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SUSTAINABLE WASTE MANAGEMENT USING IOT AND AI TECHNOLOGIES

An identification of optimal waste disposal method for dumpsite remediation using the Fermatean fuzzy multi-criteria decision-making method

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Abstract

Improperly managed wastes that have been dumped in landfills over the years pose various challenges, but they also offer potential benefits. The feasibility of recycling such waste depends on the type of wastes, the condition of dumpsites, and the technology implemented for disposal. The selection of an alternative waste disposal method from the many available options for dumpsite remediation is a complex decision-making process among experts. The primary aim of this study is to assist in an extended multi-criteria decision-making (MCDM) method to reduce complexity in the proposed dumpsite remediation problem influenced by multiple criteria and to identify the optimal waste disposal method. Data uncertainties are managed with the proposed Fermatean fuzzy preference scale, and the importance of all socio-economic criteria is assessed using the full consistency method (FUCOM). The final ranking results of the weighted aggregated sum product assessment (WASPAS) method identify that the Waste-to-Energy (WtE) process could play a significant role in the disposal of land-filled unprocessed wastes, promoting sustainable waste management. Meanwhile, the methodology explores the idea that financial and logistical constraints may limit the feasibility of large-scale recycling efforts. This combination of environmental science and decision science addresses real-world challenges, helping municipal solid waste management authorities implement sustainable waste management practices.

Keywords Municipal solid waste management · Uncontrolled dumpsites · Contamination and its effects · Dumpsites rehabilitation · Fermatean fuzzy preferences · Multi-criteria decision-making

Introduction

The dumpsite, also known as an open dump or uncontrolled landfill, is a location where waste is disposed of without following proper waste management methods (Rouf et al. 2022). Sustainable waste management entails a variety of measures designed to reduce environmental impact and increase resource recovery. Dumpsite management should be included in that list of waste management strategies, because most of the world's massive sanitary territorial zones began to overflow due to the continuous dumping of millions of tonnes of unprocessed waste over the last 50 years (Kang et al. 2023). Dumpsites, if not properly handled, can pose a significant environmental risk. According to the literature review, dumpsites represent considerable environmental and human health problems, including soil and water contamination from leachates, air pollution, and groundwater contamination (Yinbang et al. 2022). Dumpsite management may include techniques such as remediation and rehabilitation of dumpsites, as well as a shift from uncontrolled dumping to more ecologically friendly and sustainable waste management practices (Siddiqua et al. 2022). Regulatory compliance, community participation, and the installation of proper dumpsite waste disposal processes are all part of the remediation operations, but selecting the best waste disposal method is difficult (Kannan et al. 2021). Because many typical waste disposal strategies are available in actions, but dumpsites require a technique to break down all sorts of garbage, such as organic, inorganic, recyclable, industrial, and hazardous waste into distinct forms. Policymakers

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need a multidimensional methodology, such as multi-criteria decision-making (MCDM), to meet this identified challenge. The use of the MCDM approach in dumpsite management allows for a new dimensional waste management research that includes a full and systematic examination of potential recycling procedures while taking into account numerous criteria and expert opinions.

The limitations on implementing fuzzy MCDM technique in waste management scenarios include careful consideration of the specific context, continuous refinement of models, and an awareness of the inherent uncertainties in decision-making processes. Hence, this article combines the full consistency technique (FUCOM) for evaluating criterion weights (A_j) with the weighted aggregated sum product assessment (WASPAS) approach for analyzing alternatives (R_i) under the suggested Fermatean fuzzy preference scale. Because decision-makers and MCDM approaches frequently meet unclear and uncertain circumstances when assessing the relative significance of one aspect to another, linguistic values with fuzzy preference scales can be provided in place of crisp judgments (Seikh et al. 2022). The Fermatean fuzzy set (FFS) is especially effective at representing more realistic preference values on both belongingness and non-belongingness degrees to handle uncertainty (Mishra et al. 2022). In addition, designing and utilizing fuzzy sets for weight determination and performance evaluation is not a novel concept in soft computing. FUCOM, on the other hand, is a relatively recent multi-criteria approach for finding weight coefficients. The FUCOM technique is an indirect and subjective method in which experts judge the relevance of criteria based on their point of view (Narayanamoorthy et al. 2023). The performance of FUCOM is based on specified priority and pairwise comparison of criteria; only a minimal number of comparisons are required. Another advantage of this technology is its built-in model verification capability and assured consistency (Pamučar et al. 2018; Ocampo 2022). Furthermore, because of its capacity to deliver more accurate findings through weighted sum and product evaluation, the WASPAS approach is now widely acknowledged as an efficient decision-making tool (Kizielewicz and Baczkiewicz 2021; Kang et al. 2023). This informed decision-making technique might assist waste management authorities in developing repair and rehabilitation programs for dumpsites, developing rules for regulated waste disposal, and dealing with waste management uncertainty.

Motivation and contribution

Identified research limitations

The discovered research gap and environmental advantages in dumpsite management utilizing proposed MCDM approaches are the motivation for this research work and serve as objectives to achieve in this research study. The constraints are as follows:

- Through literature surveys, the research contribution of the MCDM approach in waste management is found to be significant, but there are certain constraints to overcome, such as computational complexity, data uncertainty, and a lack of contribution on dumpsite waste management.
- The literature review on contamination and the long-term impacts of dumpsites demonstrates the importance of the remediation procedure in saving the ecosystem from pollution.
- Implementing an effective alternative waste disposal approach can result in an overall improvement in dumpsite remediation operations and environmental pollution control. However, there are limitations to the research study on identifying optimal waste disposal techniques for dumpsite repair in the MCDM platform.
- An integrated FUCOM-WASPAS method combines the benefits of two distinct and efficient MCDM methodologies, but it has limitations in areas such as modeling, assessing, and finding results for extensive strategic environmental management applications.

Contributions

- The key contributions begin with the development of a new FFS preference scale to overcome information ambiguity and indirect preferences.
- In the FUCOM technique, we introduced Fermatean fuzzy preferences and developed an algorithm for determining criterion weights collectively.
- We expanded the WASPAS method's applicability to performance evaluation in the presence of ambiguity and alternative rankings.
- By examining four alternatives and seven influencing variables, we identified the MCDM challenge of selecting feasible dumpsite waste disposal solutions to promote dumpsite rehabilitation.
- The MCDM techniques FUCOM and WASPAS are combined under FFS preferences, which efficiently managed data uncertainty, decreased computing complexity, saved time, and increased the correctness of the findings.

This article is organized as follows: Section 2 contains the required literature reviews. Section 3 provides early definitions of fuzzy sets and their attributes. Section 4 illustrates the suggested MCDM approaches' algorithms; Section 5 describes the empirical study and mathematical evaluations; Section 6 addresses comparative and sensitive analysis; Section 7 discusses the results, implications and limitations; Section 8 presents conclusion and future directions.

Literature reviews

Decision-making on waste management

Many researchers have developed many MCDM algorithms and successfully applied them to a wide range of environmental management challenges, including waste management, renewable energy, water resource management, climate change, and strategic analysis (Mardani et al. 2017). We are now concentrating on the efficacy of MCDM in managing waste as in Table 1. Alao et al. (2022) created a combined MCDM approach that used conventional AHP (Analytical Hierarchical Process), ENTROPY, and MULTUIMOORA (Full Multiplicative Form of Multi-Objetive Optimization by Ration Analysis) methods to select integrated anaerobic digestion and gasification process as optimal waste-to-energy technique, and they discovered that information vagueness should be managed with fuzzy preferences. Torkayesh and Simic (2022) established and verified a stratified targeting technique in the BWM (Best-Worst Method) method to find sustainable healthcare waste management locations. They also discovered that data ambiguity is a barrier to obtaining optimal answers. Using AHP and TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) methodologies, Shahnazari et al. (2020) discovered that plasma technology is an excellent energy recovery approach from municipal solid waste. Kang et al. (2023) discovered that plasma technology is the best waste-to-energy method for dumpsite plastic waste disposal, employing layered AHP and WASPAS techniques to assure long-term sustainability. However, both hybrid MCDM approaches must enhance computational ease. Seikh and Mandal (2023) created a group decision-making issue utilizing SWARA (Stepwise Weight Assessment Ratio Analysis) and PROMETHEE-II (Preference Ranking Organization METHod for Enrichment of Evaluations) methodologies to determine if the biochemistry lab is competent for dangerous bio-medical waste. Mandal and Seikh (2023) used ENTROPY, the deviation-based technique, and MABAC (Multi-Attributive Border Approximation area Comparison) with dombi aggregation operators for criterion weights and alternative ranking evaluation to determine that recycling is the most sustainable way of disposing of plastic garbage. Rahman et al. (2023) used a ranking technique with a fuzzy parameterized possibility single valued neutrosophic hypersoft set to find the best location for various solid waste management systems. Narayanamoorthy et al. (2023) used FUCOM and MABAC to increase computation ease and select recycling with recovery strategy as the best option for disposing of inorganic solid waste. Meanwhile, Shahnazari et al. (2021) employed AHP and VIKOR (VIsekriterijumska optimizacija i KOmpromisno Resenje) techniques to choose vermicomposting as an ideal organic fertilizer-producing technology from organic municipal solid waste.

Contamination and effects of dumpsites

Contamination associated with dumpsites results from the improper disposal and dumping of various types of waste over the past five decades (Alao 2023). The contamination and its environmental effects vary in multiple forms, including soil and water contamination, air pollution, human health risks, habitat degradation, and social impacts (Yinbang et al. 2022; Siddiqua et al. 2022). One prevalent form of contamination is leachates, which are liquids containing harmful substances such as heavy metals, hazardous chemicals, and other pollutants. Leachates have the ability to leach into the soil, degrading its quality and posing risks to terrestrial ecosystems (Anand et al. 2022; Issac and Kandasubramanian 2021). Leachates pose a subsequent risk by polluting aquatic ecosystems in two ways: groundwater pollution and surface water pollution (Rouf 2022). Through soil contamination, leachates reach groundwater sources, posing risks to human health. Simultaneously, runoff water from dumpsites during rainfall events carries contaminants into nearby surface water bodies, harming aquatic life and water users (Alao 2023; Anand et al. 2022). The decomposition of organic wastes in dumpsites releases greenhouse gases (GHGs), and accidental burns or unapproved incineration in dumpsites release particulate matters into the environment, contributing to air pollution and climate change (Salami and Popoola 2023). These contaminations have various effects on human health, including respiratory illnesses, transmissible diseases facilitated by disease vectors, and other health issues (Siddiqua 2022). These effects are not limited to humans; they also impact natural habitats, affecting plants, animals, birds, and other species, turning their ecosystems uninhabitable (Li et al. 2023). The identified effects last for a long period, leading to and initiating long-term damages in ecosystems, economic development, and societal well-being (Somani et al. 2022).

Dumpsites remediation

The remediation of dumpsites is a complex issue because it should mitigate the environmental pollution, health risks, and uncontrolled waste disposal (Massoud et al. 2023). It has different categories of approaches, each process carrying dedicated procedure and objectives (Mondal et al. 2023). Suppose, to minimize further contamination, the closing and capping technique can be processed because it stops accepting the waste to dump and covers its leakages to avoid surface water pollution (Massoud et al. 2023). Also, emission of GHG like methane in environment after decomposition can be avoided with landfill gas management technique, which

Table 1 Various decision-making approaches in waste management studies

Method	Application	Addressing issue	Optimal solution	Limitations	Cite code
AHP-ENTROPHY-MULTIMOORA	Solid waste management	Optimal waste-to-energy technique selection problem	Integrated anaerobic digestion and gasification	Need to use fuzzy preferences to manage ambiguous information	Alao et al. (2022)
BWM-COCOSO-WASPAS	Healthcare waste management	Sustainable site selection problem in Istanbul	Pendik district	Data uncertainty	Torkayesh and Simic (2022)
AHP-WASPAS	Dumpsites plastic waste management	Optimal waste-to-energy technique selection problem to dispose dumpsites waste plastic	Plasma technology	Needs to improve computational easiness	Kang et al. (2023)
AHP-TOPSIS	Municipal solid waste management	Optimal energy recovering thermo-chemical technique selection problem for proper waste disposal	Plasma technology	Needs sustainability analysis	Shahnazari et al. (2020)
SWARA-PROMETHEE-II	Bio-medical waste management	Selecting capable organization to handle bio-medical wastes problem	Bio-chemistry lab	Needs more experts for group decision-making and computational easiness	Seikh and Mandal (2023)
ENTROPHY-MABAC	Plastic waste management	Identifying sustainable method of plastic waste management problem	Recycling	Computational complexity and lack of wide range application	Mandal and Seikh (2023)
Sanchez	Solid waste management	Problem to select suitable site for optimal solid waste management system	Landfills	Needs to address computational complexity and to improve uncertainty handling efficiency	Rahman et al. (2023)
ANN	Waste management	Developing artificial intelligence powered waste sorting for recycling	Digital-enabled circular economy vision with 91.7% accuracy	Needs extensive research to reduce time and computational cost complexities and to improve technology applicability	Mohammed et al. (2022)
SVM	Medical waste management	Developing artificial intelligence powered medical waste sorting especially COVID-19 waste for recycling	Digital-enabled circular economy vision with 96.5% accuracy	Needs extensive research to reduce time and computational cost complexities, to improve technology applicability in all types of waste, and to address data uncertainty	Kumar et al. (2021)
FUCOM-MABAC	Inorganic solid waste management	Identifying optimal inorganic solid waste management technique problem	Energy recovery and refused-derived fuel techniques	Lack of machine learning computation	Narayanamoorthy et al. (2023)
AHP-VIKOR	Municipal solid waste management	Identifying optimal organic fertilizer production method from municipal solid waste problem	Vermicomposting	Data uncertainty	Shahnazari et al. (2021)

collects and manages GHG using gas collection infrastructure (Mondal et al. 2023). The groundwater contamination and its spreads can be reduced in large amount with leachates treatment technique; it collects and treats the percolate liquids through dedicated infrastructure (Anand et al. 2022). The polluted soil treatments can be performed through phytoremediation, bioremediation, or soil washing to improve the quality of contaminated soil (Marsum et al. 2022). The complete dumpsites waste disposal activities to reduce environment pollution can be performed through an optimal alternative waste disposal technique better than uncontrolled landfills (Karimi 2023; Kang et al. 2023). This could be supported by waste sorting and removal technique. Furthermore, long-term dumpsite management monitoring and community engagement with education about proper waste disposal could support dumpsite remediation process well (Mor and Ravindra 2023).

Preliminaries

The fundamental definitions of FFS and its properties to introduce in FUCOM and WASPAS methods (Keshavarz-Ghorabaee et al. 2020) are described as follows:

Definition 1 Let the universal discourse be W and the subset called FFS provides Fermatean relation, $F_i \in W$ is in the form of $F_i = \{\langle f,\ M_i(f),\ N_i(f)\rangle \,|\, f \subset W\}$, here $M_i(f) : W \to [0, 1] \implies$ the belongingness degree and $N_i(f) : W \to [0, 1]$ of $f \in W \implies$ non-belongingness degree, which satisfies the condition $0 \leq M_i(f)^3 + N_i(f)^3 \leq 1$. The indeterminacy of an element f can be calculated using $\pi(f) = \sqrt[3]{1 - M_i^3 - N_i^3} \mid \forall f \in W$ and $i = 1, 2, 3, \ldots, x$.

Definition 2 Let F_i be a FFS set, then the score function, $S(F_i)$ and the accuracy function, $A(F_i)\ \forall\ i = 1, 2, 3, \ldots, x$ can be defined as $S(F_i) = M_i(f)^3 - N_i(f)^3$ should satisfy $-1 \leq S(F_i) \leq 1$ and $A(F_i) = M_i(f)^3 + N_i(f)^3$ wherein $0 \leq A(F_i) \leq 1$.

Remark 1 Table 2 represents FFS form of preference scale or fixed membership grades according to the linguistic variables for construction of pair-wise comparative decision matrix, DM. In Fig. 1a and b, the range of accuracy and de-fuzzification of proposed FFS membership values are demonstrated and which satisfies its boundary conditions, $0 \leq A(F_i) \leq 1$ and $-1 \leq S(F_i) \leq 1$.

Remark 2 Table 3 represents the FFS form of preference scale or fixed membership grades with linguistic variables for providing pair-wise comparative preference between criteria based on its significance values. In Fig. 2a and b, the range of accuracy and de-fuzzification of proposed FFS membership values are demonstrated and which satisfies the boundary conditions, $0 \leq A(F_i) \leq 1$ and $-1 \leq S(F_i) \leq 1$.

Table 2 Preference scale 1: FFS common comparison scale

Linguistic scale	M_i	N_i
VVLP	0.15	0.9
VLP	0.25	0.8
LP	0.35	0.7
MLP	0.45	0.6
MP	0.55	0.5
MHP	0.65	0.4
HP	0.75	0.3
VHP	0.85	0.2
VVHP	0.95	0.1
V-Very	L-Low	M-Medium
H-High	P-Preference	

Definition 3 For any two FFS, $F_1 = (M_1(f),\ N_1(f))$ and $F_2 = (M_2(f),\ N_2(f))$ where $(M_i(f), N_i(f)) \in [0, 1]$ and $\lambda > 0$, then, the basic set operations between F_1 and F_2 are defined as

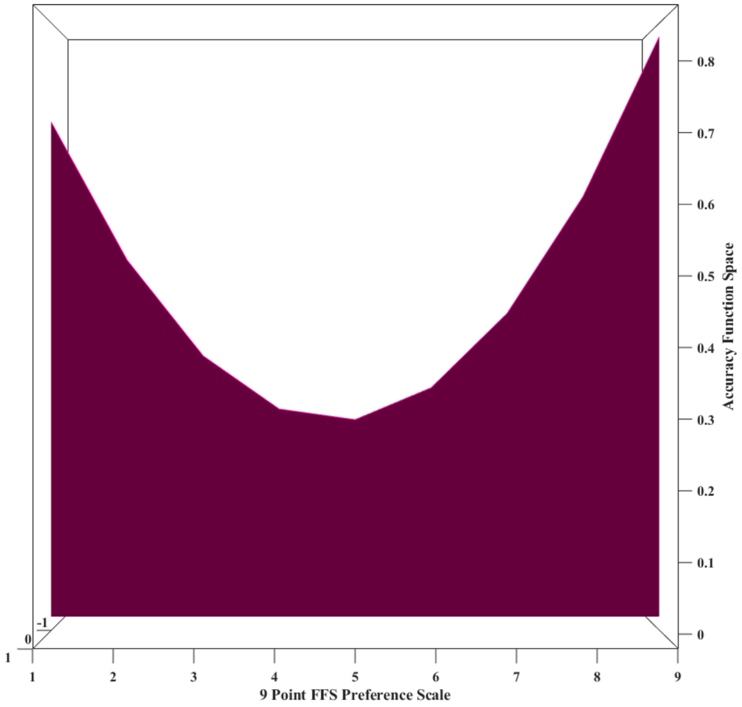
(i) $F_1 \cap F_2 = (\min\{M_1(f),\ M_2(f)\}, \max\{N_1(f),\ N_2(f)\})$
(ii) $F_1 \cup F_2 != (\max\{M_1(f),\ M_2(f)\}, \min\{N_1(f),\ N_2(f)\})$
(iii) $F_1^c = (N_1(f),\ M_1(f))$
(iv) $F_1 \oplus F_2 = \left(\sqrt[3]{M_1(f)^3 + M_2(f)^3 - M_1(f)^3 M_2(f)^3}, N_1(f) N_2(f)\right)$
(v) $F_1 \otimes F_2 = \left(M_1(f) M_2(f),\ \sqrt[3]{N_1(f)^3 + N_2(f)^3 - N_1(f)^3 N_2(f)^3}\right)$
(vi) $F_1 \ominus F_2 = \{\left(\sqrt[3]{\frac{M_1(f)^3 - M_2(f)^3}{1 - M_2(f)^3}},\ \frac{N_1(f)}{N_2(f)}\right) | if\, M_1(f) \geq M_2(f), N_1(f) \leq N_2(f)\}$
(vii) $F_1 \oslash F_2 = \left(\frac{M_1(f)}{M_2(f)},\ \sqrt[3]{\frac{N_1(f)^3 - N_2(f)^3}{1 - N_2(f)^3}} | if\, M_1(f) \leq M_2(f), N_1(f) \geq N_2(f)\right)$
(viii) $\lambda F_1 = \left(\sqrt[3]{1 - (1 - M_1(f)^3)^\lambda},\ N_1(f)^\lambda\right)$
(ix) $F_1^\lambda = \left(M_1(f)^\lambda,\ \sqrt[3]{1 - (1 - N_1(f)^3)^\lambda}\right)$

The proposed preference values proved these assertions representing the commutative, associative, and distributive laws through following theorems:

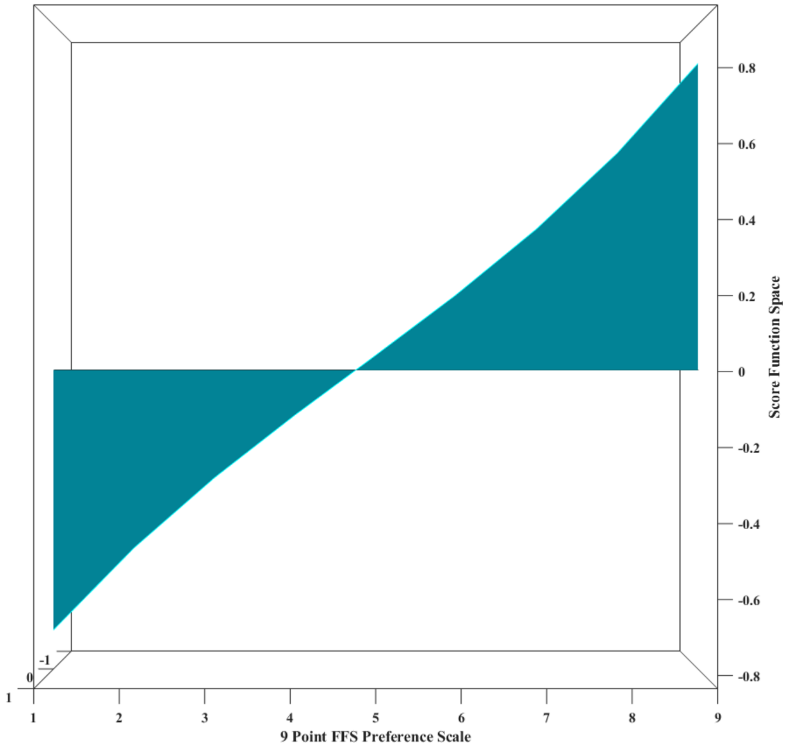
Theorem 1 *Let F_1 and F_2 be any two FFS satisfies the commutative law of intersection, union, addition, and multiplication as*

(i) $F_1 \cap F_2 = F_2 \cap F_1$
(ii) $F_1 \cup F_2 = F_2 \cup F_1$
(iii) $F_1 \oplus F_2 = F_2 \oplus F_1$
(iv) $F_1 \otimes F_2 = F_2 \otimes F_1$

Fig. 1 Validation of the proposed FFS preference scale 1



(a) Accuracy state of nine point preference scale



(b) De-fuzzification state of nine point preference scale

Table 3 Preference scale 2: FUCOM comparison scale

Linguistic scale	$M_i(f)$	$N_i(f)$
VVLS	0.2	0.1
VLS	0.3	0.15
LS	0.4	0.2
MLS	0.5	0.25
MS	0.6	0.3
MHS	0.7	0.35
HS	0.8	0.4
VHS	0.9	0.45
VVHS	0.95	0.5
V-Very	L-Low	M-Medium
H-High	S-Significance	

Example 3.1 Let $F_1 = (0.95, 0.1)$ and $F_2 = (0.15, 0.9)$; then according to Definition 3, the assertions from Theorem 1 are verified as, (i) $F_1 \cap F_2 = (0.95, 0.1) \cap (0.15, 0.9) = (0.15, 0.9) = F_2 \cap F_1$, (ii) $F_1 \cup F_2 = (0.95, 0.1) \cup (0.15, 0.9) = (0.95, 0.1) = F_2 \cup F_1$, (iii) $F_1 \oplus F_2 = (0.95, 0.1) \oplus (0.15, 0.9) = (0.9502, 0.09) = F_2 \oplus F_1$ and (iv) $F_1 \otimes F_2 = (0.95, 0.1) \otimes (0.15, 0.9) = (0.1425, 0.9) = F_2 \otimes F_1$.

Theorem 2 *Let F_1, F_2, and F_3 be any three FFS satisfies the associative law of intersection, union, addition, and multiplication as*

$$(v)\ F_1 \cap (F_2 \cap F_3) = (F_1 \cap F_2) \cap F_3$$
$$(vi)\ F_1 \cup (F_2 \cup F_3) = (F_1 \cup F_2) \cup F_3$$
$$(vii)\ F_1 \oplus (F_2 \oplus F_3) = (F_1 \oplus F_2) \oplus F_3$$
$$(viii)\ F_1 \otimes (F_2 \otimes F_3) = (F_1 \otimes F_2) \otimes F_3$$

Example 3.2 Let $F_1 = (0.95, 0.1)$, $F_2 = (0.85, 0.2)$, and $F_3 = (0.15, 0.9)$; then according to Definition 3, the assertions from Theorem 2 are verified as (v) $F_1 \cap (F_2 \cap F_3) = (0.95, 0.1) \cap ((0.85, 0.2) \cap (0.15, 0.9)) = (0.95, 0.1) \cap (0.15, 0.9) = (0.15, 0.9) = (F_1 \cap F_2) \cap F_3$, (vi) $F_1 \cup (F_2 \cup F_3) = (0.95, 0.1) \cup ((0.85, 0.2) \cup (0.15, 0.9)) = (0.95, 0.1) \cup (0.85, 0.2) = (0.95, 0.1) = (F_1 \cup F_2) \cup F_3$, (vii) $F_1 \oplus (F_2 \oplus F_3) = (0.95, 0.1) \oplus ((0.85, 0.2) \oplus (0.15, 0.9)) = (0.95, 0.1) \oplus (0.8506, 0.18) = (0.9814, 0.018) = (F_1 \oplus F_2) \oplus F_3$ and $(viii)$ $F_1 \otimes (F_2 \otimes F_3) = (0.95, 0.1) \otimes ((0.85, 0.2) \otimes (0.15, 0.9)) = (0.95, 0.1) \otimes (0.1275, 0.9009) = (0.1211, 0.9010) = (F_1 \otimes F_2) \otimes F_3$.

Theorem 3 *Let F_1 and F_2 be any three FFS and $\lambda_1, \lambda_2 > 0$ satisfies the distributive law as*

$$(ix)\ \lambda_1.(F_1 \oplus F_2) = \lambda_1.F_1 \oplus \lambda_1.F_2$$
$$(x)\ (\lambda_1 \oplus \lambda_2).F_1 = \lambda_1.F_1 \oplus \lambda_2.F_1$$
$$(xi)\ \lambda_1.(F_1 \cup F_2) = \lambda_1.F_1 \cup \lambda_1.F_2$$
$$(xii)\ (F_1 \cup F_2)^{\lambda_1} = F_1^{\lambda_1} \cup F_2^{\lambda_1}$$

Example 3.3 Let the membership grades are $F_1 = (0.85, 0.2)$ and $F_2 = (0.15, 0.9)$ and the positive constants are $\lambda_1 = 0.6$, $\lambda_2 = 0.4$; then according to Definition 3, the assertions from Theorem 3 are verified as **(ix)** $\lambda_1.(F_1 \oplus F_2) = ((0.6).((0.85, 0.2) \oplus (0.15, 0.9))) = ((0.6).(0.8506, 0.18)) = (0.7585, 0.3574) = \lambda_1.F_1 \oplus \lambda_1.F_2$, **(x)** $(\lambda_1 \oplus \lambda_2).F_1 = (0.6 + 0.4).(0.85, 0.2) = (0.85, 0.2) = (0.7578, 0.3807) + (0.6817, 0.5253) = (0.6).(0.85, 0.2) + (0.4).(0.85, 0.2) = \lambda_1.F_1 \oplus \lambda_2.F_1$, **(xi)** $\lambda_1.(F_1 \cup F_2) = (0.6)((0.85, 0.2) \cup (0.15, 0.9)) = (0.6).(0.85, 0.2) = (0.7578, 0.3807) = (0.7578, 0.3807) \cup (0.1260, 0.9387) = ((0.6).(0.85, 0.2)) \cup ((0.4).(0.15, 0.9)) = \lambda_1.F_1 \cup \lambda_1.F_2$ and **(xii)** $(F_1 \cup F_2)^{\lambda_1} = ((0.85, 0.2) \cup (0.15, 0.9))^{0.6} = (0.85, 0.2)^{0.6} = (0.9071, 0.1687) = (0.85, 0.2)^{0.6} \cup (0.15, 0.9)^{0.6} = F_1^{\lambda_1} \cup F_2^{\lambda_1}$.

Methodology

The hierarchical structure (Fig. 3) represents the concept of integrated FFS-FUCOM-WASPAS method. Let $A_j | j = 1, 2, 3, \ldots, y$ represents criteria and $R_i | i = 1, 2, 3, \ldots, x$ represents alternatives of a decision-making problem. The computational algorithms of extended FFS-FUCOM and FFS-WASPAS methods are described as follows:

FFS-FUCOM algorithm

Step (i) Identify most important criteria from a set of shortlisted criteria $(A_j | j = 1, 2, 3, \ldots, y)$, then determine the criteria rank set $(A_j^r | r = 1, 2, 3, \ldots, z \quad \& \quad r = rank)$ as

$$A_j^1 > A_j^2 > A_j^3 > \ldots > A_j^z$$

Step (ii)

Determine the significance of criteria $(K(A_j^r))$ by pairwise comparison of adjacent attributes and proposed FFS comparison scale preferences (Table 3).

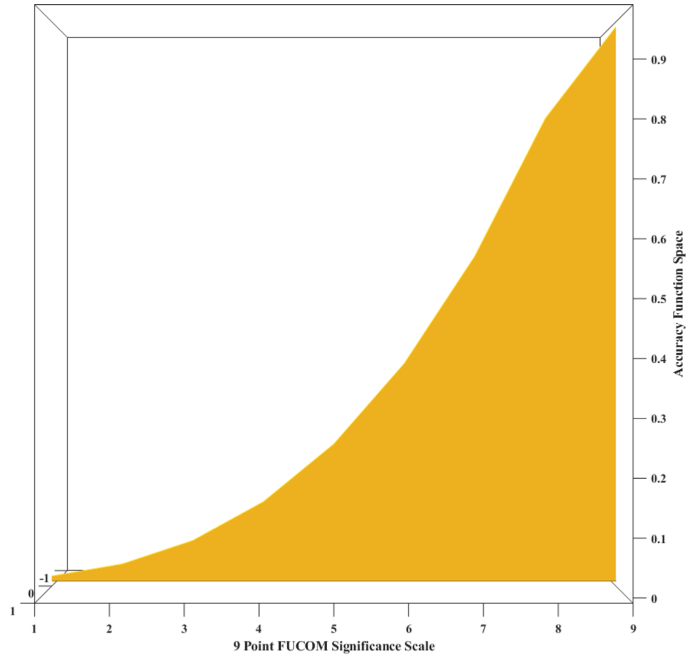
Step (iii) Evaluate the comparative significance values of preferred criteria as $\psi = (\psi_{1/2}, \psi_{2/3}, \psi_{3/4}, \ldots, \psi_{z-1/z})$ using

$$\psi_{r/r+1} = K(A_j^1)/K(A_j^2)$$

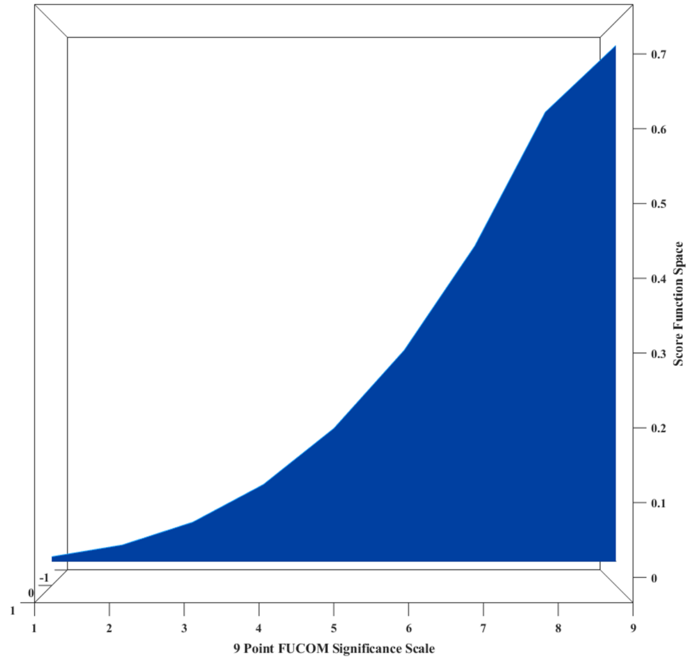
where $r = 1, 2, 3, \ldots, z$ denotes the rank of criteria.

Step (iv) The final criteria weight coefficients $(p_1, p_2, \ldots, p_7)$ can be calculated by solving the nonlinear constrained

Fig. 2 Validation of the proposed FUCOM FFS preference scale 2



(a) Accuracy state of nine point FUCOM significance scale



(b) De-fuzzification state of nine point FUCOM Significance scale

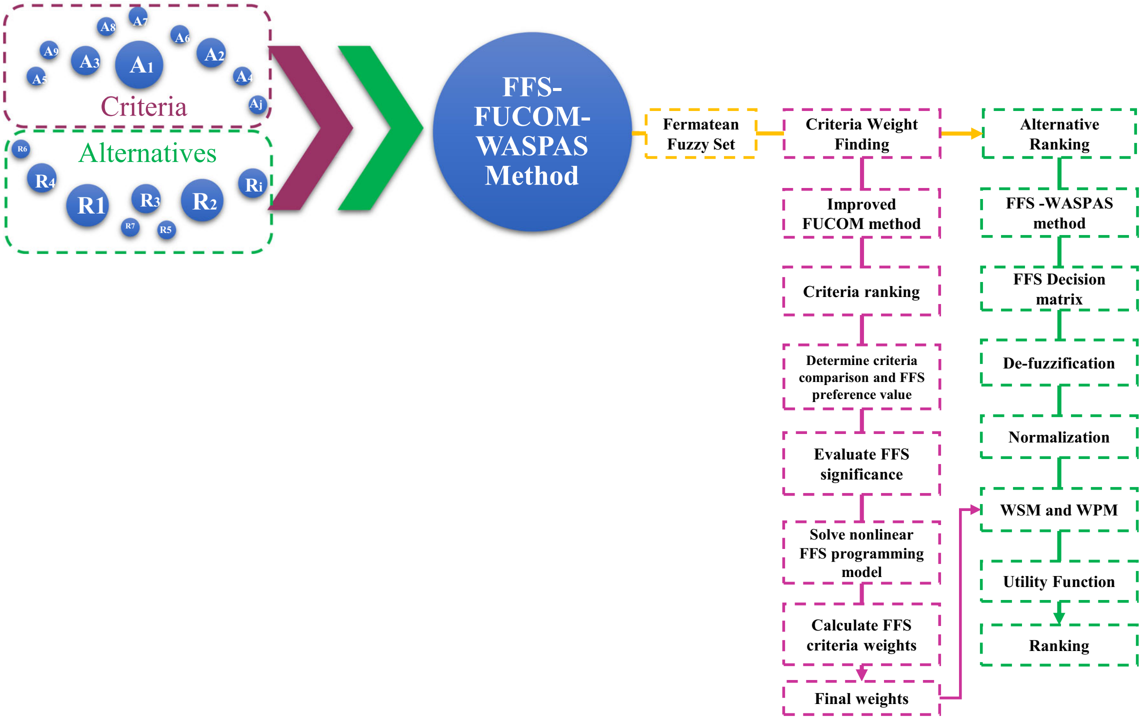


Fig. 3 Hierarchy of the proposed MCDM method

programming model Eq. (1), and it should satisfy the following two conditions:

- (i) The ranked criteria (A_j^r and A_j^{r+1}) should have weight coefficient ratio equal to the criteria comparative significance ($\psi_{r/r+1}$), determined in Step (iii), that is,

  $$p_r/p_{r+1} = \psi_{r/r+1}$$

- (ii) The final criteria weight coefficients should satisfy its transitivity of criteria comparative significance values, that is, $\psi_{r/r+1} \times \psi_{r+1/r+2} = \psi_{r/r+2}$ and $p_r/p_{r+1} \times p_{r+1}/p_{r+2} = p_r/p_{r+2}$ which implies

  $$p_r/p_{r+2} = \psi_{r/r+2}$$

The novel fermatean fuzzy nonlinear programming model construction to calculate the final criteria weights $(p_j | j = 1, 2, 3, \ldots, y)$ is

$$\begin{aligned}
&\min \quad \Delta,\\
&subject \quad to\\
&\left|\frac{p_j^m}{p_j^m} - \psi^m_{r/r+1}\right| \leq \Delta, \quad \left|\frac{p_j^n}{p_j^n} - \psi^n_{r/r+1}\right| \leq \Delta,\\
&\left|\frac{p_j^m}{p_j^m} - \psi^m_{r/r+2}\right| \leq \Delta, \quad \left|\frac{p_j^n}{p_j^n} - \psi^n_{r/r+2}\right| \leq \Delta,\\
&\sum_{j=1}^{y}\left((p_j^m)^3 - (p_j^n)^3\right) = 1, \forall j\\
&p_j^m, p_j^n \geq 0 \forall j
\end{aligned} \tag{1}$$

where ^{m} and ^{n} represent the belongingness and non-belongingness values.

Step (v) Determine the de-fuzzified criteria weight using Definition 2, and it should satisfy $\sum_{j=1}^{y} p_j = 1, \forall j$.

FFS-WASPAS algorithm

The evaluation procedure of an improved weight-dependent performance analysis and ranking method, FFS-WASPAS, is described as follows:

Step (i)

The decision matrix (D_1) from experts with the set of alternatives, $(R_i | i = 1, 2, 3, \ldots, x)$ and criteria $(A_j | j = 1, 2, 3, \ldots, y)$ with ordered pairs of preferences as $\Gamma_{ij} = \{\langle f_{ij}, m(f_{ij}), n(f_{ij})\rangle | f \in W\}$.

Step (ii)

Defuzzify the ordered pairs of preferences (Γ_{ij}) by performing aggregation operator $S(\Gamma_i)$ from Definition 2 to determine scored decision matrix ($D_2 = \bar{f}_{ij}$).

Step (iii)

Evaluate the linear ratio-based normalized decision matrix (D_3) from D_2 to get balanced decision matrix based on the beneficial and non-beneficial factors using

$$\tilde{\tilde{\bar{f}}}_{ij} = \frac{\bar{f}_{ij}}{\max\limits_{i} \ \bar{f}_{ij}} \quad for \quad \max\limits_{i}$$

$$\tilde{\tilde{\bar{f}}}_{ij} = \frac{\min\limits_{i} \ \bar{f}_{ij}}{\bar{f}_{ij}} \quad for \quad \min\limits_{i}$$

where $i = 1, 2, 3, \ldots, x$ and $j = 1, 2, 3, \ldots, y$.

Step (iv)

Substitute FFS-FUCOM weights (p_j) in normalized decision matrix ($D_3 = [\tilde{\tilde{\bar{f}}}_{ij}]$) $\forall\ i, j = 1, 2, 3, \ldots, x, y$, then calculate weighted sum model (WSM) and weighted product model (WPM) using,

$$WSM = \hat{\hat{\bar{f}}}_{ij} = \tilde{\tilde{\bar{f}}}_{ij} \times p_j$$

$$WPM = \hat{\hat{\bar{f}}}_{ij} = \left(\tilde{\tilde{\bar{f}}}_{ij}\right)^{p_j}$$

Step (v)

The utility value of all alternatives ($R_i | i = 1, 2, 3, \ldots, x$) can be calculated using

$$U_i = (\lambda)\, K_i + (1 - \lambda)\, L_i \ where$$

$$\lambda = \frac{\sum\limits_{i=1}^{x} L_i}{\sum\limits_{i=1}^{x} K_i + \sum\limits_{i=1}^{x} L_i} \in [0, 1], \ K_i = \sum_{j=1}^{y} \hat{\hat{\bar{f}}}_{ij} \ and \tag{2}$$

$$L_i = \prod_{j=1}^{y} \hat{\hat{\bar{f}}}_{ij}$$

since λ is the balancing operator, K_i is the weighted sum, and L_i is the weighted product values of alternatives. Rank the alternatives, R_i, in descending order of U_i values.

Empirical study

Several technologies may be used to aid in dumpsite remediation, addressing environmental and health hazards connected with poorly managed garbage sites. The literature review, research constraints, and aims emphasize the need for alternate waste disposal strategies beyond traditional dumpsites for a variety of environmental, health, and sustainability concerns. The technique used is determined by elements such as waste kind, local restrictions, and available infrastructure. The hierarchical structure (Fig. 4) shows the need for an empirical investigation to discover an ideal waste disposal technique utilizing multi-criteria decision-making (MCDM) methodologies, and the different ways that have been shortlisted are

R_1 - Waste-to-energy process

Many energy recovery procedures are used in the waste-to-energy process, including incineration, pyrolysis, gasification, plasma technologies, and anaerobic digestion. The waste-to-energy process decreases the volume of garbage discharged, turns waste into energy, recovers landfill gas, reclaims land for productive use, and produces economic advantages for local communities. The waste-to-energy process also minimizes disease transmission, groundwater pollution, and the discharge of dangerous compounds into the environment, reducing the demand for new landfill space and assisting in the remediation of overburdened dumpsites.

R_2 - Controlled sanitary landfills

Controlled sanitary landfills are purpose-built structures that store and isolate garbage from the surrounding environment. This reduces leachate discharge into the land and groundwater. Other advantages include landfill gas recovery, landfill reclamation and rehabilitation, the preservation of environmental norms and standards, the management of smells and other possible risks, and the support of community interactions.

R_3 - Mechanical recycling

Mechanical recycling is a waste management method that entails collecting, sorting, and processing recyclable materials in order to create new goods. This strategy is critical in dumpsite remediation because it reduces waste, conserves resources, has a lesser environmental effect, and promotes a more sustainable and circular approach to waste management.

R_4 - Bio-degradation process

Microorganisms break down organic materials into simpler chemicals during the natural process of bio-degradation. This technology reduces methane emissions, improves leachate quality, soil remediation, odor management, increases biodiversity, and reduces the danger of hazardous material discharges into the environment.

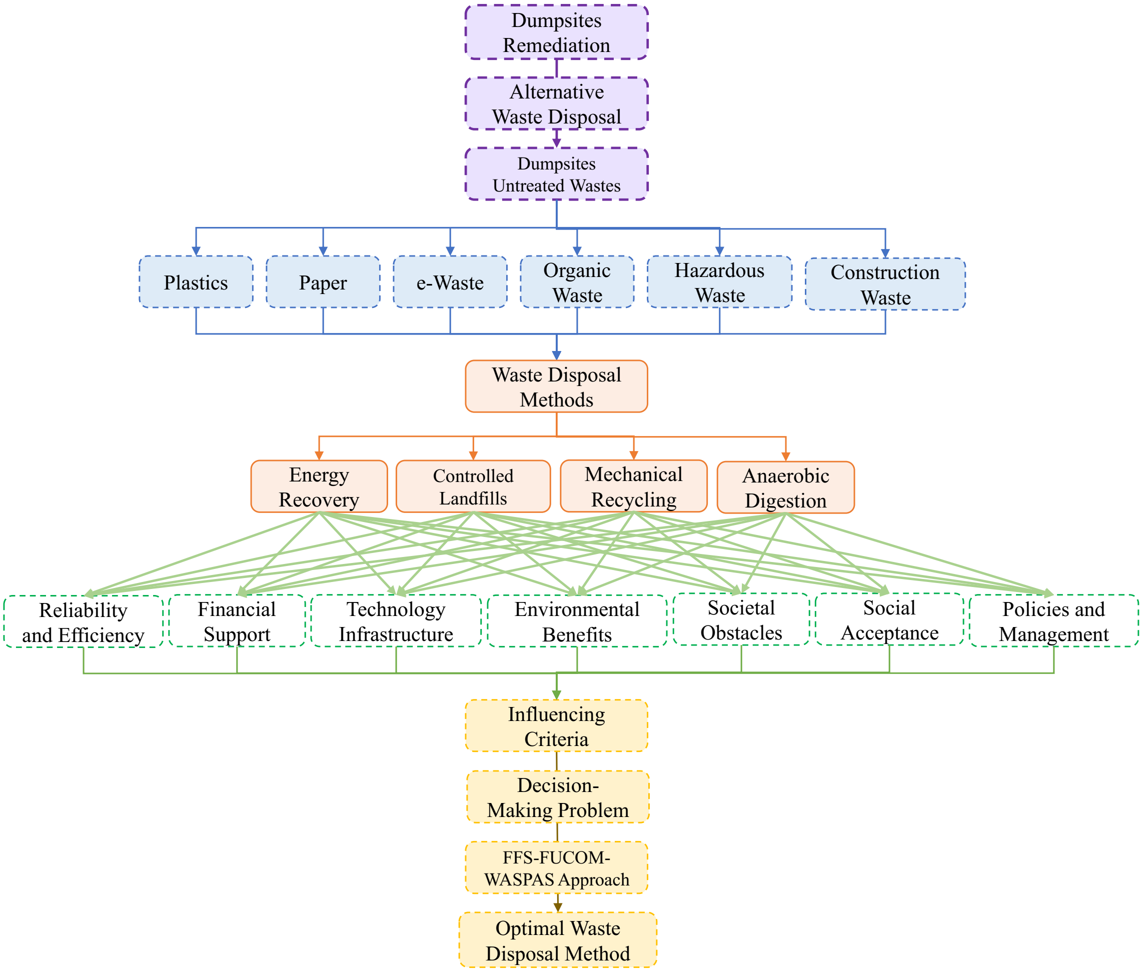


Fig. 4 Hierarchical structure of decision-making problem

Furthermore, seven influencing factors on dumpsite waste management have been identified from recent study articles and globally available information:

A_1- Reliability and efficiency
A_2- Financial and logistical supports
A_3- Technology availability
A_4- Environmental benefits
A_5- Socio-economic obstacles
A_6- Social acceptance and job prospects
A_7- Government policies and community engagements

The attributes such as alternatives and criteria are integrated and developed as a unique decision-making framework in the research field dumpsite remediation. To discover its preferences, we studied and reviewed the research papers through literature review and available information about waste management, dumpsite operations, and rehabilitation activities because this problem facing data uncertainty. Then, experts preferred the pair-wise comparison priorities in the form of FFS preference values, which is then incorporated with FFS-FUCOM-WASPAS method and evaluated.

Criteria weight finding

By strictly adhering to the expanded MCDM method, FFS-FUCOM for criterion weights assessment as follows:

Step (i)

According to the ecological importance of a criteria $(A_j|j = 1, 2, 3, \ldots, 7)$ are ranked by creating a ranking set. In our set of criteria, A_4- environmental benefits seems to be the most preferring criteria followed by A_3, A_2, ... Hence, the ranking set $(A_j^r|j = 1, 2, \ldots, 7 \quad \& \quad r = rank)$ is

$$A_4^1 > A_3^2 > A_2^3 > A_1^4 > A_7^5 > A_5^6 > A_6^7$$

Step (ii)

Determined the significance of criteria by pair-wise comparison of adjacent attributes in the form of FFS preference values (Table 3) are mentioned in Table 4.

Step (iii)

Evaluated the comparative significance values ($\psi_{r/r+1}$) of preferred criteria as $\psi = (\psi_{1/2}, \psi_{2/3}, \psi_{3/4}, \psi_{4/5}, \psi_{5/6}, \psi_{6/7})$ in Table 4. For example, the comparative significance of first and second rank criterion is calculated as $\psi_{1/2} = (0.95, 0.5)/(0.9, 0.45) = (1.0556, 0.3340)$ and so on.

Step (iv)

The FFS form of final criteria weights $(p_1, p_2, \ldots, p_7)$ has been calculated as in Table 4 by solving the developed nonlinear constrained programming model Eq. (3) and satisfied the conditions:

- (i) The ranked criteria weight coefficient ratio equals the criteria comparative significance value, for example, $\frac{p_4}{p_3} = \psi_{1/2} = (1.0556, 0.3340)$ and so on.
- (ii) The transitive condition on ranked criteria weight coefficient ratio also equals its respective comparative significance value, for example, $\frac{p_4}{p_2} = \psi_{1/3} = \psi_{1/2} \times \psi_{2/3} = (1.0556, 0.3340) \times (1.1250, 0.3072) = (1.1875, 0.4024)$ and so on are mentioned in Table 4.

The non-linear FFS programming model determined to evaluate final criteria weights $(p_j | j = 1, 2, \ldots, 7)$ is

$$
\begin{aligned}
&\min \quad \Delta, \\
&subject \quad to \\
&\left|\frac{p_4^m}{p_3^m} - 1.0556\right| \le \Delta, \left|\frac{p_4^n}{p_3^n} - 0.3340\right| \le \Delta, \left|\frac{p_3^m}{p_2^m} - 1.1250\right| \le \Delta, \left|\frac{p_3^n}{p_2^n} - 0.3072\right| \le \Delta, \\
&\left|\frac{p_2^m}{p_1^m} - 1.1429\right| \le \Delta, \left|\frac{p_2^n}{p_1^n} - 0.2805\right| \le \Delta, \left|\frac{p_1^m}{p_7^m} - 1.1667\right| \le \Delta, \left|\frac{p_1^n}{p_7^n} - 0.2536\right| \le \Delta, \\
&\left|\frac{p_7^m}{p_5^m} - 1.5\right| \le \Delta, \left|\frac{p_7^n}{p_5^n} - 0.2676\right| \le \Delta, \left|\frac{p_5^m}{p_6^m} - 2\right| \le \Delta, \left|\frac{p_5^n}{p_6^n} - 0.1668\right| \le \Delta, \\
&\left|\frac{p_4^m}{p_2^m} - 1.1875\right| \le \Delta, \left|\frac{p_4^n}{p_2^n} - 0.4024\right| \le \Delta, \left|\frac{p_3^m}{p_1^m} - 1.2857\right| \le \Delta, \left|\frac{p_3^n}{p_1^n} - 0.3694\right| \le \Delta, \\
&\left|\frac{p_2^m}{p_7^m} - 1.3333\right| \le \Delta, \left|\frac{p_2^n}{p_7^n} - 0.3363\right| \le \Delta, \left|\frac{p_1^m}{p_5^m} - 1.75\right| \le \Delta, \left|\frac{p_1^n}{p_5^n} - 0.3276\right| \le \Delta, \\
&\left|\frac{p_7^m}{p_6^m} - 3\right| \le \Delta, \left|\frac{p_7^n}{p_6^n} - 0.2873\right| \le \Delta, \\
&\sum_{j=1}^{7} \left((p_j^m)^3 - (p_j^n)^3\right) = 1, \forall j \\
&p_j^m, p_j^n \ge 0 \forall j
\end{aligned}
\tag{3}
$$

Step (v)

De-fuzzified the FFS form of criteria weights using Definition 2 and plotted in Fig. 5.

Alternative waste disposal methods ranking assessments

The alternatives, $R_i | i = 1, 2, 3, 4$, compete with shortlisted criteria $(A_1, A_2, \ldots, A_7)$ using the FFS-WASPAS method, and the step-wise evaluation is follows:

Step 1

The observed data are transformed into Fermatean fuzzy preferences and constructed the decision matrix (D_1) as in Table 5.

Step 2

De-fuzzified the decision matrix (D_1) using score value formula from Definition 2 and determined the scored decision matrix (D_2) in Table 6.

Step 3

We normalized the decision matrix, D_2, by using following the evaluation procedure and determined the balanced decision matrix in Table 7:

(i) For beneficial criteria (A_1, A_3, A_4, A_7), the normalized decision matrix values are calculated using $\tilde{\bar{f}}_{ij} = \frac{\bar{f}_{ij}}{\max_i \bar{f}_{ij}}$. For example, the normalized value of an alternative R_1

Table 4 Calculated step-wise results of FFS-FUCOM method

Ranked criteria	A_4^1	A_3^2	A_2^3	A_1^4	A_7^5	A_5^6	A_6^7
Significance value	0.95,0.5	0.9,0.45	0.8,0.4	0.7,0.35	0.6,0.3	0.4,0.2	0.2,0.15
ψ	$\psi_{1/2}$	$\psi_{2/3}$	$\psi_{3/4}$	$\psi_{4/5}$	$\psi_{5/6}$	$\psi_{6/7}$	
ψ	1.0556,0.3340	1.1250,0.3072	1.1429,0.2805	1.1667,0.2536	1.5000,0.2676	2.0000,0.1668	
Coefficient ratio	$\frac{p_4}{p_3}$	$\frac{p_3}{p_2}$	$\frac{p_2}{p_1}$	$\frac{p_1}{p_7}$	$\frac{p_7}{p_5}$	$\frac{p_5}{p_6}$	
	1.0556,0.3340	1.1250,0.3072	1.1429,0.2805	1.1667,0.2536	1.5000,0.2676	2.0000,0.1668	
Transitive ratio	$\frac{p_4}{p_2}$	$\frac{p_3}{p_1}$	$\frac{p_2}{p_7}$	$\frac{p_1}{p_5}$	$\frac{p_7}{p_6}$		
	1.1875,0.4024	1.2857,0.3694	1.3333,0.3363	1.7500,0.3276	3.0000,0.2873		
Criteria weights	p_1	p_2	p_3	p_4	p_5	p_6	p_7
(p_j^m, p_j^n)	0.5009,0.000008	0.5724,0.00002	0.6440,0.00002	0.6798,0.000023	0.2862,0.0000	0.1431,0.0000	0.4293,0.0000
$\sum_{j=1}^{7} p_j = 1$	0.1257	0.1875	0.2671	0.3142	0.0234	0.0029	0.0791

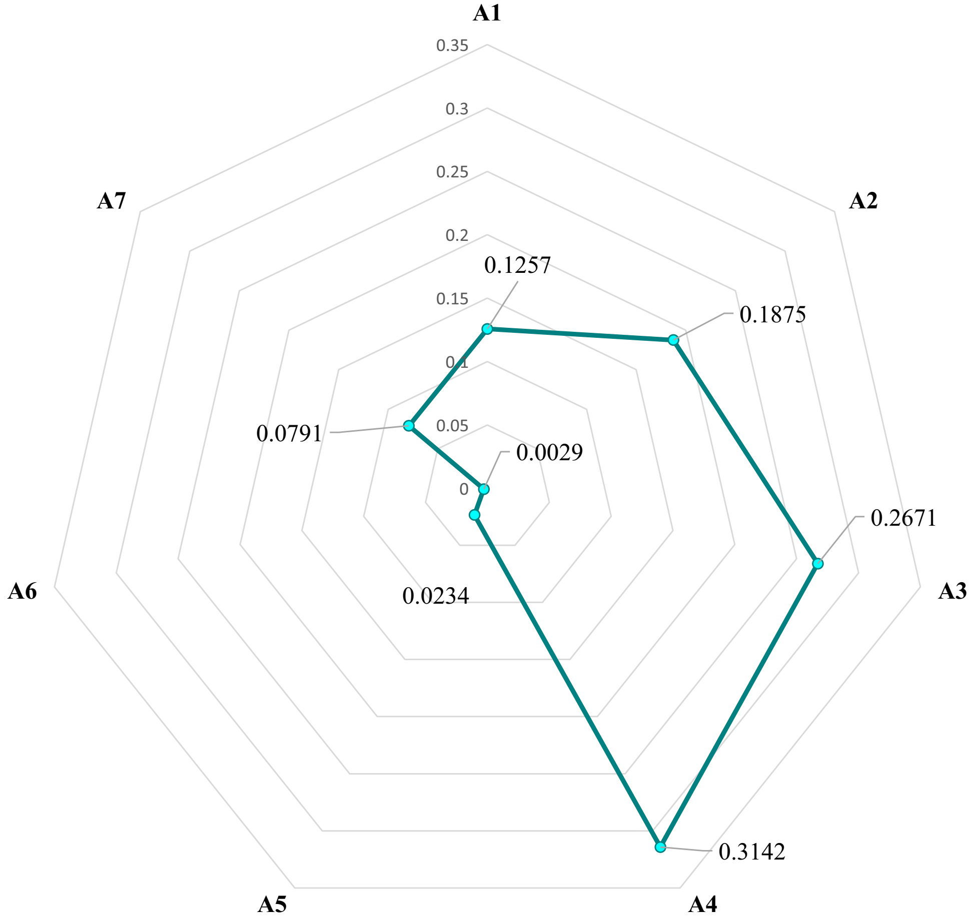


Fig. 5 The final criteria weights, p_j

Table 5 Fermatean fuzzy decision matrix, D_1

D_1	A_1	A_2	A_3	A_4	A_5	A_6	A_7
R_1	0.6500,0.4000	0.8500,0.2000	0.8500,0.2000	0.9500,0.1000	0.7500,0.3000	0.3500,0.7000	0.8500,0.2000
R_2	0.7500,0.3000	0.7500,0.3000	0.6500,0.4000	0.7500,0.3000	0.8500,0.2000	0.6500,0.4000	0.2500,0.8000
R_3	0.8500,0.2000	0.6500,0.4000	0.5500,0.5000	0.5500,0.5000	0.4500,0.6000	0.7500,0.3000	0.6500,0.4000
R_4	0.4500,0.6000	0.8500,0.2000	0.7500,0.3000	0.6500,0.4000	0.8500,0.2000	0.8500,0.2000	0.5500,0.5000

Table 6 Score valued decision matrix, D_2

D_2	A_1	A_2	A_3	A_4	A_5	A_6	M_7
R_1	0.4563	0.8462	0.8462	0.9788	0.6544	0.0692	0.8462
R_2	0.6544	0.6544	0.4563	0.6544	0.8462	0.4563	0.0230
R_3	0.8462	0.4563	0.2843	0.2843	0.1543	0.6544	0.4563
R_4	0.1543	0.8462	0.6544	0.4563	0.8462	0.8462	0.2843

Table 7 Normalized decision matrix

D_3	M_1	M_2	M_3	M_4	M_5	M_6	M_7
R_1	0.5392	0.5392	1.0000	1.0000	0.2357	1.0000	1.0000
R_2	0.7733	0.6972	0.5392	0.6686	0.1823	0.1517	0.0272
R_3	1.0000	1.0000	0.3359	0.2904	1.0000	0.1058	0.5392
R_4	0.1823	0.5392	0.7733	0.4661	0.1823	0.0818	0.3359

Table 8 Weighted sum model

D_4	M_1	M_2	M_3	M_4	M_5	M_6	M_7
R_1	0.0678	0.1011	0.2671	0.3142	0.0055	0.0029	0.0791
R_2	0.0972	0.1307	0.1440	0.2101	0.0043	0.0004	0.0022
R_3	0.1257	0.1875	0.0897	0.0913	0.0234	0.0003	0.0426
R_4	0.0229	0.1011	0.2066	0.1465	0.0043	0.0002	0.0266

in beneficial criteria A_4- Environmental benefits is calculated as $\tilde{\bar{f}}_{14} = \frac{\bar{f}_{14}}{\max_i \bar{f}_{14}} = \frac{0.9788}{0.9788} = 1$ and so on.

(ii) For non-beneficial criteria (A_2, A_5, A_6), the normalized decision matrix values are calculated using $\tilde{\bar{f}}_{ij} = \frac{\max_i \bar{f}_{ij}}{\bar{f}_{ij}}$. For example, the normalized value of an alternative R_1 in non-beneficial criteria A_5- Social and economical barriers is calculated as $\tilde{\bar{f}}_{15} = \frac{\max_i \bar{f}_{15}}{\bar{f}_{15}} = \frac{0.1543}{0.6544} = 0.2357$ and so on.

Step 4

The weighted sum and product models are determined as in Tables 8 and 9 by substituting the FFS-FUCOM criteria weights (Fig. 5).

Step 5

The utility function values are calculated for all alternatives $(R_i | i = 1, 2, 3, 4)$ using $U_i = (\lambda)\, K_i + (1 - \lambda)\, L_i$ $\forall\ i = 1, 2, 3, 4$, where, $K_i = \sum_{j=1}^{7} \hat{\bar{f}}_{ij}$, $L_i = \prod_{j=1}^{7} \hat{\bar{f}}_{ij}$ and $\lambda = 0.4713$. The calculated final ranking values are $U_1 = 0.8160$, $U_2 = 0.5344$, $U_3 = 0.5176$, and $U_4 = 0.4839$.

Comparative and sensitive analysis

We compared the ranking results of well-known VIKOR, TOPSIS, MABAC, and WASPAS methods integrated with two closely related criteria weighing methods FUCOM and BWM. This hybridization makes seven different combinations like FUCOM-TOPSIS, FUCOM-MABAC, FUCOM-VIKOR, BWM-TOPSIS, BWM-MABAC, BWM-VIKOR, and BWM-WASPAS are compared with FUCOM-WASPAS, and the results are plotted in Fig. 6. Moreover, the Spearman's rank correlation coefficient analysis the significance levels and the similarities of the set of MCDM methods using Eq. 4.

$$S = 1 - \frac{6 \sum_{i=1}^{4} (g_i - h_i)^2 ((4 - x_i + 1) + (4 - y_i + 1))}{4^4 + 4^3 - 4^2 - 4} \quad (4)$$

Figure 7 shows the similarity results from Eq. (4), which show that FUCOM-TOPSIS with FUCOM-MABAC and BWM-MABAC; FUCOM-VIKOR with BWM-VIKOR; FUCOM-MABAC with BWM-MABAC shows the higher correlation at 1, BWM-WASPAS with FUCOM-WASPAS, FUCOM-VIKOR, BWM-VIKOR; FUCOM-TOPSIS with BWM-TOPSIS; BWM-TOPSIS with FUCOM-WASPAS, FUCOM-VIKOR, BWM-VIKOR, FUCOM-MABAC, BWM-MABAC shows average correlation between > 0.75 and the remaining combinations are weak correlation with less significance. As a result, the recommended method, known as FUCOM-WASPAS, appears to be more distinctive, stable, and significant with hopeful and satisfactory results.

The sensitivity of the proposed FFS-FUCOM procedure analyzed with the set of changed criteria weights W_1, W_2, and W_3 as in Fig. 8. Figure 9 evident the significant changes in the positions of alternatives in each set of criteria weights. The alternatives R_2 and R_3 are highly sensitive while changing criteria weights, whereas R_1 and R_4 are more stable in their positions.

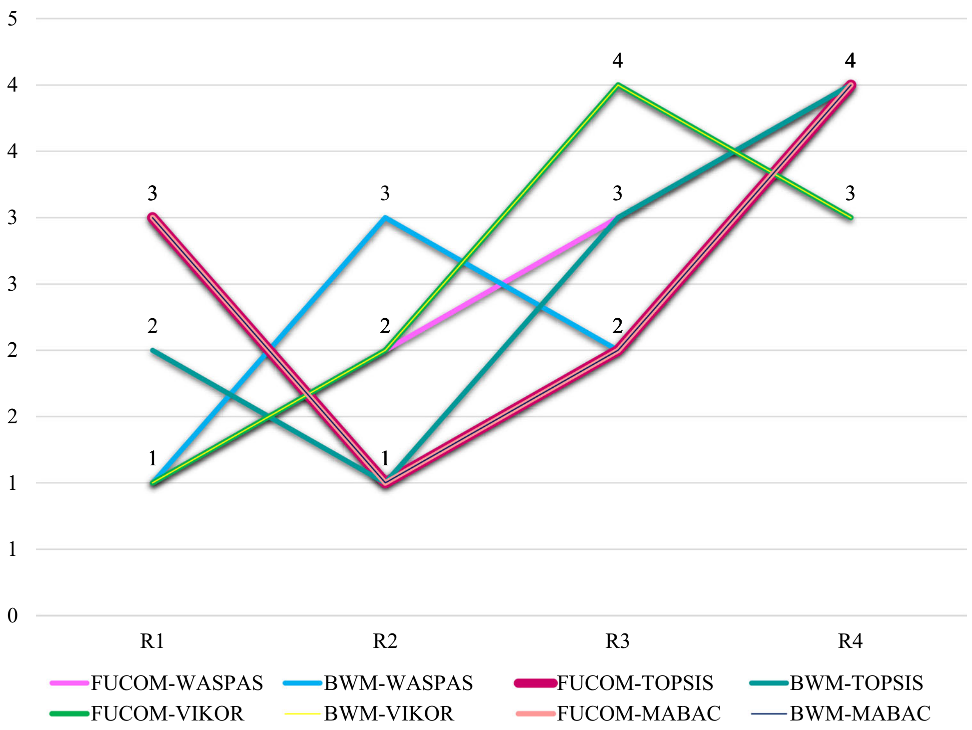
Discussion on results

According to Fig. 10, the final ranking result of a novel integrated FFS-FUCOM-WASPAS method has been ranked as $U_1 = 0.8160 > U_2 = 0.5344 > U_3 = 0.5176 > U_4 = 0.4839$. The waste-to-energy technologies (R_1) were evaluated as the best option for disposing of discharged garbage

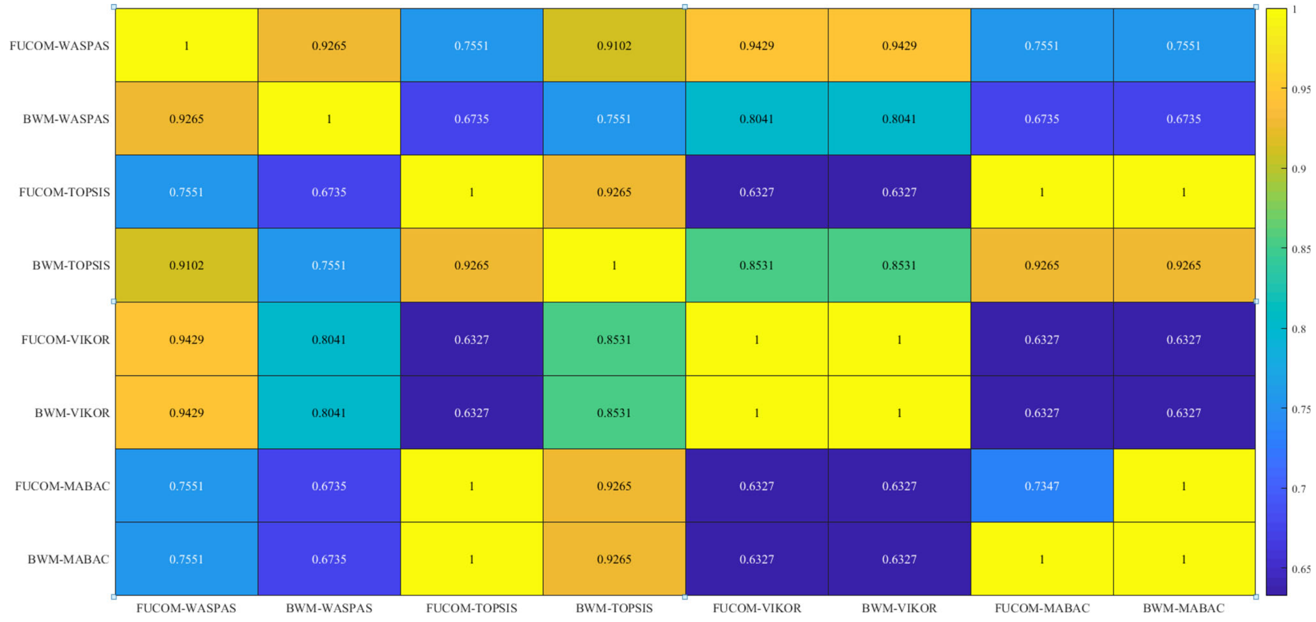
Table 9 Weighted product model

D_5	M_1	M_2	M_3	M_4	M_5	M_6	M_7
R_1	0.9253	0.8906	1.0000	1.0000	0.9668	1.0000	1.0000
R_2	0.9682	0.9346	0.8479	0.8812	0.9610	0.9945	0.7519
R_3	1.0000	1.0000	0.7473	0.6781	1.0000	0.9935	0.9523
R_4	0.8074	0.8906	0.9336	0.7868	0.9610	0.9928	0.9173

Fig. 6 Ranking comparison of various MCDM methods with FUCOM-WASPAS



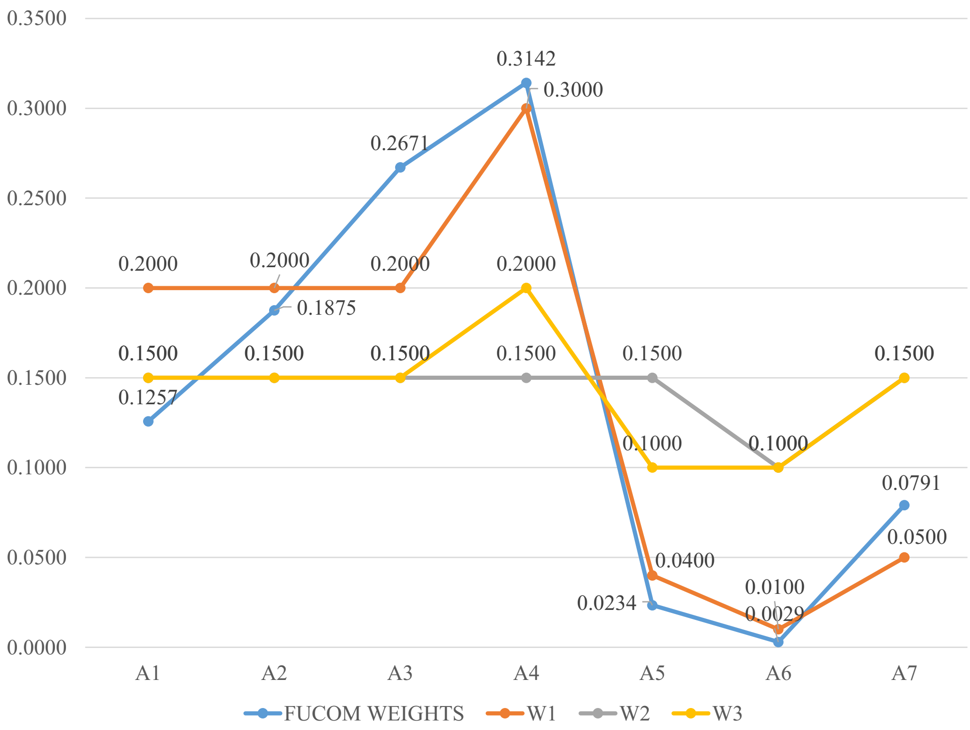
and ensuring the dumpsite remediation process. A significant priority is the capacity to transform non-recyclable, mixed, and unprocessed waste into energy, such as electricity or heat. Furthermore, controlled sanitary landfills (R_2) can provide a systematic and designed waste disposal option, considerably contributing to the restoration of open dumpsites by limiting environmental concerns. Meanwhile, mechanical recycling (R_3), by decreasing waste, preserving resources, and fostering a circular economy approach to waste management, can play an important part in dumpsite restoration. Although biodegradation (R_4) is a natural process, in dumpsite rehabilitation settings, management approaches may be



	FUCOM-WASPAS	BWM-WASPAS	FUCOM-TOPSIS	BWM-TOPSIS	FUCOM-VIKOR	BWM-VIKOR	FUCOM-MABAC	BWM-MABAC
FUCOM-WASPAS	1	0.9265	0.7551	0.9102	0.9429	0.9429	0.7551	0.7551
BWM-WASPAS	0.9265	1	0.6735	0.7551	0.8041	0.8041	0.6735	0.6735
FUCOM-TOPSIS	0.7551	0.6735	1	0.9265	0.6327	0.6327	1	1
BWM-TOPSIS	0.9102	0.7551	0.9265	1	0.8531	0.8531	0.9265	0.9265
FUCOM-VIKOR	0.9429	0.8041	0.6327	0.8531	1	1	0.6327	0.6327
BWM-VIKOR	0.9429	0.8041	0.6327	0.8531	1	1	0.6327	0.6327
FUCOM-MABAC	0.7551	0.6735	1	0.9265	0.6327	0.6327	0.7347	1
BWM-MABAC	0.7551	0.6735	1	0.9265	0.6327	0.6327	1	1

Fig. 7 Spearman's rank correlation heat map of various fuzzy MCDM methods for comparison study

Fig. 8 Different set of criteria weights for sensitive analysis



required to enhance conditions for microbial activity and speed up the breakdown process.

The performance of alternative waste disposal strategies in each criterion is depicted in Fig. 11. The FFS-FUCOM-WASPAS technique investigates the influence of criteria and ineffective performance of alternatives, which acts as a practical benefit in improving the performance of the dumpsite remediation process. That is, the waste-to-energy process outperformed alternative ways with minimal socioeconomical barriers and conventional governing rules in terms of offering environmental benefits and technical assistance. Meanwhile, the cost efficacy and dependability of alternate garbage disposal techniques must be considered. The controlled sanitary landfill option provides average performance in practically all criteria with low socioeconomic barriers, but it takes foresighted governmental regulations to use this waste disposal approach. Similarly, with low socioeconomic barriers and foresighted management practices, the

Fig. 9 Alternatives ranking sensitivity

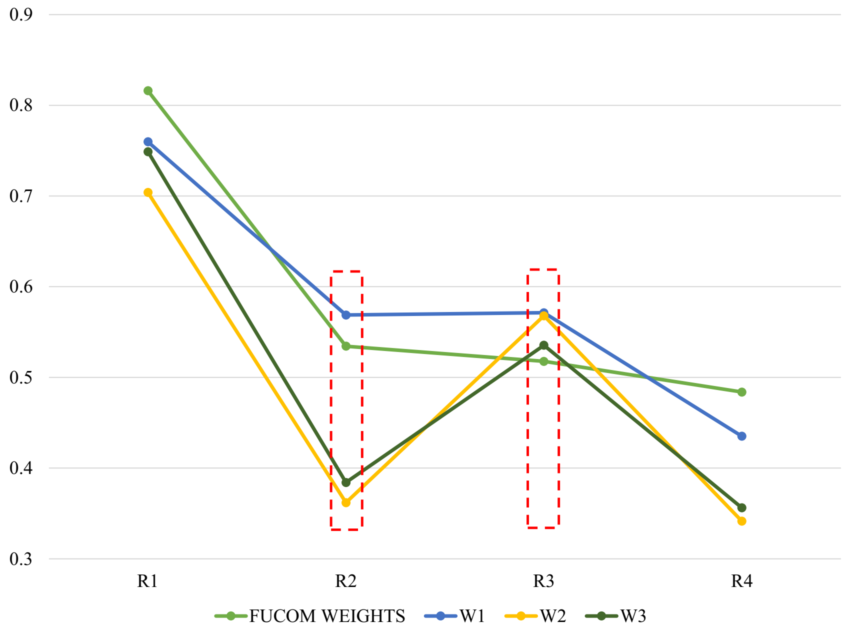


Fig. 10 The ranking results, U_i

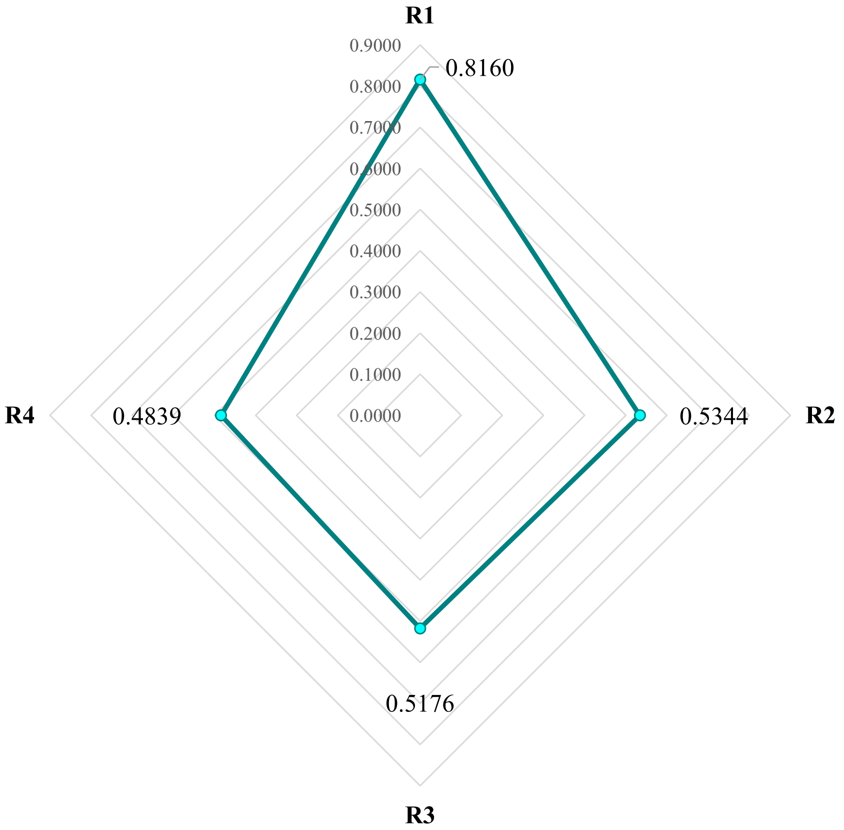


Fig. 11 The performance level of alternatives in each criteria

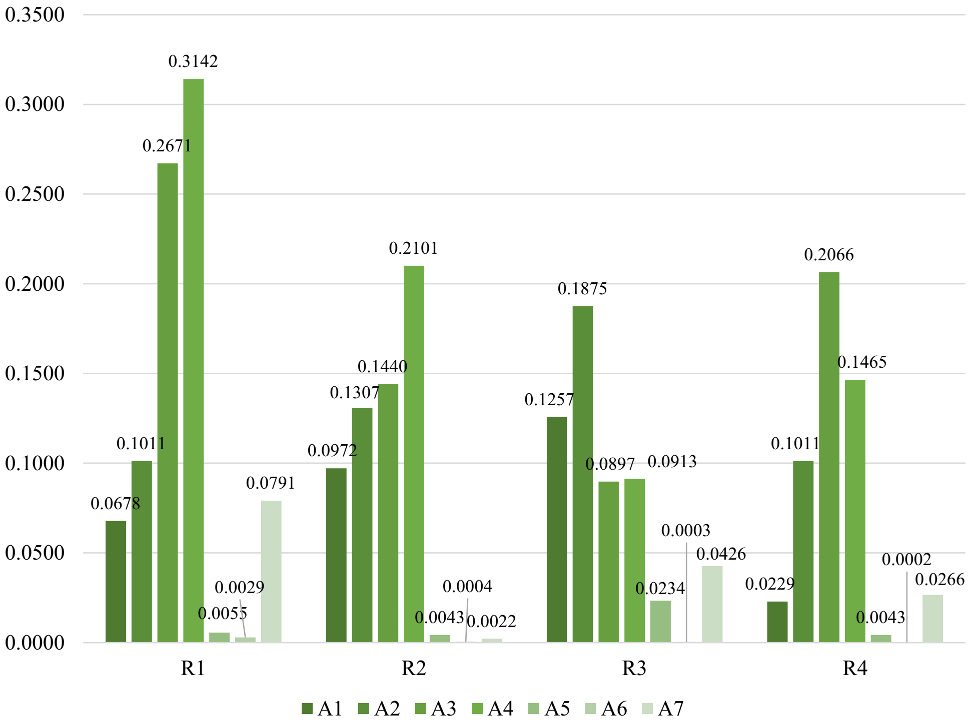


Table 10 Qualitative comparison analysis

MCDM tools	Multiple criteria support	Qualitative/quantitative analysis	Transparent procedure	Adaptability	Sensitivity analysis	Consistent decision-making	Group decision-making	Dealing uncertainty	Computational easiness	Decision-maker preferences
AHP	1	0.5	1	1	1	0.5	0.5	1	0.5	0.5
BWM	1	1	0.5	1	1	0.5	1	1	0.5	1
FUCOM	1	1	0.5	1	1	1	1	1	1	1
TOPSIS	1	1	1	0.5	1	0.5	0.5	1	0.5	0.5
VIKOR	1	1	1	0.5	1	0.5	0.5	1	0.5	0.5
MABAC	1	1	1	0.5	1	0.5	1	1	0.5	1
WASPAS	1	1	1	1	1	1	1	1	1	1

mechanical recycling approach performed well in practically every criterion. Because of its limited dependability, efficiency, and applicability, the bio-degradation process is regarded as the least effective waste disposal technique. Overall, there is an urgent need to address the lack of focus in developing community participation and societal acceptability by promoting responsible waste disposal techniques and job opportunities.

The suggested MCDM technique is chosen based on the unique characteristics of the dumpsite waste disposal decision problem, the nature of criteria and alternatives, and decision-maker's preferences. Recent developments in MCDM research involve the hybridization of FUCOM and WASPAS approaches to meet specific dumpsite waste disposal method identification concerns. We proceeded to investigate methods for dealing with uncertainty, and we added FFS preferences to the proposed FUCOM-WASPAS technique. Based on the literature review, we compared our suggested techniques to several other distinct MCDM methods by assigning ratings (satisfying - 1, not satisfying - 0, and average - 0.5) to represent the level of logic and efficacy. The number of pair-wise comparisons for the FUCOM technique is quite low when compared to the classic AHP and closely similar BWM methods, that is, FUCOM= $(n-1) <$ BWM= $(2n-3) <$ AHP= $n(n-1)/2$. Furthermore, the Spearman's rank correlation comparison and sensitivity analysis demonstrate that the suggested hybridized MCDM technique is improved in terms of resilience, uniqueness, highly significant, computational ease, consistency, and accuracy when dealing with uncertain decision-making issues.

Practical implications and limitations

The proposed FUCOM and WASPAS method's practical implications include its ability to provide a comprehensive evaluation, handle ambiguous information, maintain transparency, conduct sensitivity analysis, accommodate decision-maker preferences, and apply to a variety of decision problems in waste management (Table 10). This research study is confined to four different waste disposal systems, a set of seven criteria, and identified secondary preferences; it requires more investigation into wider applicability and case studies. Though the waste-to-energy technology was selected as the best solution for dumpsite waste disposal, there is a restriction in that it is not a one-size-fits-all solution; instead, combining different technologies in a full rehabilitation plan frequently provides more effective outcomes. The absence of stratified analysis for long-term planning and decisions in environmental management problems is a limitation of the FFS-FUCOM-WASPAS technique.

Conclusion

Dumpsite remediation is frequently an organized and multidisciplinary process that necessitates coordination among environmental engineers, waste management specialists, ecologists, and legislators. A detailed site evaluation and understanding of the unique issues faced by the dumpsites should be needed to identify remediation strategies. By combining FUCOM and WASPAS methodologies with FFS preferences, the substantial research study addressed the indicated research questions. The FFS is ideally adapted to dealing with ambiguous information in dumpsite remediation challenges that need sophisticated prioritizing. This is demonstrated by the performance results of alternatives in each criterion, demonstrating a more realistic approach. This enhanced FFS-FUCOM-WASPAS approach that has shown its speed, consistency, and efficiency makes strategical research investigations more attractive for decision-makers. In that way, FFS-FUCOM-WASPAS identified waste-to-energy approach most effective waste disposal method, which holds ability to minimize the massive amount of waste in uncontrolled landfills while also contributing to sustainable energy practices. This technology not only helps the generation of sustainable energy, but also provides an economic incentive for the development of waste-to-energy plants. The detailed literature study supported highly to achieve the research objectives. Furthermore, researching the efficacy of public awareness initiatives and community involvement programs can give useful insights into encouraging proper waste disposal methods. The future direction is to address the limitations of this research study as well as a few problematic scenarios, such as enhancing the MCDM methodology with machine learning algorithms to assess large numbers of data sets with uncertainty, extending the FFS-FUCOM-WASPAS method with stratified target concept to ensure the sustainability of the implication of optimal solution, and addressing various uncovered waste management problems with complicated larger number of attributes and uncertain data sets.

Author Contributions All authors contributed to the study conception and design. The formal analysis, validation, and funding performed were by Jeonghwan Jeon. The conceptualization, methodology, software, data processing, and writing—original draft, review and editing were performed by Thangaraj Manirathinam. The data curation, supervision, results evaluation, writing review and editing were performed by Samayan Narayanamoorthy and Selvaraj Geetha. The validation, software, and visualization were performed by Mehdi Salimi and Ali Ahmadian. All authors read and approved the final manuscript.

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Declarations

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Consent for publication Not applicable.

Conflict of interest The authors declare no competing interests.

References

Alao JO (2023) Impacts of open dumpsite leachates on soil and groundwater quality. Groundw Sustain Dev 20:100877

Alao MA, Popoola OM, Ayodele TR (2022) A novel fuzzy integrated MCDM model for optimal selection of waste-to-energy-based-distributed generation under uncertainty: a case of the City of Cape Town. South Africa. J Clean Prod 343:130824. https://doi.org/10.1016/j.jclepro.2022.130824

Anand N, Palani SG (2022) A comprehensive investigation of toxicity and pollution potential of municipal solid waste landfill leachate. Sci Total Environ 838(1):155891

Issac MN, Kandasubramanian B (2021) Effect of microplastics in water and aquatic systems. Environ Sci Pollut Res 28:19544–19562. https://doi.org/10.1007/s11356-021-13184-2

Jessieleena AA, Nambi IM (2022) Distribution of microplastics in the catchment region of Pallikaranai marshland, a Ramsar site in Chennai. India. Environ Pollut 120890. https://doi.org/10.1016/j.envpol.2022.120890

Kang D, Manirathinam T, Geetha S, Narayanamoorthy S, Ferrara M, Ahmadian A (2023) An advanced stratified decision-making strategy to explore viable plastic waste-to-energy method: a step towards sustainable dumped wastes management. Appl Soft Comput 143:110452

Kannan K, Vimalkumar K (2021) A review of human exposure to microplastics and insights into microplastics as obesogens. Front Endocrinol 12:724989. https://doi.org/10.3389/fendo.2021.724989

Karimi N (2023) Assessing global waste management: alternatives to landfilling in different waste streams-a scoping review. Sustainability 15(18):13290

Keshavarz-Ghorabaee M, Amiri M, Hashemi-Tabatabaei M, Zavadskas EK, Kaklauskas A (2020) A new decision-making approach based on Fermatean fuzzy sets and WASPAS for green construction supplier evaluation. Mathematics 8:2202. https://doi.org/10.3390/math8122202

Kizielewicz B, Baczkiewicz A (2021) Comparison of fuzzy TOPSIS, fuzzy VIKOR, fuzzy WASPAS and fuzzy MMOORA methods in the housing selection problem. Procedia Comput Sci 192:4578–4591. https://doi.org/10.1016/j.procs.2021.09.236

Kumar NM, Mohammed MA, Abdulkareem KH, Damasevicius R, Mostafa SA, Maashi MS, Chopra SS (2021) Artificial intelligence-based solution for sorting COVID related medical waste streams and supporting data-driven decisions for smart circular economy practice. Process Saf Environ Prot 152:482–494

Li Y, Xiao P, Donnici S, Cheng J, Tang C (2023) Spatial and seasonal distribution of microplastics in various environmental compartments around Sishili Bay of North Blue Sea. China. Mar Pollut Bull 186:114372. https://doi.org/10.1016/j.marpolbul.2022.114372

Mandal U, Seikh MR (2023) Interval-valued spherical fuzzy MABAC method based on Dombi aggregation operators with unknown attribute weights to select plastic waste management process. ppl Soft Comput 110516

Mardani A, Zavadskas EK, Khalifah Z, Zakuan N, Jusoh A, Nor KM, Khoshnoudi M (2017) A review of multi-criteria decision-making applications to solve energy management problems: two decades from 1995 to 2015. Renew Sust Energy Rev 71:216–256

Marsum AT, Slamet K, Wardoyo S (2022) Phytoremediation as a barrier to heavy metal distribution in open dumping landfill in peatlands. J Ecol Eng 23(6)

Massoud MA, Abdallah C, Merhbi F, Khoury R, Ghanem R (2023) Development and application of a prioritization and rehabilitation decision support tool for uncontrolled waste disposal sites in developing countries. Integr Environ Assess 19(2):436–445

Mishra AR, Rani P, Pandey K (2022) Fermatean fuzzy CRITIC-EDAS approach for the selection of sustainable third-party reverse logistics providers using improved generalized score function. J Ambient Intell Humaniz Comput 13:295–311. https://doi.org/10.1007/s12652-021-02902-w

Mohammed MA, Abdulhasan MJ, Kumar NM, Abdulkareem KH, Mostafa SA, Maashi MS, Layth SK, Hayder SA, Chopra SS (2022) Automated waste-sorting and recycling classification using artificial neural network and features fusion: a digital-enabled circular economy vision for smart cities. Multimed Tools Appl 1-16

Mondal T, Choudhury M, Kundu D, Dutta D, Samanta P (2023) Landfill: an eclectic review on structure, reactions and remediation approach. Waste Manag 164:127–142

Mor S, Ravindra K (2023) Municipal solid waste landfills in lower-and middle-income countries: environmental impacts, challenges and sustainable management practices. Process Saf Environ Prot 174:510–530

Narayanamoorthy S, Manirathinam T, Geetha S, Salahshour S, Ahmadian A, Kang D (2022) An approach to assess PWR methods to cope with physical barriers on plastic waste disposal and exploration from developing nations. Expert Syst Appl 207:117996. https://doi.org/10.1016/j.eswa.2022.117996

Narayanamoorthy S, Anuja A, Pragathi S, Sandra M, Ferrara M, Ahmadian A, Kang D (2023) Assessment of inorganic solid waste management techniques using full consistency and extended MABAC method. Environ Sci Pollut Res 1-11

Ocampo L (2022) Full consistency method (FUCOM) and weighted sum under fuzzy information for evaluating the sustainability of farm tourism sites. Soft Comput 26:12481–12508. https://doi.org/10.1007/s00500-022-07184-8

Pamučar D, Stević Ž, Sremac S (2018) A new model for determining weight coefficients of criteria in MCDM models: full consistency method (FUCOM). Symmetry 10:393. https://doi.org/10.3390/sym10090393

Rahman AU, Saeed M, Mohammed MA, Abdulkareem KH, Nedoma J, Martinek R (2023) Fppsv-NHSS: fuzzy parameterized possibility single valued neutrosophic hypersoft set to site selection for solid waste management. Appl Soft Comput 140:110273

Rouf AB, Dig VS, Humaira Q, Gowhar HD, Moonisa AD, Shakeel AB, Bengu TU, Munir O, Khalid RH, Balal Y (2022) Vulnerability of municipal solid waste: an emerging threat to aquatic ecosystems. Chemosphere 287(3):132223

Salami L, Popoola LT (2023) A comprehensive review of atmospheric air pollutants assessment around landfill sites. Air Soil Water Res 16:11786221221145380

Seikh MR, Mandal U (2022) Multiple attribute group decision making based on quasirung orthopair fuzzy sets: application to electric vehicle charging station site selection problem. Eng Appl Artif Intell 115:105299. https://doi.org/10.1016/j.engappai.2022.105299

Seikh MR, Mandal U (2023) Interval-valued Fermatean fuzzy Dombi aggregation operators and SWARA based PROMETHEE II method to bio-medical waste management. Expert Syst Appl 226:120082

Shahnazari A, Rafiee M, Rohani A, Nagar BB, Ebrahiminik MA, Aghkhani MH (2020) Identification of effective factors to select energy recovery technologies from municipal solid waste using multi-criteria decision making (MCDM): a review of thermochemical technologies. Sustain Energy Technology Assess 40:100737

Shahnazari A, Pourdej H, Kharage MD (2021) Ranking of organic fertilizer production from solid municipal waste systems using analytic hierarchy process (AHP) and VIKOR models. Biocatal Agric Biotechnol 32:101946

Siddiqua A, Hahladakis JN, Al-Attiya WAKA (2022) An overview of the environmental pollution and health effects associated with waste landfilling and open dumping. Environ Sci Pollut Res 29:58514–58536

Somani M, Datta M, Ramana GV, Ingo H, Sundaram R, Sreekrishnan TR (2022) Effect of depth of landfill on the characteristics of soil-like material of aged waste: a case study of Bhalswa dumpsite. India. J Mater Cycles Waste Management 24(5):1902–1912

Torkayesh AE, Simic V (2022) Stratified hybrid decision model with constrained attributes: recycling facility location for urban healthcare plastic waste. Sustain Cities Soc 77:103543. https://doi.org/10.1016/j.scs.2021.103543

Yinbang R, Zhenying Z, Man H (2022) A review on settlement models of municipal solid waste landfills. Waste Manag 149:79–95

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