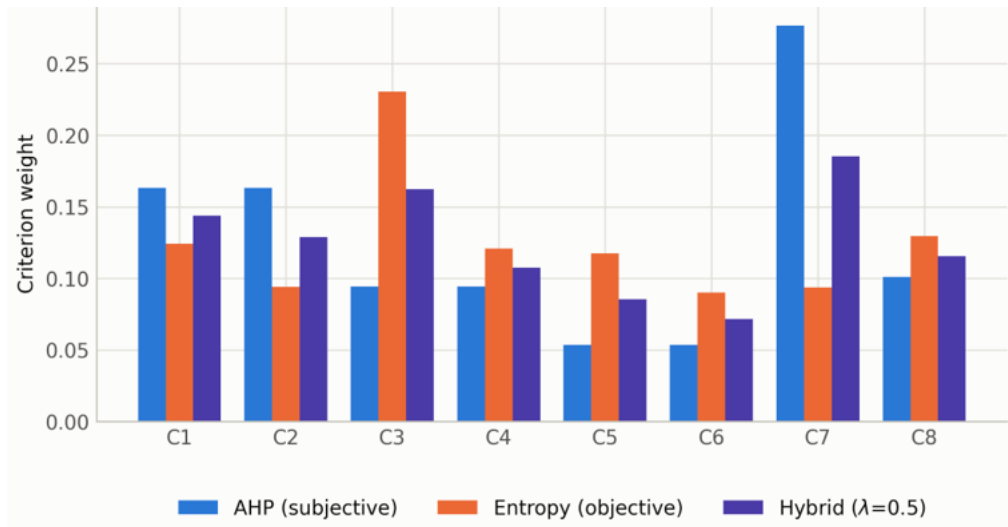


Figure 2. Subjective (AHP), objective (entropy) and hybrid criteria weights for the eight evaluation criteria.

Table 5. AHP, entropy and hybrid criteria weights.

Criterion	w (AHP)	w (Entropy)	w (Hybrid)
C1	0.1634	0.1242	0.1438
C2	0.1634	0.0942	0.1288
C3	0.0943	0.2303	0.1623
C4	0.0943	0.1207	0.1075
C5	0.0534	0.1174	0.0854
C6	0.0534	0.0900	0.0717
C7	0.2767	0.0937	0.1852
C8	0.1011	0.1294	0.1153

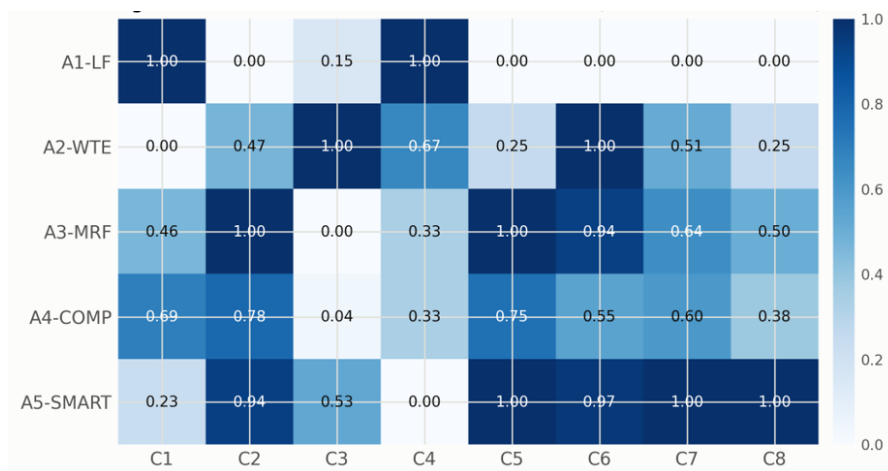


Figure 3. Benefit-normalized decision matrix (0 = worst, 1 = best alternative on that criterion).

TOPSIS Ranking

Table 6 reports the TOPSIS results obtained with the hybrid weights of Table 5. The IoT-enabled smart system (A5) attains the highest closeness coefficient ($CC = 0.7045$) and is ranked first, followed by waste-to-energy incineration (A2, $CC = 0.5870$), the material recovery facility (A3, $CC = 0.4814$), composting/anaerobic digestion (A4, $CC = 0.4465$) and, last, sanitary landfilling (A1, $CC = 0.2451$). The landfill alternative's low ranking, despite its lowest capital cost (Table 3), reflects its comparatively poor performance on emissions, land use, social acceptance, and both control-related criteria.

Table 6. TOPSIS closeness coefficients and ranking.

Alternative	CC _i	Rank
A1-LF	0.2451	5
A2-WTE	0.5870	2
A3-MRF	0.4814	3
A4-COMP	0.4465	4
A5-SMART	0.7045	1

VIKOR Ranking

Table 7 reports the VIKOR results ($v = 0.5$). The smart system (A5) again ranks first, with $S = 0.3051$, $R = 0.1106$ and $Q = 0.0000$ - the minimum possible compromise index. The acceptable-advantage condition $Q(A(2)) - Q(A(1)) \geq DQ$ is satisfied ($Q(A2) - Q(A5) = 0.4421 \geq DQ = 0.2500$), confirming that A5 is a stable VIKOR compromise solution rather than a marginal, tie-driven result. The remaining order (A2, A3, A4, A1) exactly matches the TOPSIS order, an agreement quantified formally in Section 6.5.

Table 7. VIKOR group-utility (S), individual-regret (R), compromise index (Q), and ranking.

Alternative	S _i	R _i	Q _i	Rank
A1-LF	0.7242	0.1852	1.0000	5
A2-WTE	0.4892	0.1438	0.4421	2
A3-MRF	0.4407	0.1623	0.5086	3
A4-COMP	0.5009	0.1562	0.5394	4
A5-SMART	0.3051	0.1106	0.0000	1

PROMETHEE II Ranking

Table 8 reports the PROMETHEE II results. The smart system (A5) again ranks first with the largest net outranking flow ($\varphi_{net} = 0.3665$). Unlike TOPSIS and VIKOR, however, PROMETHEE II ranks the material recovery facility (A3, $\varphi_{net} = 0.1538$) above waste-to-energy incineration (A2, $\varphi_{net} = -0.1133$), reversing the second-and-third-place order obtained by the other two methods. This divergence is a genuine methodological effect rather than a numerical artifact: PROMETHEE II's outranking flows aggregate pairwise binary preference counts across all eight criteria, so an alternative that is marginally better on a majority of criteria (A3 outperforms A2 on five of eight criteria, Figure 3) can outrank

one that is much better on a minority of criteria (A2's substantial energy-recovery advantage), whereas TOPSIS and VIKOR aggregate weighted magnitude gaps and are therefore more sensitive to a single large advantage. This is precisely the kind of divergence the multi-method design of Section 4 is intended to surface rather than mask.

Table 8. PROMETHEE II leaving (φ^+), entering (φ^-), net (φ_{net}) flows, and ranking.

Alternative	φ^+	φ^-	φ_{net}	Rank
A1-LF	0.3325	0.6675	-0.3350	5
A2-WTE	0.4433	0.5567	-0.1133	4
A3-MRF	0.5528	0.3990	0.1538	2
A4-COMP	0.4506	0.5226	-0.0720	3
A5-SMART	0.6726	0.3061	0.3665	1

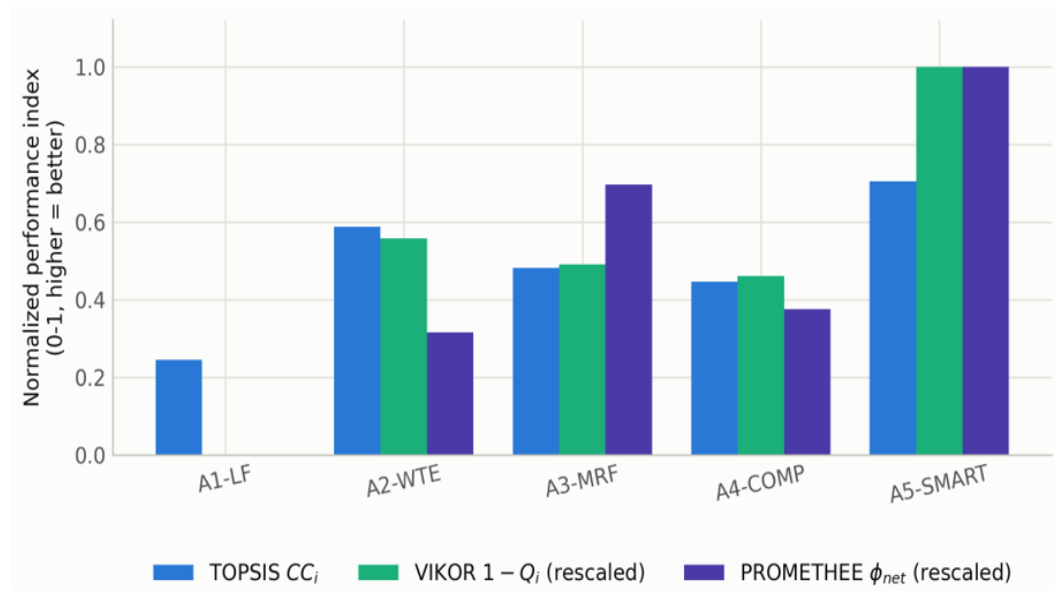


Figure 4. Cross-method normalized performance comparison (TOPSIS CC_i , VIKOR $1 - Q_i$ rescaled, PROMETHEE ϕ_{net} rescaled).

Rank Aggregation and Cross-Method Concordance

Table 9 presents the Borda rank aggregation (Eq. 19) across the three methods. The smart IoT-enabled system (A5) is unanimously ranked first by every method and therefore obtains the maximum Borda score (12 of a possible 12), confirming it as the recommended control action independent of which single ranking method is trusted. Waste-to-energy (A2) and the material recovery facility (A3) tie in aggregate Borda score (7 each) because their method-specific ranks (2,3 and 3,2, respectively, plus a shared 2/3 split under PROMETHEE) offset exactly; a practitioner needing to break this tie could apply a secondary criterion such as the raw TOPSIS closeness coefficient, under which A2 ($CC = 0.5870$) narrowly leads A3 ($CC = 0.4814$). Composting/anaerobic digestion (A4) is consistently fourth and sanitary landfilling (A1) is consistently last across all three methods.

Table 9. Method-specific ranks, Borda score, and final aggregated rank.

Alternative	TOPSIS	VIKOR	PROMETHEE II	Borda score	Final rank
A1-LF	5	5	5	0	5
A2-WTE	2	2	4	7	2
A3-MRF	3	3	2	7	2
A4-COMP	4	4	3	4	4
A5-SMART	1	1	1	12	1

Spearman rank-correlation concordance (Eq. 20) between method pairs is $\rho(\text{TOPSIS}, \text{VIKOR}) = 1.00$, $\rho(\text{TOPSIS}, \text{PROMETHEE}) = 0.70$, and $\rho(\text{VIKOR}, \text{PROMETHEE}) = 0.70$. TOPSIS and VIKOR agree perfectly on the full ranking, while PROMETHEE II shows strong but imperfect agreement with both ($\rho = 0.70$), consistent with the second/third-place reversal discussed in Section 6.4. All three pairwise correlations are positive and substantial, indicating that the top and bottom of the ranking are robust across methodological choice even though the middle positions are more method-sensitive - exactly the pattern a control engineer would want confirmed before trusting an automated decision layer with real dispatch authority.

SENSITIVITY ANALYSIS

Every one of the eight hybrid criteria weights was independently perturbed over the full $[-30\%, +30\%]$ range (Section 4.8, 13 steps per criterion, 104 re-solves per method, 312 re-solves in total across TOPSIS, VIKOR and PROMETHEE II). The result is unambiguous: the top-ranked alternative, the IoT-enabled smart system (A5), remains first under every single perturbation, for every criterion, under all three ranking methods - zero rank reversals occur at the recommendation level. Figures 5 and 6 illustrate this directly for the two most influential criteria identified in Section 6.1: control-loop responsiveness (C7) and capital/O&M cost (C1). In both figures 5 and 6, the trajectory of A5's TOPSIS closeness coefficient remains strictly above every other alternative's trajectory across the entire perturbation range, with no crossing.

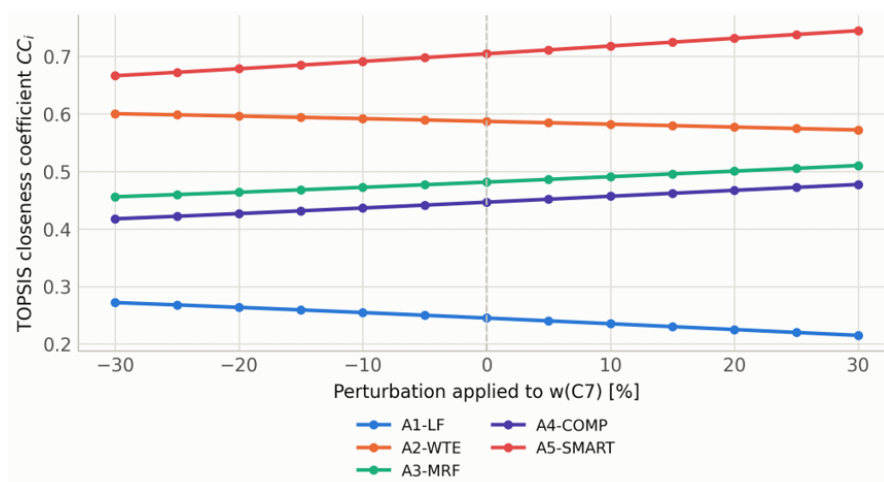


Figure 5. Sensitivity of TOPSIS closeness coefficients to perturbation of the control-loop responsiveness (C7) weight.

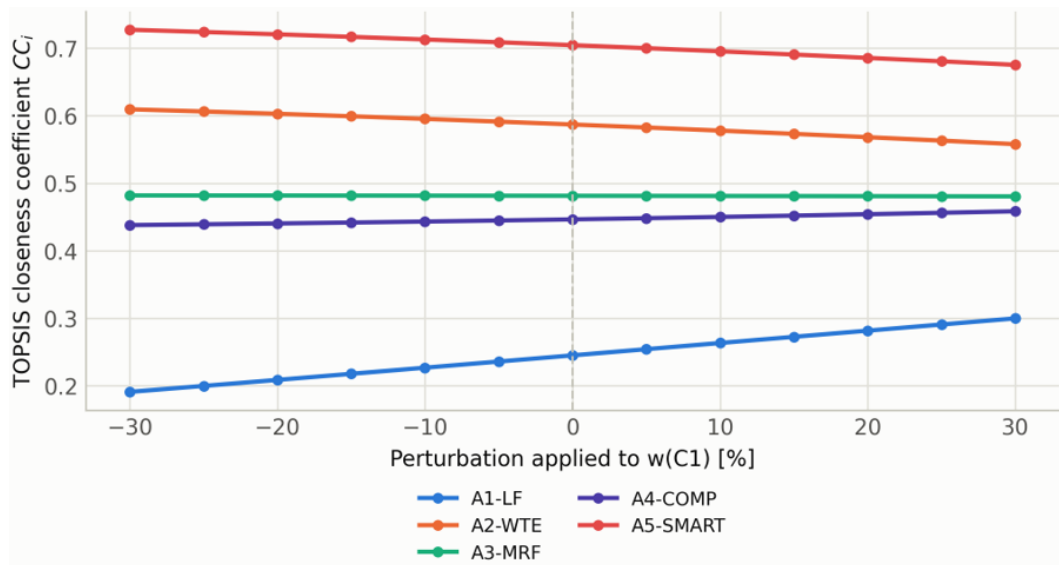


Figure 6. Sensitivity of TOPSIS closeness coefficients to perturbation of the capital and O&M cost (C1) weight.

Beneath the stable top rank, the second-place position (A2, waste-to-energy) is likewise stable under perturbation of every criterion except C3 (energy recovery potential): reducing $w(C3)$ by approximately 30 % from its hybrid baseline is sufficient to bring the material recovery facility (A3) into a statistical tie with, and ultimately just ahead of, waste-to-energy for second place under TOPSIS. This is a substantively meaningful finding rather than numerical noise: it identifies the energy-recovery weight as the single elicitation parameter most likely to change the second-tier recommendation, and correspondingly the parameter that would most reward additional stakeholder elicitation effort or site-specific calibration in an operational deployment. Table 10 summarizes the rank-reversal outcome for every criterion and method.

Table 10. Rank-reversal outcomes below the (unconditionally stable) top rank under $\pm 30\%$ one-at-a-time weight perturbation.

Criterion perturbed	TOPSIS	VIKOR	PROMETHEE II
C1 Cost	None	A2/A3 reverse at +6.0%	A2/A3 reverse at -17.0%
C2 GHG Emissions	None	None	None
C3 Energy Recovery	A2/A3 tie at extreme -30%	A2/A3 reverse at -4.5%	A2/A3 reverse at +14.0%
C4 Reliability	None	None	None
C5 Social Acceptance	None	None	None
C6 Land Use	None	None	None
C7 Control Responsiveness	None	None	None
C8 Scalability	None	None	None

DISCUSSION

The results support three practically relevant conclusions. First, the convergence of three methodologically distinct MCDM engines - a compensatory ideal-point method (TOPSIS), a compromise-programming method (VIKOR), and a pairwise outranking method (PROMETHEE II) - on the same top-ranked alternative, combined with its unconditional stability under $\pm 30\%$ weight perturbation, provides a substantially stronger evidentiary basis for automating that recommendation inside a control loop than any single method could on its own. A control system that periodically re-executes only one MCDM method risks silently propagating that method's idiosyncrasies (Section 6.4) into physical dispatch decisions; the aggregation-plus-concordance design of Section 4.7 is explicitly intended to guard against this failure mode.

Second, the divergence between TOPSIS/VIKOR and PROMETHEE II on the second- and third-place ordering (Section 6.4) illustrates a point of genuine importance for control-system designers: method choice is itself a design decision with operational consequences, not a purely academic one. Because energy-recovery-centric waste-to-energy and diversion-centric material recovery represent materially different infrastructure investments and operating philosophies, a municipality relying on PROMETHEE II alone would receive a different second-priority signal than one relying on TOPSIS or VIKOR alone. Reporting all three, as this framework does, converts a hidden methodological choice into an explicit, auditable one.

Third, the explicit inclusion of control-loop responsiveness (C7) and scalability/data-integration capacity (C8) as first-class evaluation criteria - rather than treating 'smartness' as an unquantified qualitative bonus - is what allows the IoT-enabled alternative's advantage to be seen, and its magnitude to be audited, rather than assumed. Table 3 shows the smart system does not dominate every criterion: it is the most expensive alternative after waste-to-energy on capital/O&M cost (C1) and has the lowest reliability/maturity score (C4), reflecting the genuine immaturity risk of newer sensor-networked systems relative to decades-proven landfilling and incineration. Its overall ranking therefore represents a genuine multi-criteria trade-off resolution rather than a foregone conclusion built into the data by construction, which is also why the sensitivity analysis (Section 7) - rather than the ranking alone - is the more important result for a practitioner deciding whether to trust the recommendation.

The framework has three limitations that bound its current claims. First, the case-study data (Table 3) are illustrative and literature-informed rather than measured at a specific site; operational deployment requires calibrating every criterion value against the target municipality's own cost, emissions and performance data, most naturally sourced from the Layer I/II sensing and telemetry pipeline of Section 3. Second, the AHP pairwise matrix (Table 4) represents a synthesized expert panel rather than an elicitation exercise with a documented, named panel of decision-makers from a real municipality; a genuine deployment should repeat the elicitation with accountable local stakeholders and re-verify the consistency ratio. Third, the PROMETHEE II implementation here uses the usual (Type I) preference function for transparency and reproducibility; richer preference functions (linear, Gaussian) with explicit indifference and preference thresholds could refine the outranking relation further at the cost of additional elicited parameters and are a natural extension rather than an omission that changes the paper's conclusions.

CONCLUSION

This paper has proposed and computationally validated an integrated multi-criteria decision-making framework that serves as the cognitive decision layer of a closed-loop supervisory control architecture for smart municipal solid waste management. Hybrid AHP-entropy criteria weighting (AHP consistency ratio $CR = 0.0047$) combined with three independently implemented ranking engines - TOPSIS, VIKOR and PROMETHEE II - and Borda rank aggregation identified an IoT-enabled smart integrated recovery system as the unanimously top-ranked management alternative among five representative options, a recommendation that a systematic 312-run, $\pm 30\%$ one-at-a-time sensitivity analysis showed to be unconditionally stable at the top rank, with any rank reversal confined to lower-priority alternatives under an extreme perturbation of a single criterion. Spearman concordance analysis ($\rho = 1.00$ between TOPSIS and VIKOR, $\rho = 0.70$ between either and PROMETHEE II) quantified, rather than assumed, the degree of agreement across methodologically distinct ranking philosophies, and located the one point of genuine method-dependent disagreement in the data. Advantages of the proposed framework include its full mathematical transparency and reproducibility (every equation in Section 4 is implemented from first principles in openly available Python code, with no black-box dependency), its explicit reconciliation of subjective expert judgment with objective data dispersion, and its built-in robustness diagnostics (AHP consistency ratio, VIKOR acceptable advantage, cross-method concordance, and weight-sensitivity analysis) that a control system operator can monitor continuously rather than trusting blindly. Its principal limitation, as discussed in Section 8, is that the present case study uses illustrative rather than field-calibrated data; the natural next step is deployment on a live sensor network with continuously updated criteria values, together with an investigation of adaptive weight-learning schemes (for example, reinforcement-learning-based weight adjustment driven by realized control outcomes) and digital-twin-based validation of the closed-loop architecture proposed in Section 3 before field deployment.

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CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest associated with this publication.

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