

# An Integrated Life-Cycle, System-Dynamics, Artificial-Intelligence, Multi-Criteria, and Reinforcement-Learning Framework for Sustainable Municipal Solid Waste Management in India

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**Abstract:** Municipal solid waste management in India is a complex socio-technical challenge shaped by rapid urbanization, changing consumption patterns, heterogeneous waste composition, infrastructure deficits, informal recycling networks, environmental externalities, and evolving policy mandates. This paper presents an integrated decision-support methodology for evaluating and optimizing urban waste-management systems in the Indian context. The proposed framework combines five complementary analytical layers: life-cycle assessment for environmental quantification, system dynamics for long-term, feedback-rich simulation, artificial-intelligence-based forecasting for waste-generation prediction, fuzzy TOPSIS for technology ranking under uncertainty, and reinforcement learning for adaptive policy sequencing. The framework is designed around Indian municipal realities, including high organic fractions, variable collection efficiency, monsoon effects, festival-linked waste spikes, legacy dumpsites dependence on the informal sector, and limited municipal finance. Recent policy and empirical context is incorporated, including the expansion of Swachh Bharat Mission–Urban 2.0, India’s urban waste generation of approximately 150,000 tonnes per day, and global projections that municipal solid waste may increase substantially by 2050. The methodology supports comparative assessment of sanitary landfilling, composting, anaerobic digestion, material recovery, waste-to-energy, refuse-derived fuel systems, and biomining of legacy waste. By coupling environmental, economic, technical, social, and policy variables, the framework provides a reproducible, transparent, and adaptive basis for sustainable waste-management planning in Indian cities.

**Keywords:** *Municipal Solid Waste; India; Life Cycle Assessment; System Dynamics; Artificial Intelligence; Fuzzy TOPSIS; Reinforcement Learning; Circular Economy; Swachh Bharat Mission urbanization simulation.*

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## I. INTRODUCTION

Municipal solid waste management has become one of the most pressing urban sustainability challenges in India. Rapid urbanisation, rising incomes, growth in packaged consumption, and changing lifestyles have increased both the quantity and complexity of waste streams. Indian cities generate approximately 150,000 tonnes of municipal waste

per day, and the burden is expected to rise with continuing urban expansion, population growth, and programmatic development [3, 5]. At the same time, global waste generation is also accelerating: the United Nations Environment Programme estimates that municipal solid waste could grow from about 2.1 billion tonnes in 2023 to 3.8 billion tonnes by 2050 [1]. These trends underline the need for integrated, evidence-based behavioral planning frameworks.

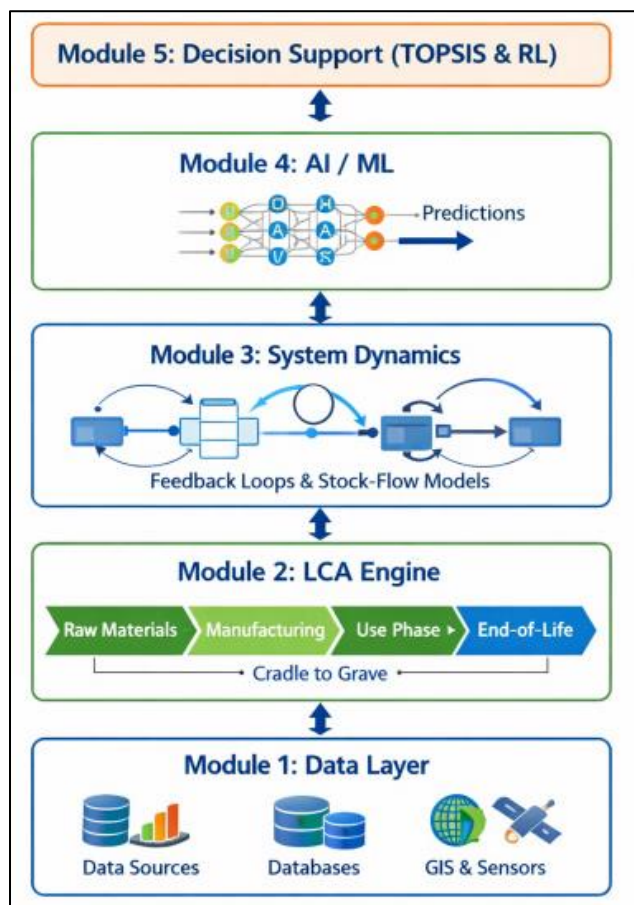


Fig 1 Graphical Abstract

India’s waste-management challenge is not merely a technical problem. It is a coupled environmental, economic, institutional, behavioural, and social problem. Waste composition varies by city size, income level, season, and source type. Organic fractions remain high in many Indian cities. Plastic and packaging waste are increasing. Collection systems are uneven, treatment capacity is often insufficient, and legacy dumpsites continue to create land, air, water, and public-health risks. Under Swachh Bharat Mission–Urban 2.0, the Government of India has emphasised garbage-free cities, source segregation, remediation of legacy dumpsites, and circular-economy approaches [6]. However, life-cycle assessment requires careful sequencing of investments and policies.

Conventional waste-management studies frequently apply a single analytical method, such as life cycle assessment, cost-benefit analysis, or multi-criteria decision-making. Although valuable, such approaches often fail to capture the dynamic feedbacks, uncertainties, behavioural responses, and long-term policy interactions that shape real municipal systems. For instance, a waste-to-energy project may appear attractive from an energy-recovery perspective but may perform poorly if waste has low calorific value, source segregation is weak, informal recycling is displaced, or emissions controls are inadequate. Similarly, composting or anaerobic digestion may be environmentally favourable but may fail if feedstock contamination, market demand, and operational capacity are not addressed.

This paper proposes an integrated methodology that combines life cycle assessment (LCA), system dynamics (SD), artificial intelligence (AI), fuzzy TOPSIS, and reinforcement learning (RL). The objective is to provide a scientifically rigorous and policy-relevant framework for comparing waste-management technologies, adaptive-optimization, simulating long-term system behaviour, ranking alternatives under uncertainty, and identifying robust policy sequences.

- *The Main Contributions of this Paper are as follows:*
  - It develops an integrated multi-layered methodology tailored to Indian municipal solid waste systems.
  - It links LCA, SD, AI forecasting, fuzzy TOPSIS, and RL into a unified decision-support architecture.
  - It incorporates Indian contextual factors, including monsoon effects, festival seasonality, informal-sector recycling, legacy waste, and fiscal constraints.
  - It proposes validation, uncertainty, and stakeholder-engagement protocols for practical deployment in representative Indian cities.
  - It provides a reproducible computational structure suitable for scenario analysis and policy optimisation.

➤ *The Integrated Assessment Can be Expressed as:*

$$IA = f(LCA, SD, AI, TOPSIS, RL), \tag{1}$$

Where each component contributes distinct analytical capability while exchanging data through a common architecture.

## II. LIFE CYCLE ASSESSMENT METHODOLOGY

LCA is used to quantify environmental burdens and avoided impacts associated with alternative waste-treatment pathways. The assessment follows ISO 14040 and ISO 14044 principles [8, 9] and is adapted to Indian waste composition, electricity mix, transport distances, treatment conditions, and policy priorities.

➤ *Goal, Scope, and Functional Unit*  
 The goal is to compare the environmental performance of major municipal solid waste treatment and disposal technologies in Indian cities. The functional unit is defined as the management of one metric tonne of mixed municipal solid waste received at the treatment or disposal facility boundary.

The assessed technology options include sanitary landfill with gas recovery, windrow and in-vessel composting, anaerobic digestion, material recovery facilities, refuse-derived fuel systems, waste-to-energy incineration, and biomining of legacy waste. The system boundary includes upstream avoided production, core collection and treatment activities, direct emissions, residue handling, and downstream substitution credits.

➤ *Life Cycle Inventory*

For technology  $i$ , the inventory vector is represented as:

$$v_i = \sum_{k=1}^n m_k I_{ik} + E_i + C_i - A_i, \tag{2}$$

Where  $m_k$  is the mass fraction of waste component  $k$ ,  $I_{ik}$  is the process inventory for component  $k$  treated by technology  $i$ ,  $E_i$  denotes direct emissions,  $C_i$  denotes infrastructure-related burdens, and  $A_i$  represents avoided burdens from recovered energy or materials.

Waste composition is represented as:

$$M_{comp} = [f_{org}, f_{paper}, f_{plastic}, f_{metal}, f_{glass}, f_{textile}, f_{inert}], \tag{3}$$

Subject to:

$$\sum_k f_k = 1. \tag{4}$$

For landfills, methane generation is estimated using a first-Order decay structure based on IPCC guidance [10, 11]:

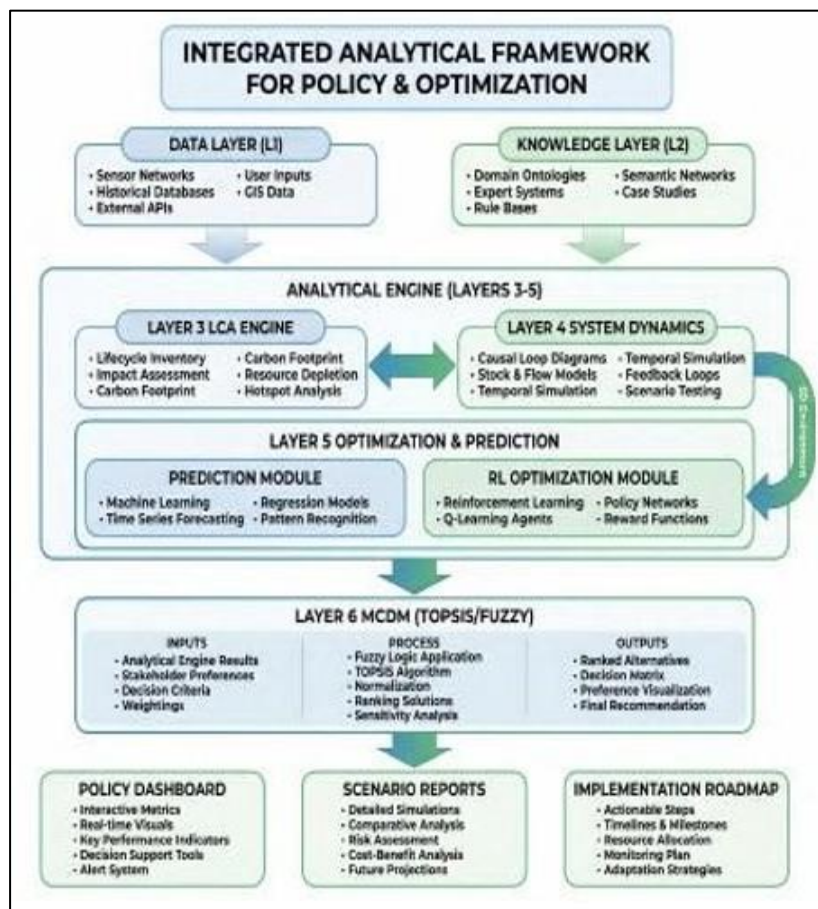


Fig 2 Conceptual Architecture of the Integrated Waste- Management Decision-Support Framework.

$$CH_4(t) = \sum_j \left[ m_j DOC_j DOC_f MCF(1 - OX) \frac{16}{12} \right] (1 - e^{-kt}) \tag{5}$$

For waste-to-energy and RDF systems, net electricity recovery is estimated as:

$$E_{net} = \eta_{overall} LHV_{waste} m_{waste} \eta_{grid}, \tag{6}$$

Where  $\eta_{overall}$  is conversion efficiency,  $LHV_{waste}$  is the lower heating value of waste, and  $\eta_{grid}$  reflects grid transmission and displacement factors. Indian grid-emission

factors are aligned with the Central Electricity Authority’s CO<sub>2</sub> baseline database Normalized2024CO<sub>2</sub>]. Integrated Framework optimization proposed framework operates across four interconnected layers: data foundation, analytical modelling, decision support, and adaptive optimisation. The data foundation includes waste-generation records, composition studies, treatment performance, economic costs, emission the principles of the principles of factse paraia l indicators, and policy variables. The analytical layer contains LCA, SD, and AI forecasting modules. The decision-support layer applies fuzzy TOPSIS to rank technologies under multiple criteria. The adaptive- optimisation layer uses RL to identify policy sequences that maximise long-term sustainability outcomes.

The integrated assessment can be expressed as:

$$IA = f(LCA, SD, AI, TOPSIS, RL), \tag{7}$$

Where each component contributes distinct analytical capability while exchanging data through a common architecture.

➤ *ImpaNormalizedent*

Environmental impacts are evaluated using midpoint categories relevant to Indian urban policy: global warming potential, particulate-matter formation, photochemical ozone formation, acidification, eutrophication, human toxicity, ecotoxicity, and resource depletion. The impact score for category *j* is:

$$IS_j = \sum_{i=1}^n CF_{ij}v_i, \tag{8}$$

Where *CF<sub>ij</sub>* is the characterisation factor.

Normalised and weighted environmental scores are computed as:

$$IS_j^{norm} = \frac{IS_j}{REF_j^{India}}, \tag{9}$$

Table 1 Selected LCA Impact Categories for Indian Waste Systems.

Category	Unit	Major contributors
Global warming	kg CO <sub>2</sub> -eq	CO <sub>2</sub> , CH <sub>4</sub> , N <sub>2</sub> O
Particulate matter	kg PM <sub>2.5</sub> -eq	PM, NO <sub>x</sub> , SO <sub>x</sub>
Acidification	mol H <sup>+</sup> -eq	SO <sub>2</sub> , NO <sub>x</sub> , NH <sub>3</sub>
Eutrophication	kg P/N-eq	Leachate, runoff
Human toxicity Resource depletion (kg Sb-eq.) Material recovery credits	kg 1.4-DCB- eq metals, dioxins	

$$ES = \sum_{j=1}^m w_j IS_j^{norm}. \tag{10}$$

treatment infrastructure, municipal budgets, public satisfaction, informal-sector participation, and environmental impacts. This approach is appropriate because waste systems evolve over years or decades and are shaped by delayed responses, nonlinear thresholds, and policy feedbacks [17, 18].

III. SYSTEM DYNAMICS MODEL

System dynamics is used to simulate long-term feedbacks among wathereby raising collectprioritiesescity,

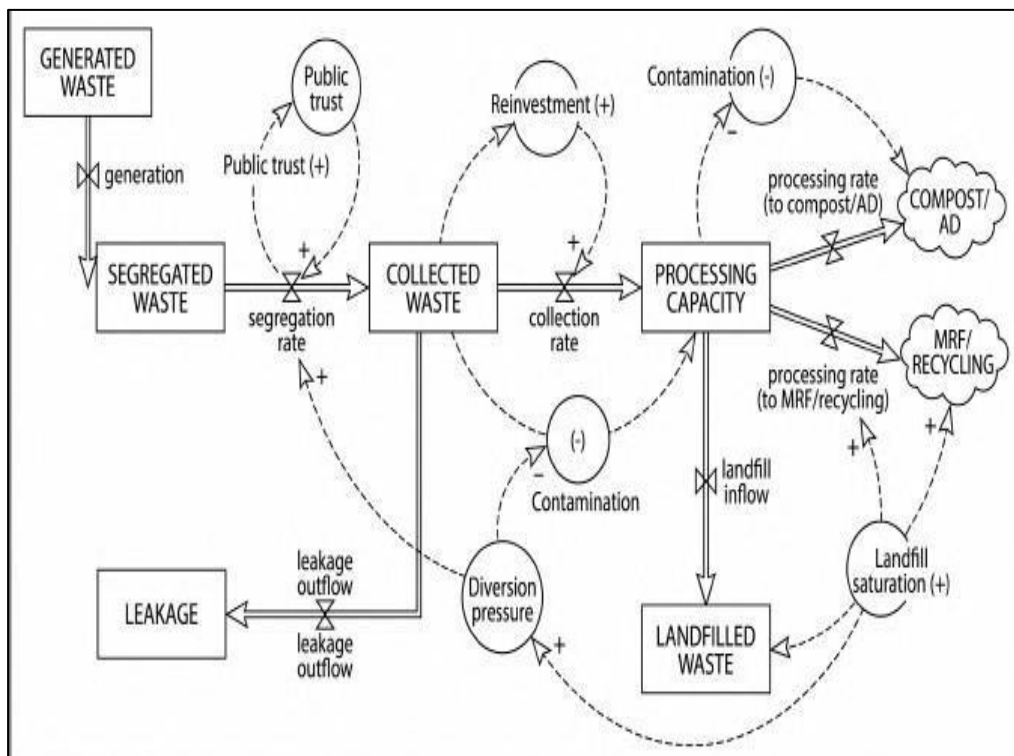


Fig 3 Waste Generation SD Model

➤ *Causal Structure*

The model includes reinforcing and balancing feedback loops. Waste-generation growth increases collection demand, which can reduce service quality if infrastructure does not expand. Environmental degradation can increase public pressure, which may raise policy priority and infrastructure investment. Informal-sector integration can increase recycling rates and

livelihoods, while technology learning can reduce costs and improve performance.

➤ *Stock-Flow Formulation*

The principal stock variables include unmanaged waste stock, treatment capacity, operational knowledge, municipal budget, and informal-sector workforce. The unmanaged waste stock.

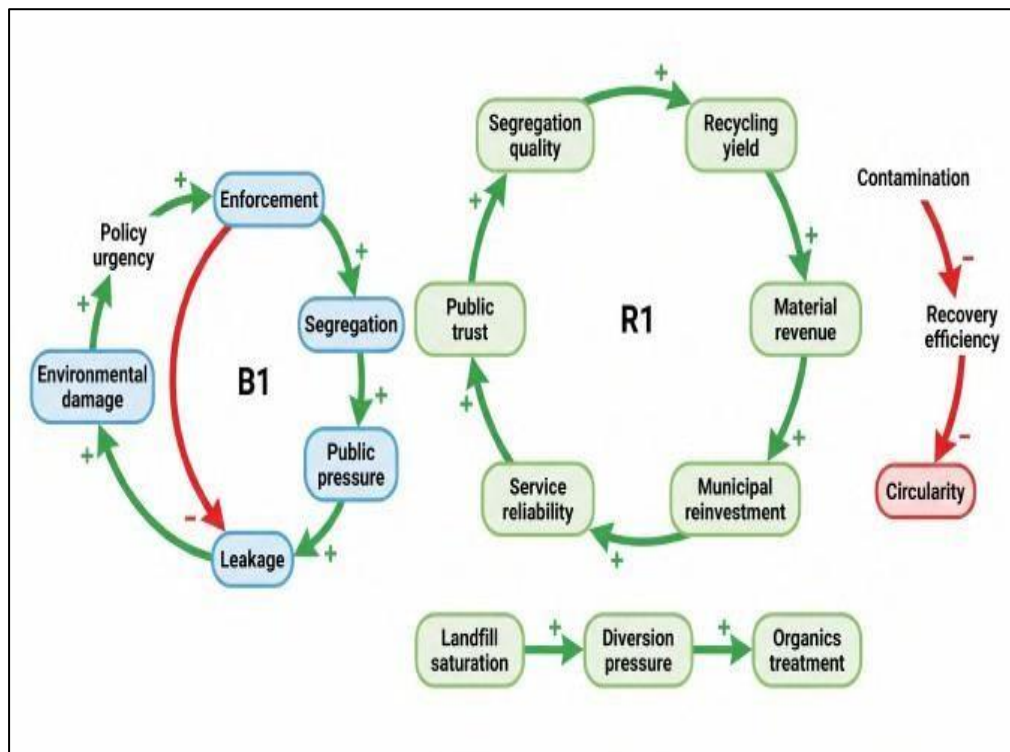


Fig 4 Waste Management SD Policy Evolves as:

$$\frac{dS_{waste}}{dt} = F_{gen}(t) - F_{collect}(t) - F_{informal}(t) - F_{treated}(t). \tag{11}$$

$$P_{gap}(t) = \frac{1}{1 + e^{-\beta(G(t) - C_{thres})}}, \tag{15}$$

Treatment capacity evolves as:

$$\frac{dS_{capacity}}{dt} = F_{invest}(t) - F_{decomm}(t). \tag{12}$$

Operational learning is represented as:

$$\frac{dS_{knowledge}}{dt} = F_{learn}(t) - F_{forget}(t), \tag{13}$$

$$F_{learn}(t) = S_{capacity}(t)\kappa(1 - e^{-\lambda t}). \tag{14}$$

A nonlinear capacity-gap pressure function is used to represent political and administrative response:

Where  $G(t)$  is the relative capacity gap and  $\beta$  determines re- sponse steepness?

**IV. AI-BASED WASTE GENERATION FORECASTING**

Accurate waste forecasting is essential for planning collection logistics, treatment capacity, financial allocations, and tech- nology deployment. The AI module uses ensemble learning to combine temporal, socioeconomic, climatic, urban, and policy variables.

The input feature vector is:

$$X_t = [X_{temporal}, X_{socioeconomic}, X_{climatic}, X_{urban}, X_{policy}]. \tag{16}$$

The target variable is daily municipal solid waste genera- tion:

$$y_t = MSW_t. \tag{17}$$

Disaggregated component predictions are also estimated:

$$y_t^{components} = [y_t^{organic}, y_t^{recyclable}, y_t^{inert}, y_t^{hazardous}]. \tag{18}$$

The ensemble prediction is:

$$\hat{y}_t = w_{LSTM} \hat{y}_t^{LSTM} + w_{GB} \hat{y}_t^{GB} + w_{RF} \hat{y}_t^{RF}, \tag{19}$$

Subject to:

$$\sum_i w_i = 1, \quad w_i \geq 0. \tag{20}$$

Model performance is evaluated using MAE, RMSE, MAPE, and  $R^2$ . Recommended targets are MAPE below 8% for aggregate predictions and below 15% for component-level predictions. Explainability is introduced through SHAP values [20], enabling policymakers to identify drivers such as population density, monsoon intensity, festivals, commercial activity, and temperature.

### V. FUZZY TOPSIS FOR TECHNOLOGY RANK- ING

Technology selection requires balancing environmental performance, cost, public acceptance, employment, technical maturity, operational complexity, and scalability. Fuzzy TOPSIS is used because many criteria involve uncertainty and linguistic judgement [21, 22].

The alternatives are:

$$A = \{a_1, a_2, \dots, a_m\}, \tag{21}$$

Where alternatives include sanitary landfill, composting, anaerobic digestion, waste-to-energy, MRF, RDF, and biomining. The fuzzy decision matrix is:

The state vector includes:

$$s_t = [S_{waste}, S_{capacity}, S_{budget}, S_{techmix}, S_{emissions}, S_{informal}, S_{satisfaction}, S_{policy}, S_{learning}, t]^T. \tag{28}$$

$$\tilde{D} = [\tilde{x}_{ij}]_{m \times n}, \tag{22}$$

Where each  $\tilde{x}_{ij} = (l_{ij}, m_{ij}, u_{ij})$  is a triangular fuzzy number. For benefit criteria, normalisation is:

$$\tilde{r}_{ij} = \left( \frac{l_{ij}}{u_j^{max}}, \frac{m_{ij}}{u_j^{max}}, \frac{u_{ij}}{u_j^{max}} \right). \tag{23}$$

For cost criteria:

$$\tilde{r}_{ij} = \left( \frac{l_j^{min}}{u_{ij}}, \frac{l_j^{min}}{m_{ij}}, \frac{l_j^{min}}{l_{ij}} \right). \tag{24}$$

The weighted normalised value is:

$$\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \tilde{w}_j. \tag{25}$$

The closeness coefficient is:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}, \tag{26}$$

Where  $D^+$  and  $D^-$  are distances from the fuzzy positive and  $i$  negative ideal solutions. Higher  $C_i$  value indicates stronger overall suitability.

### VI. REINFORCEMENT LEARNING FOR POLICY SEQUENCING

The final layer optimises the sequence and timing of policy interventions. The problem is formulated as a finite-horizon Markov Decision Process:

$$M = \langle S, A, T, R, \gamma, H \rangle. \tag{27}$$

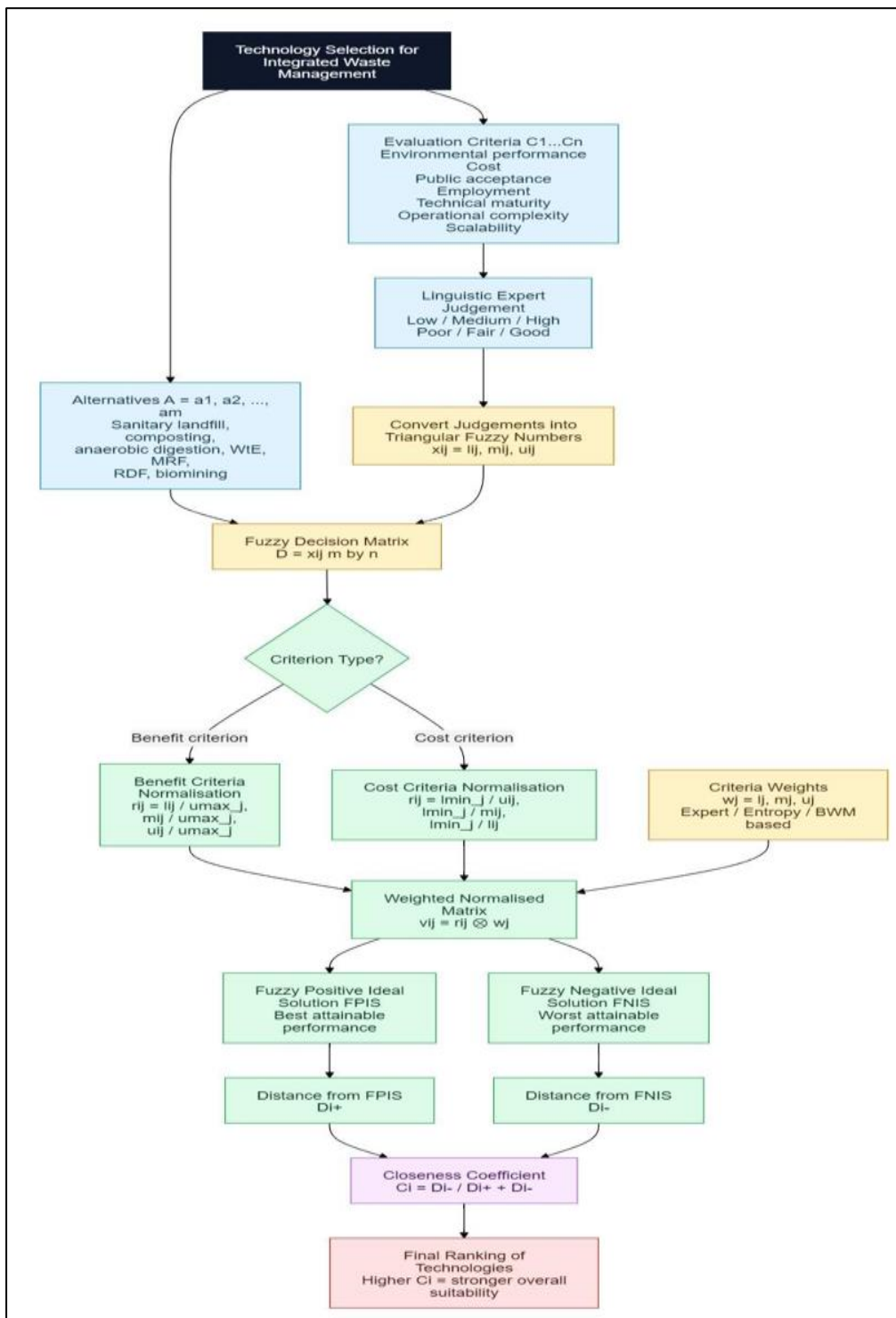


Fig 5 Fuzzy TOPSIS

Table 2 Representative TOPSIS Criteria.

Dimension	Criterion	Direction
Environmental	GWP, toxicity, land use	Minimise
Environmental	Energy/material recovery	Maximise
Economic	Capital and optimizes cost	Minimise
Economic	Revenue potential	Maximise
Social	Employment, acceptance	Maximise
Social	Health risk	Minimise
Technical	Ma turity, scalability	Maximise
Technical	Complexity	Minimise

The action space includes investment in landfill, composting, anaerobic digestion, waste-to-energy, MRFs, biomining, informal-sector integration, awareness campaigns, EPR enforcement, capacity building, and no-action options.

The reward function is a weighted sustainability objective:

$$R(s_t, a_t) = \sum_{k=1}^K \omega_k r_k(s_t, a_t) + R_{penalty}, \tag{29}$$

Where reward components represent environmental, economic, social, and technical performance. Constraint penalties are applied when budgets are exceeded, capacity thresholds are violated, or technology prerequisites are unmet.

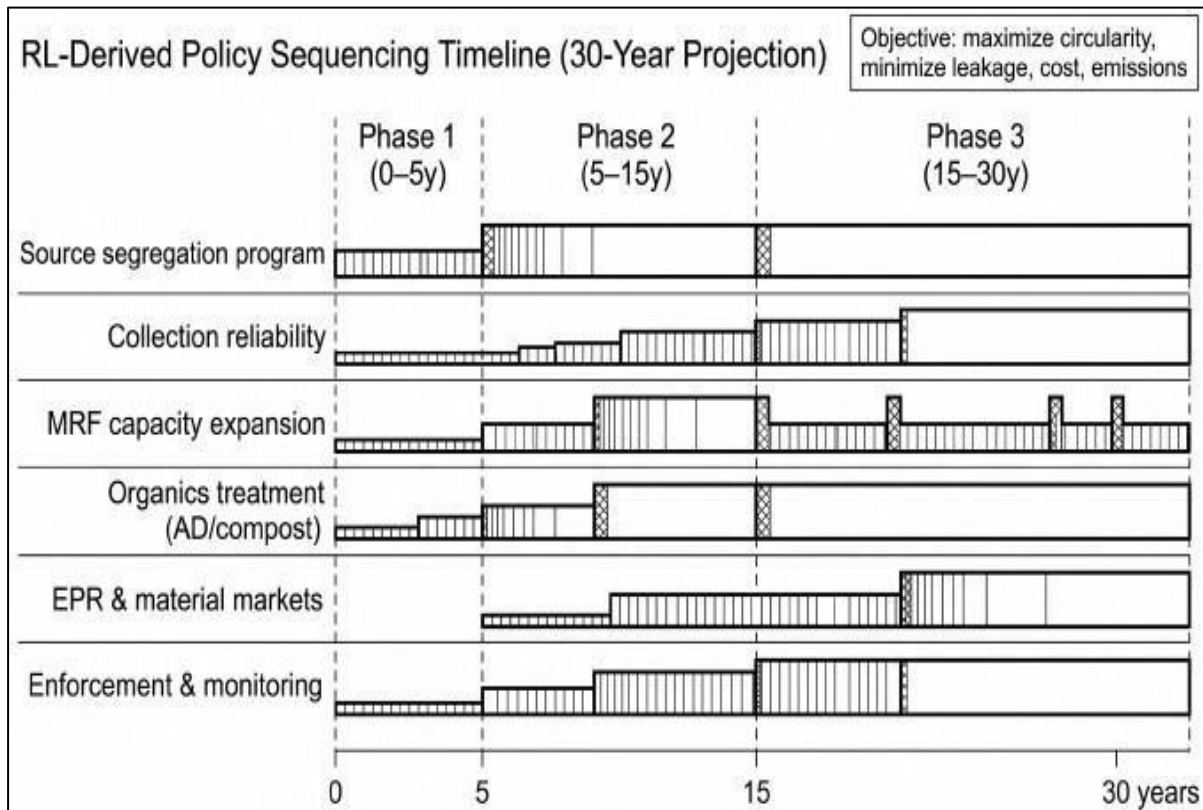


Fig 6 Policy Intervention Timeline

A Deep Q-Network Initializes the action-value function:

$$Q^*(s, a; \theta) \approx Q(s, a). \tag{30}$$

The temporal-difference loss is:

$$L(\theta) = E \left[ \left( r + \gamma \max_{a'} Q(s', a'; \theta^-) - Q(s, a; \theta) \right)^2 \right] \tag{31}$$

### VII. CASE STUDY DESIGN

The framework is in waste characterization across three representative Indian cities: one Tier-1 city, one Tier-2 city, and one Tier-3 city. This stratification captures variation in population, financial capacity, infrastructure maturity, waste generation, collection efficiency, and dominant disposal practice.

#### Algorithm 1 Constraint-aware DQN training

- Require:** SD simulator, action set  $A$ , replay buffer  $D$ , network  $Q$
- 1: Initialise  $Q(a, \theta)$  and target network  $Q(a, \theta^-)$  areaode = 1 to  $M$
  - 2: Initialise city state  $s_0$
  - 3: **for**  $t = 0$  to  $H - 1$  **do**
  - 4: Determine feasible actions  $A_{valid}(s_t)$
  - 5: Select  $a_t$  using  $\epsilon$ -greedy policy
  - 6: Execute  $a_t$  in SD simulator
  - 7: Observe  $s_{t+1}$  and reward  $r_t$
  - 8: Store transition in replay buffer
  - 9: Sample mini-batch and update  $\theta$
  - 10: Periodically update target network
  - 11: **end for**
  - 12: Decay exploration rate  $\epsilon$
  - 13:
  - 14: **return** optimal policy  $\pi^*$

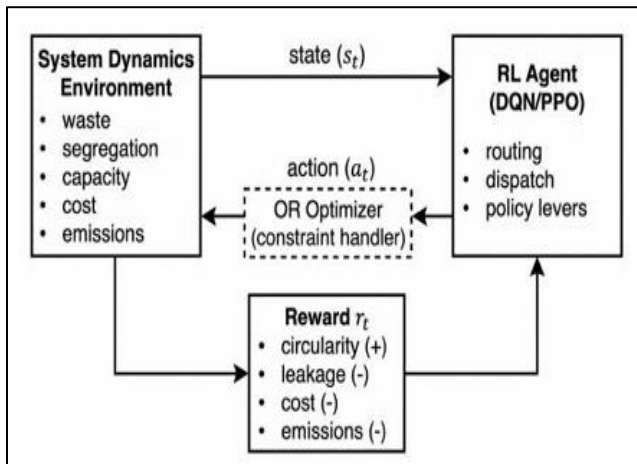


Fig 7 RL DQNT Training

Primary data include household surveys, seasonal waste-characterisation studies, stakeholder interviews, facility audits, transport-route information, and cost records. Secondary data include CPCB reports, State Pollution Control Board records, Swachh Bharat Mission dashboards, Census data, satellite imagery, and published LCA and waste-composition studies [2–4].

➤ *Scenario Design*

The model evaluates eight policy scenarios: baseline, business-as-usual, technology-focused, informal-sector integration, zero-waste transition, low-cost compliance, climate-priority, and integrated sustainability. Each scenario specifies technology targets, investment schedules, policy-intervention timing, fiscal constraints, source-segregation assumptions, and informal-sector participation.

Technology Portfolios	Environment	Circularity	Cost	Feasibility	Social	TOPSIS Rank
AI-enabled MRF + Digital EPR						<b>1</b>
Anaerobic Digestion (AD)						<b>2</b>
Decentralized Composting						<b>3</b>
RDF / Co-processing						<b>4</b>
Landfill (baseline)						<b>5</b>

Note: Higher score = better performance/ranking, indicated by darker grayscale shading.

Fig 8 TOPSIS Rankings for Waste Management

Table 3 Indicative Case-study Selection Structure.

Criterion	City 1	City 2	City 3
Tier	Metro	Tier-2	Tier-3
Population	8–15 M	1–5 M	0.5–1 M
Waste	5000–8000 t/d	500–1500 t/d	100–500 t/d
Collection	80–90%	60–70%	40–60%
Infrastructure	Advanced	Developing	Basic
Finance	High	Medium	Low

The informal sector is especially important in India because waste pickers and small aggregators contribute substantially to material recovery, particularly for plastics, paper, metals, and other recyclables [26–29]. Therefore, technology pathways that displace informal workers without integration may reduce social sustainability even if formal processing capacity increases.

➤ *Validation and Uncertainty Analysis*

The framework uses module-specific and integrated validation. LCA outputs are benchmarked against published Indian and international studies, IPCC guidance, and ecoinvent datasets [13–15]. System dynamics validation includes structure tests, dimensional checks, historical fit,

extreme-condition tests, and sensitivity analysis. AI models are validated through walk-forward cross-validation and holdout testing. TOPSIS rankings are tested against weight perturbations and alternative MCDM methods such as VIKOR, ELECTRE, and PROMETHEE. RL policies are evaluated against random baselines, expert heuristics, simplified optimal solutions, and perturbed scenarios.

Monte Carlo simulation propagates parameter uncertainty:

$$\theta_i \sim D(\mu_i, \sigma_i), \tag{32}$$

$$CI_{95\%} = [\mu_{out} - 1.96\sigma_{out}, \mu_{out} + 1.96\sigma_{out}]. \tag{33}$$

### VIII. COMPUTATIONAL IMPLEMENTATION

The implementation uses open and reproducible computational tools. LCA can be implemented in openLCA and Brightway2; system dynamics in Vensim, Ventity, or PySD; AI forecasting in Python using TensorFlow, PyTorch, and scikit-learn; fuzzy TOPSIS in Python or MATLAB; and RL using Stable-Baselines3 or a custom Gymnasium-compatible simulation environment.

➤ *Ethical Considerations*

The framework requires responsible data governance and inclusive stakeholder engagement. Household surveys and stakeholder interviews should be based on informed consent, anonymisation, and secure storage. Sampling must include low-income communities, informal workers, women workers, and marginalised groups whose livelihoods are directly affected by municipal waste reforms.

Table 4 Suggested Software Stack.

Module	Tools
LCA	openLCA, Brightway2, ecoinvent
System dynamics	Vensim, Ventity, PySD
AI forecasting	Python, TensorFlow, PyTorch, scikit-learn
MCDM	Python, MATLAB, custom fuzzy TOPSIS
RL	Stable-Baselines3, Gymnasium, PyTorch
Data management	PostgreSQL, DVC, Git
Documentation	Jupyter, Sphinx, README repositories

Model outputs should not be treated as automatic policy prescriptions. They are decision-support tools that require interpretation, public deliberation, and local institutional judgement. Particular care is needed when evaluating waste-to-energy, landfill closure, mechanised sorting, and informal-sector formalisation because these interventions can redistribute risks, costs, and benefits across communities.

### IX. LIMITATIONS

The proposed framework is data-intensive and depends on the quality of municipal records, waste-characterisation studies, emissions factors, and stakeholder inputs. Behavioural functions and policy responses are necessarily simplified. AI forecasts may degrade when urban systems experience shocks such as pandemics, floods, major policy changes, or sudden migration. RL policies learned in simulation require careful validation before real-world implementation. Transferability across cities requires recalibration.

### X. CONCLUSION

This paper presents an integrated methodology for sustainable municipal solid waste planning in India. By combining LCA, system dynamics, AI forecasting, fuzzy

TOPSIS, and reinforcement learning, the framework addresses both technology evaluation and long-term policy sequencing. It is designed to support Indian cities facing heterogeneous waste composition, infrastructure deficits, climate and public-health risks, informal-sector dependence, and fiscal constraints.

The framework advances beyond single-method assessment by linking environmental impacts, dynamic capacity evolution, predictive analytics, stakeholder-informed technology ranking, and adaptive optimisation. Applied carefully, it can help policymakers compare treatment pathways, test alternative futures, identify robust investment sequences, and align municipal waste systems with circular-economy, climate, public-health, and social-equity goals.

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