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Industrial Waste Management Planning Evaluation Using Integrated Best-Worst Technique With Fuzzy TOPSIS

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ABSTRACT

The sustainable management of industrial and electronic waste has emerged as a critical challenge in the recent global context. Industrialization, combined with inadequate planning, results in the continuous generation of industrial byproducts and waste, posing critical problems to both the environment and society. Consequently, such waste leads to soil and water contamination, degradation of air quality, and significant threats to ecosystems and human health. To keep society safe from the detrimental consequences of waste, it's essential to have sustainable and efficient planning for managing industrial waste. In this paper, we have discussed how an expert-based multi-criteria decision-making technique can aid in implementing an effective industrial waste management strategy by analyzing various expert reviews and public opinions. Multiple waste management strategies are reviewed in response to various important factors, including environmental, social, legal, compliance, cost, and technical considerations. These decision-making factors are analyzed and ranked based on their weights using the Best-Worst technique. Subsequently, the ranking for the effective industrial waste management(IWM) strategy is obtained through the fuzzy TOPSIS(FTOPSIS) ranking technique. A sensitivity analysis has been conducted based on different factor weights. Finally, the ranking of the management strategy has been verified by utilizing another well-established decision-making technique.

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1. Introduction

Decision-making has become increasingly complex due to the presence of multiple, interrelated factors and inherent uncertainties in real-world problems. Fields such as business, urban planning, engineering, and environmental management demand advanced decision-support approaches capable of addressing such complexity. Traditional decision-making methods, which rely on rigid assumptions and precise or deterministic inputs, often prove inadequate in practical applications. These methods have limited capacity to manage ambiguity, imprecision, and fuzziness, and consequently struggle to identify robust or optimal solutions under uncertain conditions. Whereas, fuzzy decision-support techniques have emerged to better accommodate the uncertainties and complexities inherent in contemporary decision environments [1]. Which is frequently constrained by multiple interrelated complex criteria in the decision-making process. In such domain like, finance [2], supply chain management [3], [4] healthcare [5], management and sustainability [6], [7] decision problems are often highly imprecise and inexact. Researchers in these areas must find ways to balance conflicting objectives, account for uncertainty, and derive solutions that lead to more informed, rational, and sustainable decisions. Fuzzy MCDM helps to solve decision-making problems that involve many different conflicting factors [8], [9]. It gives a clear way to compare and rank the choice of alternatives, even when some goals conflict with each other [10]. This method is especially useful in situations where the final decision affects many different and sometimes competing needs, helping decision-makers choose more confidently under uncertainty. Fuzzy MCDM with a multi-method approach helps in making better decisions for industrial waste management, where many different conflicting factors are involved. It provides a robust framework to compare and rank waste management strategies, considering multiple goals, such as technical, safety, cost, and environmental protection. The industrial waste management involves many important goals at the same time, helping managers choose the most balanced and effective solution under uncertainty with respect to legal compliance policy.

The selection of optimal waste management strategies for a large and rapidly growing city such as Kolkata is considered a complex decision-making problem, addressed in this study using a fuzzy hybrid MCDM approach. Although fuzzy MCDM techniques have been widely used to evaluate difficult situations and support effective decisions from personnel selection [11] to industrial suppliers [12]. The decision-making process becomes even more challenging due to uncertainties in data, legal and regulatory compliance, and stakeholder preferences. To address such uncertainty, triangular fuzzy numbers(TFNs) are particularly effective, as they can represent imprecise, vague, or incomplete information in a systematic manner. In this context, the Best-Worst [13] approach is considered to rank multiple factors and their weights, and different waste management strategies are evaluated based on these closeness factors using the FTOPSIS [14] technique to identify the most suitable and balanced solution for handling industrial waste. Although only a few studies [15] have combined MCDM with BWM and FTOPSIS for supplier selection problems, some modeling efforts can be found. [16] showed some advantages of BWM and formulated a linear model on it [17]. Additionally, some applications [18] of the method have been observed, such as hybrid BWM for e-waste management along with TOPSIS, and energy [19], renewable source selection, etc. Here are some useful fuzzy MCDM methods and their applications, such as AHP, PROMETHEE, and ELECTRE, that have been used in energy planning to promote sustainability [20]. A suitable location for the nuclear power plant selection has been studied by AHP and ELECTRE [21] methodologies. Additionally, Seker et al. [22] utilised the IVIF-AHP and CODAS methods for the evolution of sustainable transport management, and the selection of the sustainable electric vehicle transit problem was studied based on the MOORA [23] and TOPSIS methods, along with the application of MCDM to energy planning for regional development using the PROMETHEE technique [24]. Although the proposed study of the industrial waste management problem has been addressed using the FTOPSIS method, along with the BWM criteria evaluation technique. However, there are multiple case studies that have been done in this context, such as a case study on solid waste management for Shamsabad industrial complexes [25], a sustainable multi-functional machine selection for industry waste control using fuzzy MCDM. A study of fuzzy MCDM has been done on a sustainable waste-to-energy strategy model [26] for industrial waste utilization, along with a gas treatment system assessment. The study demonstrated for sustainable waste management of the Iron and steel industry [27]. Additionally, Van et al. showed the application of fuzzy MCDM for infectious industrial waste management [28], etc. Here, we have listed a literature as shown in Table 1 on multiple decision-making techniques and their applications for several selection purposes.

Table 1
Relevant past studies on MCDM methods and their application in decision-making

Author and Year	Case Study	Ranking Techniques	Fuzzy Environment	Criteria Selection Approach
Maddah et al. (2022) [29]	Automobile manufacturer	MABAC	–	BWM
Afrasiabi et al. (2022) [30]	Manufacturing industry	GRA, TOPSIS	✓	FBWM
Kayani et al. (2023) [31]	Pharmaceutical industry	FTOPSIS	✓	FAHP
Tavakoli et al. (2023) [32]	An online marketplace	Markovian-based FBWM	✓	FBWM
Garai (2025a) [33]	Wastewater management	MCDM	✓	Bipolar expected value
Nemati et al. (2024) [34]	Supplier selection	MULTIMOORA	✓	–
Fetana et al. (2015) [35]	Offshore wind farm	DEMATEL, ELECTRE	✓	ANP
Bonab et al. (2023) [36]	IoT supplier company	TRUST	✓	SFS–BWM
Ambilkar et al. (2024)[37]	Additive Manufacturing Industry	N-BWM	✓	FDM
Nayeri et al. (2023) [38]	Healthcare system	SFBWM	✓	MSDMF
Gara (2025b) [39]	Water resource management	Bipolar fuzzy	✓	FPIS, FNIS
Suryadi and Rau (2023) [40]	Construction, industrial and mining industry	AHP	–	AHP
Sheykhizadeh et al. (2024)[41]	Pharmaceutical industry	FBWM	✓	MADM
Taghav et al. (2024) [42]	Automotive industry	–	✓	Stochastic programming
Our study	Industrial waste management	FTOPSIS	✓	BWM

1.1 *Motivation*

Recent studies indicate that industrial waste management(IWM) decision-making continues to face significant challenges, highlighting the pressing need for reliable, effective, and robust evaluation mechanisms. Determining the effective and suitable industrial waste management strategy involves uncertainty and ambiguity due to the imprecise nature of expert opinions and environmental variability. A robust decision-making framework can find the solution considering environmental, economic, technical, regulatory, and social dimensions. This motivates us to model a hybrid fuzzy MCDM tool to handle ambiguity and measure multiple IWM alternatives such as landfill siting, treatment technology selection, recycling strategies, and circular economy interventions. The fuzzy hybrid MCDM provides a robust framework, where linguistic assessments can be effectively modeled using Triangular Fuzzy Numbers (TFNs). This study is framed with the FTOPSIS approach under the TFN for ranking alternatives based on multiple criteria. Whenever the criteria ranking is made based on expert rating within a proper scaling, using BWM.

This study aims to integrate the BWM and the fuzzy MCDM framework with the IWM decision problem, providing a systematic, consistent, and transparent approach for evaluating and selecting the most appropriate waste management alternatives. The proposed hybrid BWM-FTOPSIS method is expected to overcome the limitations in ranking of traditional methods, improve decision quality, and enhance the overall efficiency and robustness of the evaluation process.

1.2 *Novelties*

Considering the background and motivation of the Fuzzy Multi-Criteria Decision-Making (FMCDM) problem in the context of industrial waste management, the main contributions and novelties of this study are outlined as follows:

- Identification of alternatives and criteria: The study begins by identifying a set of feasible waste management alternatives, such as recycling, incineration, landfilling, composting, and energy recovery, and relevant evaluation criteria technical, economic, environmental, social, and legal. The linguistic assessments provided by experts are expressed using TFNs to capture the inherent uncertainty and imprecision in their judgments.

- Formulation of the fuzzy decision matrix: A fuzzy decision matrix is constructed using the linguistic ratings and fuzzy weights assigned to each criterion by experts. This approach effectively represents subjective human evaluations and reflects real-world uncertainty in waste management decision processes.

- Normalization and determination of ideal solutions: The criteria weights are evaluated by the Best-Worst technique, and using these weights, the weighted normalized matrix is calculated, and the fuzzy positive ideal solutions(FPIS) and fuzzy negative ideal solutions(FNIS) are determined using the FTOPSIS approach. This enables an objective assessment of the performance of each waste management alternative.

- Ranking and validation: Alternatives are ranked according to their closeness coefficients to the ideal solution, indicating their relative suitability. To ensure the robustness, objectivity, and internal consistency of the proposed model, comparative studies with other methodologies are conducted, validating the reliability and computational efficiency of the proposed methodology in managing industrial waste.

1.3 *Structure of the Paper*

The article is structured as follows: in Section 2, we defined some basic definitions and the necessary theorems of the triangular fuzzy membership function and properties. The methodologies for the study have been discussed in Section 3, and in Section 4, the industrial waste management problem has been described, and a step-by-step optimization process with discussion has been shown. In Section 5, the conclusion of the proposed study has been added.

2. Preliminaries

Definition 1.1 ([43]) Let R be a universal set and $\tilde{A}$ be a triangular fuzzy number of the set A, then the element $\tilde{A}$ of A is expressed by an order triplet $\tilde{A}$=$\langle e, f, g\rangle$ where $e \leq f \leq g$ with the following membership function:

$$\mu_A(x; e, f, g) = \begin{cases} 0, & \text{if } x < e \\ \frac{x-e}{f-e}, & \text{if } e \leq x \leq f \\ \frac{g-x}{g-f}, & \text{if } f \leq x \leq g \\ 0, & \text{if } x > g \end{cases} \tag{1}$$

Where e and g are respectively the upper and the lower bounds of $\tilde{A}$, and f is the median value, and if $e \geq 0$, then $\tilde{A}$ is called a positive TFN as shown in Figure 1. let $\tilde{A}_1 = \langle e_1, f_1, g_1 \rangle, \quad \tilde{A}_2 = \langle e_2, f_2, g_2 \rangle$ be two TFNs, then some basic operations on positive TFNs are defined as:

- Addition:
$$\tilde{A}_1 + \tilde{A}_2 = \langle e_1 + e_2,\ f_1 + f_2,\ g_1 + g_2 \rangle \tag{2}$$

- Scalar Multiplication: for any positive scalar $\lambda > 0$,
$$\lambda \tilde{A}_1 = \langle \lambda e_1,\ \lambda f_1,\ \lambda g_1 \rangle \tag{3}$$

- Score value of TFNs: [44] the sub-interval avrage of a TFN $\tilde{A}_1 = \langle e, f, g \rangle$ is
$$S(A) = \frac{(e + f + g)}{3} \tag{4}$$

Definition 2.2 Let $\tilde{A}_1 = \langle e_1, f_1, g_1 \rangle, \quad \tilde{A}_2 = \langle e_2, f_2, g_2 \rangle$ be two TFNs, then the Hamming distance [45] between two TFNs $\tilde{A}_1 = (e_1, f_1, g_1),$ and $\tilde{A}_2 = \langle e_2, f_2, g_2 \rangle$ is defined as,

$$d(\tilde{A}_1, \tilde{A}_2) = \frac{1}{3}\left(|e_1 - e_2| + |f_1 - f_2| + |g_1 - g_2|\right) \tag{5}$$

3. Methodologies

In this section, we discussed MCDM methodologies involved with this study. A hybrid MCDM framework of BWM-TOPSIS has been considered to measure the ranking of the waste management alternatives. The BWM was initially introduced by Rezaei [17] as an efficient multi-criteria decision-making technique to derive optimal criteria weights through pairwise comparisons. The decision-maker provides a limited number of judgments by comparing the best and the worst criteria with the other criteria. There are many advantages of BWM, but the key benefit is that it reduces the comparison burden among criteria. The technique provides more reliable and stable criteria weights compared to other weighting methods, and it provides consistent results with fewer data points. Unlike the traditional Analytic Hierarchy Process (AHP), which requires $\{n(n-1)/2\}$ pairwise comparisons among all criteria, but BWM requires only $\{2n-3\}$ pairwise comparisons. The TOPSIS [45] technique is also an efficient MCDM technique for decision-making under the TFN environment. The main principle of TOPSIS is that the best alternative must have the shortest distance from the fuzzy positive-ideal solution (FPIS) and the farthest distance from the fuzzy negative-ideal solution (FNIS), as discussed as follows.

3.1 Best-Worst Method

The step-by-step of BWM and the pairwise comparisons are described as follows :

Step 1. Pairwise comparisons: At first, pairwise comparisons are divided into two types as follows:

Reference comparisons:- If criterion i is the best criterion and/or criterion j is the worst criterion, then the comparison a_{ij} is called a reference comparison.

Secondary comparisons:- If neither i nor j is the best or worst criterion, with $a_{ij} \geq 1$, then the comparison a_{ij} is called a secondary comparison. The steps of BWM are described as follows:

Step 2. Specify the decision criteria:- Determine the set of decision criteria $\{F_1, F_2, \ldots, F_n\}$, which are to be evaluated in order to reach the final decision.

Step 3. The best and the worst criteria determination:- The best criteria (most desirable or most important) and the worst (least desirable or least important) criteria are identified. No numerical comparison is made at this stage.

Step 4. Determine the preference of the best criterion over others:- The decision-maker expresses the preference of the best criterion over each of the remaining criteria using a value between 1 and 9, where 1 denotes equal importance, and 9 denotes extreme importance. The resulting vector is given by

$$A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn}),$$

where a_{Bj} represents the preference of the best criterion B over criterion j, and $a_{BB} = 1$.
Step 5. Determine the preference of all criteria over the worst criterion:- Similarly, the decision-maker specifies the preference of each criterion with respect to the worst criterion using a value between 1 and 9. The corresponding vector is defined as

$$A_W = (a_{1W}, a_{2W}, \ldots, a_{nW}),$$

where a_{jW} denotes the preference of criterion j over the worst criterion W, and $a_{WW} = 1$.
Step 6. Compute the optimal weights:- To derive the optimal weights $(w_1^*, w_2^*, \ldots, w_n^*)$, the following optimization model is formulated:

$$\min\ \xi$$

subject to

$$\left|\frac{w_B}{w_j} - a_{Bj}\right| \leq \xi, \quad \forall j,$$

$$\left|\frac{w_j}{w_W} - a_{jW}\right| \leq \xi, \quad \forall j,$$

$$\sum_j w_j = 1, \quad w_j \geq 0,\ \forall j.$$

Here, ξ represents the maximum absolute deviation from perfect consistency. The objective is to minimize ξ, thereby obtaining the most consistent set of weights for all criteria.

Step 6: Consistency evaluation:- After solving the model, the optimal deviation ξ^* is used to compute the Consistency Ratio (CR) as:

$$CR = \frac{\xi^*}{\xi_{\max}} \tag{6}$$

where $\xi_{\max}$ is the maximum allowable deviation based on the comparison scale. If the CR is close to zero, then it shows a more consistent.

The consistent set of weights of the criteria is used for further evaluation of alternatives based on the set of criteria and their weights. The evaluation of alternatives are made by the TOPSIS method is stated step-by-step here.

3.2 *TOPSIS Method*

Step 1. Construct expert-based initial decision matrices:- First select a set of I numbers of criteria and J number of alternatives, then construct a finite number of initial decision matrices $R_1 = [k_{ij}]_{n\times m}$, $R_2 = [k_{ij}]_{n\times m}$, ... based on expert opinion. Where k_{ij} is a TFN.

Step 2. Construct the normalized decision matrices:- The normalization formula has been given for both benefit (I) and non-benefit (I') criteria as follows,

$$s_{ij} = \left(\frac{e_{ij}}{c_i^+}, \frac{f_{ij}}{c_i^+}, \frac{g_{ij}}{c_i^+}\right);\ \text{for } i \in I \quad \text{and, } s_{ij} = \left(\frac{e_i^-}{g_{ij}}, \frac{e_i^-}{f_{ij}}, \frac{e_i^-}{e_{ij}}\right);\ \text{for } i \in\ I' \tag{7}$$

$$\text{where, } c_i^+ = \max_j g_{ij}, \quad e_i^- = \min_j e_{ij}$$

Step 3. Weighted normalized decision matrix:-

$$v_{ij} = w_i.s_{ij}, \quad \sum_{j=1}^{n} w_i = 1; \quad \text{where } w_i \text{ is the weight of the } i^{\text{th}} \text{ criterion.} \tag{8}$$

Step 4. The fuzzy positive-ideal solution (FPIS) and fuzzy negative-ideal solution (FNIS):-

$$\begin{aligned} A^* &= \{v_1^*, v_2^*, \ldots, v_n^*\}, \quad v_i^* = \begin{cases} \max_j v_{ij}, & i \in I \\ \min_j v_{ij}, & i \in I' \end{cases} \\ A^- &= \left\{v_1^-, v_2^-, \ldots, v_n^-\right\}, \quad v_i^- = \begin{cases} \min_j v_{ij}, & i \in I \\ \max_j v_{ij}, & i \in I' \end{cases} \end{aligned} \tag{9}$$

where J and J' are sets of benefit and non-benefit criteria, respectively.

Step 5. Calculate the distances of each alternative from FPIS and FNIS:-

$$D_j^* = \sqrt{\sum_{i=1}^{n}(v_{ij} - v_i^*)^2}, \text{ and } \quad D_j^- = \sqrt{\sum_{i=1}^{n}(v_{ij} - v_i^-)^2};\ i = 1, 2, \ldots, n \tag{10}$$

Step 6. Calculate the closeness coefficient and rank the alternatives:-

$$C_j^* = \frac{D_j^-}{D_j^* + D_j^-}, \quad 0 \le C_j^* \le 1 \tag{11}$$

The the highest C_j^* refer best alternative, and lowest C_j^* refer worst alternative.

4. Problem Description and Optimization

4.1 *Industrial Waste Management*

Industrial activities generate various types of waste and by-products of manufacturing, processing, and production operations. These wastes differ in their physical, chemical, and biological characteristics depending on the nature of the industry and raw materials used. Understanding the different types of industrial waste is essential for choosing appropriate treatment and disposal methods to ensure environmental protection and sustainable industrial development. Industrial waste management

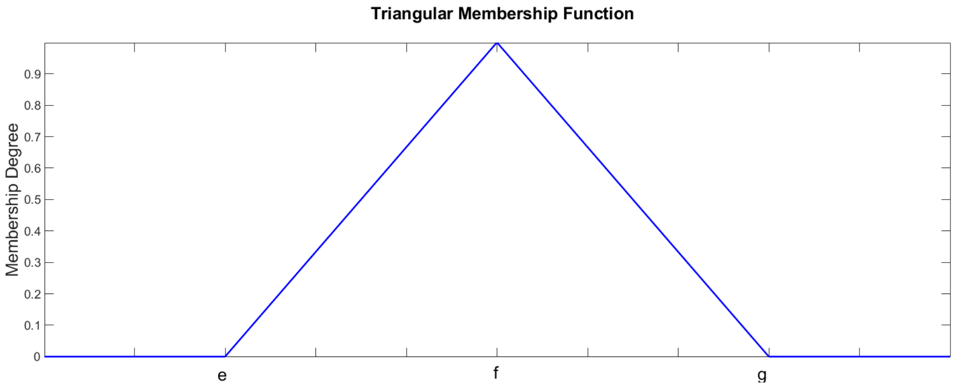

Fig. 1. The graphical representation of triangular membership function

is essential to protect the environment, human health, and natural resources. Improper disposal of industrial waste can lead to soil, water, and air pollution, causing long-term ecological damage and health hazards. Toxic chemicals and heavy metals from untreated waste can contaminate groundwater and affect food chains. Managing industrial waste properly also helps in resource recovery, energy conservation, and cost reduction through recycling and reuse. Moreover, effective waste management ensures compliance with environmental laws and regulations, prevents accidents, and promotes sustainable industrial growth. Therefore, managing industrial waste is not only an environmental necessity but also an economic and social responsibility.

Selecting and implementing an effective waste management system requires a holistic evaluation of technical, economic, social, legal, and environmental factors. Implementation of an appropriate waste management system is crucial for ensuring environmental sustainability and public health. Different types of waste require different methods of handling, treatment, and disposal. Therefore, several factors must be carefully considered before choosing a particular waste management approach. These factors include the type, quantity, and composition of waste, the availability of technology and infrastructure, economic feasibility, legal compliance, and environmental conditions. In addition, social acceptance, institutional capacity, and sustainability potential play important roles in determining the success of the system. A well-planned selection process based on these factors ensures that the chosen waste management method is efficient, cost-effective, and environmentally responsible.

4.2 *Problem Description*

The present section provides a simplified numerical illustration of triangular fuzzy values using the fuzzy MCDM method to evaluate industrial waste management strategies in India. Effective management of industrial waste is essential due to the country's rapid industrialization, increasing waste generation, and growing environmental concerns. A systematic multi-criteria assessment is therefore necessary to select the most suitable industrial waste management approach.

In this study, seven potential industrial waste management strategies, denoted as $M_1, M_2,\ M_3,\ M_4$ $,\ M_5,\ M_6$ and M_7, are considered as feasible alternatives. These alternatives are evaluated by four experts, represented as E_1, E_2, and E_3 based on five major factors, labeled as F_1, F_2, F_3, F_4, and F_5. The factors considered in the decision-making process are technical factors(F_1), economic or cost factors(F_2), Social Factors(F_3), legal factors(F_4), and environmental factors(F_5). Among these, F_1, F_3, F_4, F_5 are treated as benefit factors, so larger values indicate more desirable outcomes. In contrast, F_2 is considered a non-benefit factor or cost factor, since stricter regulatory requirements or higher compliance costs may reduce desirability. Each factor is assessed using linguistic terms that are mapped

Table 2
Important factors for evaluation of waste management systems and their key benefits

	Important Factors	Description	Key Aspects	Key Importance
1.	**Technical factors(F_1)**	Concerned with the practical feasibility and performance of the waste management system.	Type and nature of waste, availability of suitable technology, efficiency and reliability of equipment, availability of skilled manpower, infrastructure and maintenance needs.	Ensures efficient operation, safety, and long-term reliability of the system.
2.	**Economic factors(F_2)**	Relate to the financial feasibility and cost-effectiveness of implementing the system.	Initial investment cost, operating and maintenance costs, cost–benefit analysis, market value of recovered materials, financial incentives or subsidies.	Ensures cost-effectiveness, financial sustainability, and resource recovery benefits.
3.	**Social factors(F_3)**	Focus on public acceptance, awareness, and participation in waste management practices.	Public perception and community support, impact on employment and livelihood, education and awareness programs, health and safety of workers and residents.	Promotes social acceptance, community cooperation, and better public health outcomes.
4.	**Legal factors(F_4)**	Concerned with compliance with laws, regulations, and institutional capacity.	Adherence to environmental laws and waste management rules. Enforcement mechanisms, institutional responsibilities, and coordination. Licensing and reporting requirements.	Ensures legal compliance, accountability, and effective governance in waste management.
5.	**Environmental factors(F_5)**	Related to the impact of the waste management system on natural resources and ecosystems.	Emissions to air, water, and soil, energy consumption and carbon footprint, resource recovery potential, ecological and climate impacts.	Ensures environmental protection, pollution prevention, and sustainable resource use.

to triangular fuzzy numbers (TFNs). The linguistic scales and their corresponding TFN numbers are shown in Tab 4.

4.3 *Method of Numerical Optimization*

Initially, the important factors of industrial waste management have been evaluated using the Best–Worst method. Considering the environmental factors as of the highest importance, and the legal factors as of the lowest importance. The best-to-others vector a_{Bj} (preference of the best factor over each factor), and others-to-worst vector a_{jW} (preference of each factor over the worst factors) as follows,

$$a_{Bj} = [2, 3, 1, 2, 2], \quad a_{jW} = [9, 4, 8, 5, 1],$$

where the entry 9 (extreme importance) is used for a_{TW} (F_1 vs F_1). Solving the BWM linear program using Python LP solver, we got,

$$\xi^* \approx 0.1967, \qquad w = [0.2459,\ 0.1639,\ 0.2951,\ 0.2459,\ 0.0492]. \tag{12}$$

Table 3
Industrial waste management strategies, their descriptions, and key roles

	Waste Management Strategy	Description	Key Role
1.	**Waste minimization or source reduction(M_1)**	Focuses on reducing waste generation at its origin by improving production efficiency, using eco-friendly materials, and adopting cleaner technologies.	Prevents waste creation, lowers treatment costs, and conserves resources and energy.
2.	**Waste segregation(M_2)**	Involves separating waste into categories such as biodegradable, recyclable, and hazardous at the point of generation.	Ensures proper treatment and disposal, enhances recycling efficiency, and reduces environmental risks.
3.	**Recycling and reuse(M_3)**	Conversion of waste materials into usable products or reusing them for the same or different purposes.	Reduces demand for raw materials, conserves energy, and minimizes landfill usage.
4.	**Composting and biological treatment(M_4)**	Uses natural biological processes to decompose organic waste into compost or biogas.	Produces useful products like organic fertilizer and renewable energy while reducing organic waste volume.
5.	**Waste-to-energy process(M_5)**	Converts non-recyclable waste into energy through incineration, pyrolysis, or gasification.	Generates electricity or heat, reduces landfill dependency, and supports renewable energy goals.
6.	**Chemical and physical treatment(M_6)**	Applies processes like neutralization, precipitation, or filtration to reduce toxicity and volume of industrial or hazardous wastes.	Makes hazardous waste safe for disposal and minimizes pollution potential.
7.	**Safe disposal and land filling(M_7)**	Involves scientific disposal of residual waste in engineered landfills with proper liners and leach control.	Ensures safe containment of non-recyclable and hazardous wastes, preventing soil and groundwater contamination.

Thus, the ranking of the factors is $F_3 > F_1 = F_4 > F_2 > F_5$.
Using a conservative $\xi_{\max} = 1$, the Consistency Ratio is $CR \approx 0.1967$, indicating reasonably good consistency.

Now, using these criteria, the FTOPSIS technique is applied step-by-step, and the alternatives are evaluated based on the three experts' linguistic opinions.

4.4 *Result and Observation*

The most effective industrial waste management planning has been selected using the BWM and FTOPSIS methodology; the selection process is shown in Figure 2. First, we meet a few local experts who are known as experts in a specific field for their work. The qualitative opinion was collected by a three-member decision expert group from these local strategists. Here, experts who are known for their expertise in the relevant field, such as industrial professionals, management experts, and academicians. The linguistic qualitative comments for multiple management strategies were converted

Table 4
Linguistic comments of experts and corresponding triangular fuzzy numbers

Linguistic expert comments	Corresponding TFNs)
Very Good (VG)	(9, 9, 10)
Good (G)	(7, 9, 10)
Moderately Good (MG)	(5, 7, 9)
Fair (F)	(3, 5, 7)
Moderately Poor (MP)	(2, 3, 5)
Poor (P)	(1, 2, 3)
Very Poor (VP)	(0, 1, 2)

into TFNs through the three-member decision expert group. Where TFNs reflecting the quality and benefits of the management strategies are given in Tab 4. The initial expert-based matrices are formed depending on expert linguistic opinions and corresponding TFNs-based matrices, as shown in Tab 5 and Tab 6. Now, using the TFNs addition rule 2, three decision matrices are aggregated into a single matrix as in Tab 7, and using the normalization technique 7, the normalized decision matrix has been calculated in Tab 8. The criteria weights of the factors have been calculated using BWM as in 12, and multiplying with these criteria weights, the weighted normalized decision matrix is obtained as Tab 9. Using the score formula 4, the FPIS and FNIS are found in Tab 10, and the distance of each alternative has been calculated from these FPIS and FNIS. Finally, the ranking of the alternatives is obtained according to the closeness coefficient as in Tab 11. A comparative analysis has been conducted where the final ranking of the waste management alternative has been compared and verified with the other two different MCDM techniques, as in Tab 13.

4.5 Sensitivity Analysis

The main goal of sensitivity analysis is to examine how different input values of decision variables impact the output values of the mathematical model. In this model, input values represent the weights assigned to the criteria, and outputs are the ranking order of the alternatives. Here, we have shown in Tab 12 the impact of slide changes of the initial weight of five factors on the ranking order of the alternatives.

4.6 Discussion

In this study, several feasible industrial waste management strategies and important factors were identified and shortlisted as the primary set of alternatives and decision criteria, from which the most effective option is determined through the fuzzy MCDM framework. The initial fuzzy decision matrices were constructed based on expert evaluations obtained from industry professionals, waste management experts, and academicians. The final ranking shows that the composting and biological treatment strategy, i.e., (M_4), holds the first rank, and (M_3), i.e., recycling and reuse, holds the second ranking order; following these, other strategies hold different positions according to their final score values. Through comparison analysis, it was observed that the most preferred alternative is (M_4), followed by the remaining strategies in descending order of preference. This shows the effectiveness and the validity of the proposed hybrid selection strategy. The sensitivity analysis of the model shows that the changes in initial weights of the criteria affect the final ranking order. In cases 2 and 4 of Tab 12, slide changes were observed in the ranking order. The rankings obtained through the fuzzy BWM and FTOPSIS model were compared with the MOORA and VIKOR methodologies, and the ranking order for

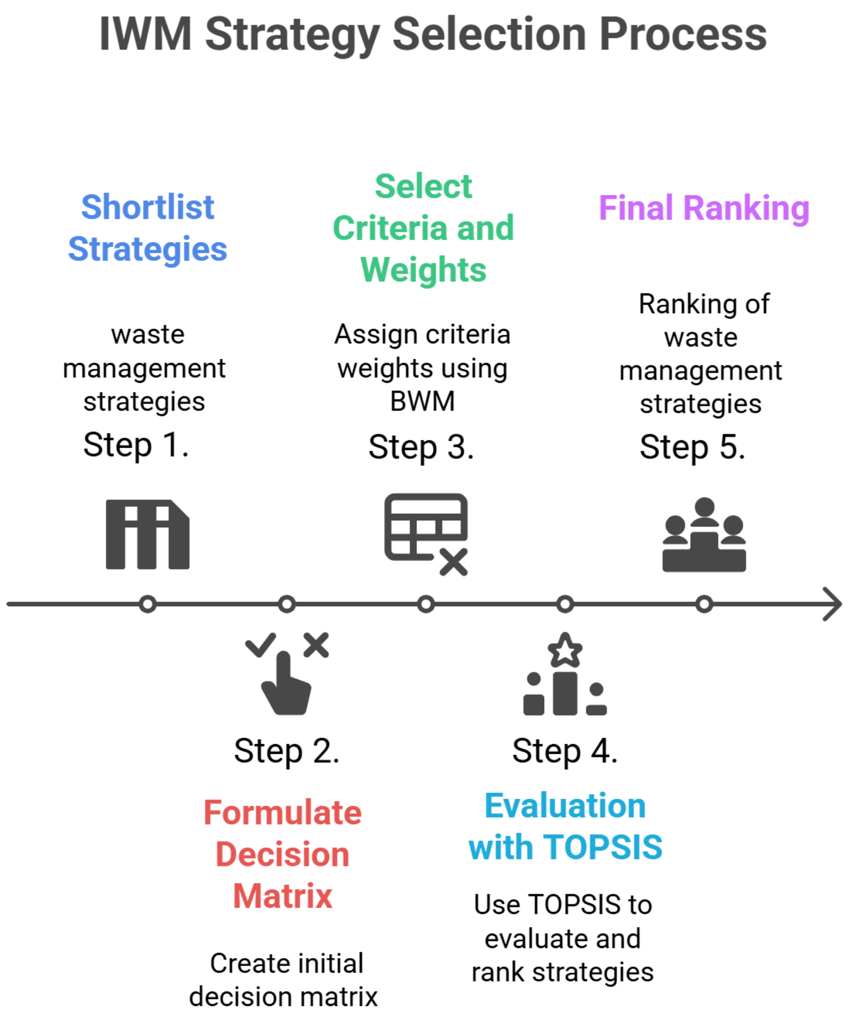

Fig. 2. Flowchart of the best IWM strategy selection process

Table 5
Initial decision matrices for different experts using linguistic variables

Criteria	Alternatives						
	M_1	M_2	M_3	M_4	M_5	M_6	M_7
	For 1^{st} expert(E_1)						
F_1	VG	G	MG	F	MP	P	VP
F_2	G	MG	F	MP	P	VP	VG
F_3	MG	F	MP	P	VP	VG	G
F_4	F	MP	P	VP	VG	G	MG
F_5	MP	P	VP	VG	G	MG	F
	For 2^{nd} expert(E_2)						
F_1	G	MG	F	MP	VG	P	VP
F_2	MG	MP	P	G	F	VP	VG
F_3	F	P	VP	MG	G	MP	VG
F_4	MP	VG	G	F	P	MG	VP
F_5	P	VP	VG	G	MG	F	MP
	For 3^{rd} expert(E_3)						
F_1	VP	P	MP	F	MG	G	VG
F_2	G	VG	MG	F	MP	P	VP
F_3	MG	G	VG	VP	P	MP	F
F_4	F	MP	P	VG	G	MG	VP
F_5	VP	F	MG	G	P	VG	MP

different MCDM techniques shows a stable order of alternatives as shown in Tab 13.

The proposed fuzzy MCDM–based analysis provides valuable insights for both industrial decision-makers and government policymakers by translating complex, uncertain, and multi-dimensional waste management challenges into clear and actionable priorities. For industrial experts, the ranking of waste management strategies assists in identifying the most efficient, cost-effective, and sustainable techniques that align with operational constraints and environmental compliance requirements. For government policymakers, the structured analytical process provides a transparent and scientifically grounded basis for assessing and comparing waste management options across different industrial sectors. As a result, industries can make more informed decisions regarding technology adoption, resource allocation, and long-term waste treatment planning.

Table 6
Decision matrices for different experts using Triangular Fuzzy Numbers (TFNs)

Criteria	Alternatives						
	M_1	M_2	M_3	M_4	M_5	M_6	M_7
	For 1^{st} expert (E_1)						
F_1	(9, 9, 10)	(7, 9, 10)	(5, 7, 9)	(3, 5, 7)	(2, 3, 5)	(1, 2, 3)	(0, 1, 2)
F_2	(7, 9, 10)	(5, 7, 9)	(3, 5, 7)	(2, 3, 5)	(1, 2, 3)	(0, 1, 2)	(9, 9, 10)
F_3	(5, 7, 9)	(3, 5, 7)	(2, 3, 5)	(1, 2, 3)	(0, 1, 2)	(9, 9, 10)	(7, 9, 10)
F_4	(3, 5, 7)	(2, 3, 5)	(1, 2, 3)	(0, 1, 2)	(9, 9, 10)	(7, 9, 10)	(5, 7, 9)
F_5	(2, 3, 5)	(1, 2, 3)	(0, 1, 2)	(9, 9, 10)	(7, 9, 10)	(5, 7, 9)	(3, 5, 7)
	For 2^{nd} expert (E_2)						
F_1	(7, 9, 10)	(5, 7, 9)	(3, 5, 7)	(2, 3, 5)	(9, 9, 10)	(1, 2, 3)	(0, 1, 2)
F_2	(5, 7, 9)	(2, 3, 5)	(1, 2, 3)	(7, 9, 10)	(3, 5, 7)	(0, 1, 2)	(9, 9, 10)
F_3	(3, 5, 7)	(1, 2, 3)	(0, 1, 2)	(5, 7, 9)	(7, 9, 10)	(2, 3, 5)	(9, 9, 10)
F_4	(2, 3, 5)	(9, 9, 10)	(7, 9, 10)	(3, 5, 7)	(1, 2, 3)	(5, 7, 9)	(0, 1, 2)
F_5	(1, 2, 3)	(0, 1, 2)	(9, 9, 10)	(7, 9, 10)	(5, 7, 9)	(3, 5, 7)	(2, 3, 5)
	For 3^{rd} expert (E_3)						
F_1	(0, 1, 2)	(1, 2, 3)	(2, 3, 5)	(3, 5, 7)	(5, 7, 9)	(7, 9, 10)	(9, 9, 10)
F_2	(7, 9, 10)	(9, 9, 10)	(5, 7, 9)	(3, 5, 7)	(2, 3, 5)	(1, 2, 3)	(0, 1, 2)
F_3	(5, 7, 9)	(7, 9, 10)	(9, 9, 10)	(0, 1, 2)	(1, 2, 3)	(2, 3, 5)	(3, 5, 7)
F_4	(3, 5, 7)	(2, 3, 5)	(1, 2, 3)	(9, 9, 10)	(7, 9, 10)	(5, 7, 9)	(0, 1, 2)
F_5	(0, 1, 2)	(3, 5, 7)	(5, 7, 9)	(7, 9, 10)	(1, 2, 3)	(9, 9, 10)	(2, 3, 5)

Table 7
Aggregated decision matrix

Criteria	Alternatives						
	M_1	M_2	M_3	M_4	M_5	M_6	M_7
F_1	(16, 19, 22)	(13, 18, 22)	(10, 15, 21)	(8, 13, 19)	(16, 19, 24)	(9, 13, 16)	(9, 11, 14)
F_2	(19, 25, 29)	(16, 19, 24)	(9, 14, 19)	(12, 17, 22)	(6, 10, 15)	(1, 4, 7)	(18, 19, 22)
F_3	(13, 19, 25)	(11, 16, 20)	(11, 13, 17)	(6, 10, 14)	(8, 12, 15)	(13, 15, 20)	(19, 23, 27)
F_4	(8, 13, 19)	(13, 15, 20)	(9, 13, 16)	(12, 15, 19)	(17, 20, 23)	(17, 23, 28)	(5, 9, 13)
F_5	(3, 6, 10)	(4, 8, 12)	(14, 17, 21)	(23, 27, 30)	(13, 18, 22)	(17, 21, 26)	(7, 11, 17)

Table 8
Normalized decision matrix

Criteria	Alternatives						
	M_1	M_2	M_3	M_4	M_5	M_6	M_7
F_1	(0.666667, 0.791667, 0.916667)	(0.541667, 0.750000, 0.916667)	(0.416667, 0.625000, 0.875000)	(0.333333, 0.541667, 0.791667)	(0.666667, 0.791667, 1.000000)	(0.375000, 0.541667, 0.666667)	(0.375000, 0.458333, 0.583333)
F_2	(0.034483, 0.040000, 0.052632)	(0.041667, 0.052632, 0.062500)	(0.052632, 0.071429, 0.111111)	(0.045455, 0.058824, 0.083333)	(0.066667, 0.100000, 0.166667)	(0.142857, 0.250000, 1.000000)	(0.045455, 0.052632, 0.055556)
F_3	(0.481481, 0.703704, 0.925926)	(0.407407, 0.592593, 0.740741)	(0.407407, 0.481481, 0.629630)	(0.222222, 0.370370, 0.518519)	(0.296296, 0.444444, 0.555556)	(0.481481, 0.555556, 0.740741)	(0.703704, 0.851852, 1.000000)
F_4	(0.285714, 0.464286, 0.678571)	(0.464286, 0.535714, 0.714286)	(0.321429, 0.464286, 0.571429)	(0.428571, 0.535714, 0.678571)	(0.607143, 0.714286, 0.821429)	(0.607143, 0.821429, 1.000000)	(0.178571, 0.321429, 0.464286)
F_5	(0.100000, 0.200000, 0.333333)	(0.133333, 0.266667, 0.400000)	(0.466667, 0.566667, 0.700000)	(0.766667, 0.900000, 1.000000)	(0.433333, 0.600000, 0.733333)	(0.566667, 0.700000, 0.866667)	(0.233333, 0.366667, 0.566667)

Table 9
Weighted normalized decision matrix multiplying by criteria weights

Criteria	Alternatives						
	M_1	M_2	M_3	M_4	M_5	M_6	M_7
F_1	(0.163933, 0.194671, 0.225408)	(0.133196, 0.184425, 0.225408)	(0.102458, 0.153688, 0.215163)	(0.081967, 0.133196, 0.194671)	(0.163933, 0.194671, 0.245900)	(0.092213, 0.133196, 0.163933)	(0.092213, 0.112704, 0.143442)
F_2	(0.005652, 0.006556, 0.008626)	(0.006829, 0.008626, 0.010244)	(0.008626, 0.011707, 0.018211)	(0.007450, 0.009641, 0.013658)	(0.010927, 0.016390, 0.027317)	(0.023414, 0.040975, 0.163900)	(0.007450, 0.008626, 0.009106)
F_3	(0.142085, 0.207663, 0.273241)	(0.120226, 0.174874, 0.218593)	(0.120226, 0.142085, 0.185804)	(0.065578, 0.109296, 0.153015)	(0.087437, 0.131156, 0.163944)	(0.142085, 0.163944, 0.218593)	(0.207663, 0.251381, 0.295100)
F_4	(0.070257, 0.114168, 0.166861)	(0.114168, 0.131732, 0.175643)	(0.079039, 0.114168, 0.140514)	(0.105386, 0.131732, 0.166861)	(0.149296, 0.175643, 0.201989)	(0.149296, 0.201989, 0.245900)	(0.043911, 0.079039, 0.114168)
F_5	(0.004920, 0.009840, 0.016400)	(0.006560, 0.013120, 0.019680)	(0.022960, 0.027880, 0.034440)	(0.037720, 0.044280, 0.049200)	(0.021320, 0.029520, 0.036080)	(0.027880, 0.034440, 0.042640)	(0.011480, 0.018040, 0.027880)

Table 10
FPIS and FNIS of the problem

	FPIS	FNIS
F_1	(0.163933, 0.194671, 0.245900)	(0.092213, 0.112704, 0.143442)
F_2	(0.023414, 0.040975, 0.163900)	(0.005652, 0.006556, 0.008626)
F_3	(0.207663, 0.251381, 0.295100)	(0.065578, 0.109296, 0.153015)
F_4	(0.149296, 0.201989, 0.245900)	(0.043911, 0.079039, 0.114168)
F_5	(0.037720, 0.044280, 0.049200)	(0.004920, 0.009840, 0.016400)

Table 11
Distance of each alternative from FPIS and FNIS along with closeness ratio and ranking

	M_1	M_2	M_3	M_4	M_5	M_6	M_7
D*	0.235014	0.257333	0.312785	0.337224	0.219934	0.156975	0.297707
D$^-$	0.214974	0.192655	0.137203	0.119594	0.230055	0.293013	0.152281
C^*	0.522267	0.571867	0.695096	0.738202	0.488754	0.348842	0.661589
Ranking	5	4	2	1	6	7	3

Table 12
Ranking of the waste management alternatives for five different sets of criteria weights

Case		Criteria weights with ranking order of the alternatives
1.	Weights	(0.2360, 0.1640, 0.2950, 0.2360, 0.0690)
	Ranking	$M_4 > M_3 > M_7 > M_2 > M_1 > M_5 > M_6$
2.	Weights	(0.2400, 0.1700, 0.3000, 0.2400, 0.0500)
	Ranking	$M_4 > M_3 > M_7 > M_2 > M_5 > M_1 > M_6$
3.	Weights	(0.2500, 0.1600, 0.2900, 0.2500, 0.0500)
	Ranking	$M_4 > M_3 > M_7 > M_2 > M_1 > M_5 > M_6$
4.	Weights	(0.2480, 0.1650, 0.2920, 0.2480, 0.0470)
	Ranking	$M_4 > M_3 > M_2 > M_7 > M_1 > M_5 > M_6$
5.	Weights	(0.2420, 0.1680, 0.2980, 0.2420, 0.0500)
	Ranking	$M_4 > M_3 > M_7 > M_2 > M_1 > M_5 > M_6$

Table 13
Validation of ranking order through BWM-MOORA and BWM-VIKOR methodologies

Methodology	Ranking order
BWM-TOPSIS	$M_4 > M_3 > M_7 > M_2 > M_1 > M_5 > M_6$
BWM-MOORA	$M_4 > M_3 > M_7 > M_2 > M_1 > M_5 > M_6$
BWM-VIKOR	$M_4 > M_3 > M_7 > M_2 > M_1 > M_5 > M_6$

5. Conclusion

This study successfully demonstrated an expert-driven fuzzy MCDM framework for evaluating sustainable industrial waste management alternatives using the BWM and FTOPSIS approach. The IWM decision-making process often involves multiple conflicting criteria, uncertain expert judgments, and qualitative assessments that are difficult to handle using traditional crisp methods. These challenges were effectively addressed by representing expert evaluations using triangular fuzzy numbers, which effectively capture uncertainty and vagueness in the decision-making process. Through the integration of expert opinions, linguistic assessments, and fuzzy membership functions, the proposed hybrid MCDM model evaluated several realistic industrial waste management alternatives and identified the most suitable option using the BWM and FTOPSIS ranking methods. It has been observed that the methodology is capable of processing a wide range of qualitative and quantitative factors, including environmental impacts, economic feasibility, technological performance, regulatory compliance, and social considerations. The results show that a fuzzy MCDM-based approach is a more reliable, transparent, and flexible decision-support mechanism for selecting optimal IWM strategies in the Management field. Also, it can be concluded that decision-making with a structured expert evaluation process improves both the feasibility and efficiency of real-life decision-making. During the study, some advantages and limitations of the hybrid BWM-FTOPSIS are identified . The method offers a systematic and transparent approach for handling the complexity and uncertainty associated with real-life decision-making problems. However, it also has certain limitations. The methodology allows multiple decision-making criteria for the overall assessment of the alternatives, ensures a complete ranking list, and can easily handle a large set of alternatives as well as decision factors, and is highly efficient in managing large datasets. But the technique is quite lengthy and requires considerable time to get final results, as it involves several complex steps, so handling data manually with pen and paper is difficult; advanced data processing software is necessary.

At last, it is hoped that the proposed fuzzy expert-based hybrid MCDM can be useful to various complex real-world contexts, including environmental sustainability, pollution control, resource recovery, and industrial process optimization. Various future works may explore integrating fuzzy MCDM techniques with emerging artificial intelligence and data analysis, including machine learning, evolutionary computation, and expert systems. These hybrid frameworks can further enhance predictive capabilities, robustness, and adaptability in broader applications such as circular economy planning, industrial supply chain sustainability, infrastructure development, environmental risk assessment, and energy–waste nexus optimization.

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Conflicts of Interest
The authors declare no conflicts of interest.

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