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TrS-RAM:Leveraging Novel MCDM Techniques for Evaluating Sustainability of Fuel Cell Vehicles Based on Tree Soft Technique

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Abstract

A smart city is an urban area that leverages technology, data, and innovation to improve the quality of life for its residents, enhance sustainability, and optimize urban services and infrastructure. Smart cities use a variety of digital technologies and solutions to address urban challenges and create more efficient, resilient, and livable communities. Smart cities employ innovative waste management solutions, such as IoT-enabled waste bins, route optimization algorithms, and recycling initiatives, to minimize waste generation, improve collection efficiency, and promote recycling and composting. A fuel cell vehicle (FCV) is a type of electric vehicle (EV) that uses a fuel cell to generate electricity on board, which powers an electric motor to propel the vehicle. FCVs generate electricity through an electrochemical reaction between hydrogen and oxygen. Integrating fuel cell vehicles (FCVs) into waste management systems can offer several benefits, particularly in terms of enhancing environmental sustainability and operational efficiency. FCVs can be used for collecting and transporting waste from various collection points to treatment facilities or disposal sites. Their long driving ranges and rapid refueling capabilities make them suitable for covering large distances efficiently. Overall, integrating FCVs into waste management systems can contribute to achieving environmental sustainability goals, reducing emissions, and improving the efficiency and effectiveness of waste collection and transportation operations. The Root Assessment Method (RAM) is a systematic approach used to analyze and evaluate problems or issues by identifying and addressing their root causes. The method is particularly useful in problem-solving scenarios where understanding the underlying causes is essential for developing effective solutions. This paper proposes the RAM method under Tree-soft set approach using Entropy weight method.

Keywords: MCDM, Entropy, RAM, TreeSoft, Fuel Cell Vehicles, Root Assessment Method.

1 | Introduction

Recent statistics data on the global population according to [1] appeared to indicate both an increase in population size and a trend of people migrating to large cities. According to these statistics, [2] reckoned there can be issues as a result, such as rising energy and service demand and consumption. The aforementioned issues drove governments and interested parties to look for ways to make cities increasingly resourceful and energy-efficient and manage the usage of resources[3]. As a solution to urbanization, environmental issues, and economic growth based on the perspective of various scholars [4], the idea of a "smart city" is becoming more and more popular across the world.

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Accordingly, many researchers have recently paid attention to smart cities, as United Nations reports indicate that more than half of the world's population currently lives in an urban environment, and the percentage is expected to rise to 70% by 2050 [5].

As urban populations continue to rise and technology progresses, smart cities are becoming more and more significant. Among the definitions of a smart city that are most often used that stated in [5] as "A city is smart when investments in social and human capital, as well as in traditional and contemporary ICT and transportation communication infrastructure, support sustainable economic growth and high standards of living while prudently managing natural resources through participatory governance."

General speaking, smart cities are leveraging information and communication technology (ICT) as internet of things (IoTs), digital twin (DT), big data analytical (BDA)….etc to reach the best solutions and improve their efficiency [6]. Confimation of that [7] where the term intelligence has been combined with cities to describe the use of technology in a smart way to optimize resources, preserve them, sustain them, and improve the quality of life in general.

Figure 1 show cases the role of these technologies in various sectors in cities to make it a civilized, livable, sustainable, and environmentally friendly city. Smart cities are often viewed as having increased efficiency, ICT connectivity, sustainable use of resources, environmental friendliness, and improved quality of life. In order for a city to be smart and sustainable, it must have several characteristics, such as the availability of entertainment areas and green spaces, its use of information and communications technology, and also artificial intelligence, and it must have strategies for reducing carbon dioxide and the effective use of resources such as water, electricity, and energy, as well as waste recycling equipment.

Among the most important applications that should be available in smart cities, waste management systems are evolving to become more efficient, sustainable, cost-effective, environmentally friendly and technologically integrated. This can be achieved through the use of waste management technologies via IoTs to determine when waste bins should be picked up, reducing annual collection costs and carbon footprint. In addition, the use of AI-powered waste bins and fill level monitoring platforms can improve waste management by providing real-time data and enabling more effective planning. One of the main features and components of smart city waste management systems is integration with other smart city systems, Waste management systems can be integrated with other urban infrastructure systems, such as traffic management, energy management, and water management.

These systems can be integrated using fuel cell electric vehicles (FCEVs) that work with fuel cells to transport waste to reduce energy consumption and climate and environmental pollution, as well as reduce noise pollution. Traditional Waste management system uses gasoline-powered vehicles, and as they move through the center of the smart city, they emit Co_2, which increases the level of pollution, as well as not using clean energies, and this violates smart city standards. Smart waste management's complexity necessitates a comprehensive multi-criteria approach, involving data collection, analytics, route planning, optimization, decision support, waste classification, and more [8]. The transportation sector accounts for 25% of total energy consumption and industrial Co_2 emissions [9]. The transportation sector is one of the major global sources of carbon emissions, accounting for more than 25% of emissions and contributing to the intensification of global warming [10]. Smart waste management demonstrates the potential for fuel cell technology to contribute to more sustainable waste management practices, as the use of fuel cells in waste management vehicles can help reduce greenhouse gas emissions. In recent years, there has been a shift towards FCEVs, as many car companies have shifted their focus from gasoline-powered cars to FCEVs.

FCEV is a type of electric vehicle that uses hydrogen fuel cells as the primary source of energy. The vehicles generate electricity through a chemical reaction between hydrogen and oxygen and produce water and heat only as byproducts. This makes them emissions-free and one of the best solutions for the environment. The first fuel cell car was the Chevrolet Electrovan, introduced by General Motors in 1966. Due to the high efficiency of the electrochemical cell reaction, FCEVs can use up to 60% more fuel than conventional fuel vehicles, which now only utilize 20% of the fuel's energy [11]. One of the challenges which facing these vehicles is developing the hydrogen infrastructure, as hydrogen refueling stations are currently limited and producing hydrogen can be energy intensive and can emit greenhouse gases depending on the method used. hydrogen refueling stations (HRSs) are one of the key points of this technology, which has been imposed as the main challenge for developed countries such as Japan and the USA by 2030 [12] .Despite these challenges, there are many automobile manufacturers that have already introduced FCEV vehicles to the market, such as Toyota, Hyundai, and Honda. These vehicles have received positive reviews for their performance and are expected to be affordable. In terms of energy efficiency and environmental benefits, hydrogen propulsion is regarded as the future and prospective of the transportation sector even though FCEVs are up to 50% more expensive than conventional internal combustion engine vehicles (ICEVs) [13]. Sweden was one of the first countries to use the first hydrogen-powered waste collection vehicle.

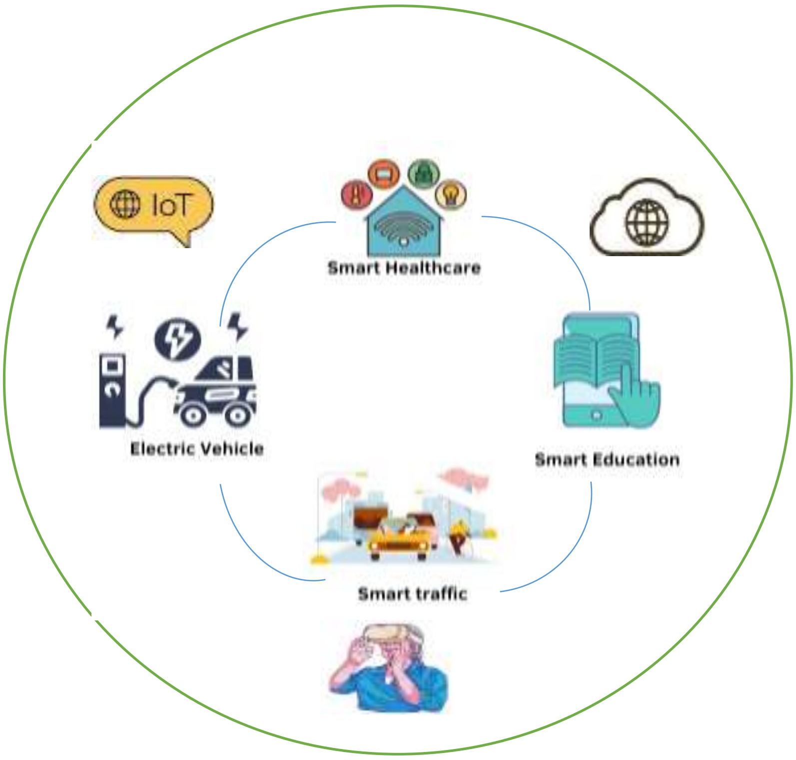

Figure 1. Implications of ICT in sectors of city.

In this context, the study's primary purpose is to address the choice of FCEV company, which embraces the notion of a waste management system through the development of a robust new decision making model with a tree-soft approach. This study proposed the entropy method to get weights and the RAM (Root Assessment Method) to rank alternatives based on a tree-soft approach. Tree-Soft sets contribute to dividing any problem into functional and non-functional attributes to make the MCDM problem more clear. Multi-criteria decision-making (MCDM) comprises three main components: several different criteria, a set of alternatives, and a comparison process between them [14]. MCDM works into two stages the first get weights for criteria and then rank alternatives based. Weighting methods can be It can be divided into 3 sections: subjective, objective, and integrated. Examples of traditional weighting methods include AHP, MACBETH, DEMATEL, CRITIC, ENTROPY, and others [15] .One of traditional Weighting method is ENTROPY. The entropy weight method is a decision-making technique commonly used in multi-criteria decision analysis (MCDA) and decision-making problems where multiple criteria or attributes need to be considered. The entropy weight method (EWM) is an important information weight model that has been extensively studied and practiced [16]. To rank alternatives for MCDM problem to make a decision we use one of ranking methods such as SAW, WASPAS, COPRAS, TOPSIS, VIKOR and EDAS. RAM of is these methods. RAM is a novel MCDM method which aims to derive the utility value of each option by aggregating its scores over decision criteria and the total ranking is achieved on the basis of these utility values [17].

1.1 | Objectives

This paper describes the research objectives of creating and developing a methodical and robust method for prioritizing sustainable approaches for a smart waste management system:

- Introducing the ENTROPY-RAM method with the tree-soft approach to obtain a reliable result in the decision-making process.
- Procedure a case study to apply the developed methodology and validate it in the situation of smart waste management.

1.2 | Organization

This paper is structured as follows: Section 2 represents a literature review for the methods used in this paper as well as presenting their methodologies in Section 3. Our case study will be defined in Section 4. Finally, Conclusion in Section 5.

2 | Literature Review

Multi-criteria decision making (MCDM) is an approach to decision making that involves evaluating and comparing alternatives based on multiple criteria or objectives. In many real-world scenarios, decisions cannot be based on a single criterion, and instead, decision-makers must consider various factors simultaneously. MCDM provides a systematic framework for handling such complex decision situations. Büşra Ayan et al. [18] proposed a comprehensive review of the novel weighting methods for multi-criteria decision-making and their methodologies.To get weights, we use Entropy method Yuxin Zhu et al. [19] introduced the methodology of the entropy weight method in decision-making. Xiaowen Ding et al. [20] introduced the entropy weight method using a fuzzy approach. The RAM method is used to rank alternatives and divide the problem criteria into beneficial and non-beneficial. The philosophy of RAM is introduced in [17], which defines its methodology, compares it with other MCDM problems, and showcases its strengths. The approach of the tree soft set was introduced by Smarandache [21], who is the founder of this approach.

3 | Methodology

This section is divided into three parts to proposed the Entropy-RAM under Tree-soft set.

3.1 | Tree Soft Set [21]

Smarandache propose the definition of TreeSoft Set as

Le Let U be a universe of discourse, and H a non-empty subset of U, with P(H) the powerset of H.

Let A be a set of attributes (parameters, factors, etc.), A= {A1, A2, … , An}, for integer n ≥ 1, where A1, A2, … , An are considered attributes of first level (since they have one-digit indexes). Each attribute Ai, 1 ≤ i ≤ n, is formed by sub-attributes: A1 = {A1,1, A1,2, …} A2 = {A2,1 , A2,2 , … } An = {An,1 , An,2 , … } where the above Ai,j are sub-attributes (or attributes of second level) (since they have two-digit indexes). Again, each sub-attribute Ai,j is formed by sub-sub-attributes (attributes of third level): Ai,j,k And so on, as much refinement as needed into each application, up to sub-sub-…-sub-attributes (or attributes of m-level (or having m digits into the indexes).

Therefore, a graph-tree is formed, that we denote as Tree(A), whose root is A (considered of level zero), then nodes of level 1, level 2, up to level m. We call leaves of the graph-tree, all terminal nodes (nodes that have no descendants). Then the TreeSoft Set is:

$$F: P(Tree(A)) \rightarrow P(H)$$

Tree(A) is the set of all nodes and leaves (from level 1 to level m) of the graph-tree, and P(Tree(A)) is the powerset of the Tree(A). All node sets of the TreeSoft Set of level m are:

$$Tree(A) = \{Ai1 \mid i1= 1, 2, ...\}$$

So, Problem must be defined as the tree structure.

3.2 | Entropy Method [19]

MCDM problem contain set of m alternative and set of n criteria to rank alternatives based on it. Entropy weight method is calculated as followed:

1. Define decision matrix where m defines a set of alternatives, n define set of criteria.

$$\mathbf{x} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

Where x_{ij} indicates that i = 1,2…..,m ; j= 1,2,…..,n

2. Normalize the decision matrix by

$$\mathcal{P}_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (2)$$

3. Calculate the entropy value of criteria by

$$E_j = \frac{\sum_{j=1}^{n} \mathcal{P}_{ij} . ln\, \mathcal{P}_{ij}}{ln\, n} \quad (3)$$

4. Calculate the degree of variation for each creation using

$$d_j = 1 - E_j \quad (4)$$

5. Finally, Calculate the criteria weights by

$$\mathcal{W}_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \quad (5)$$

3.3 | RAM Method [17]

RAM method is used to rank the alternatives based on a radical expression which its radicand and index are the sums of benefit and cost criteria of each alternative.

The criteria must be divided into beneficial and non-beneficial

1. Normalize the aggragated matrix in previous step using

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad (6)$$

2. Compute the weighted normalized matrix

$$y_{ij} = r_{ij} \, . \, w_j \quad (7)$$

Where $\mathcal{W}_j$ the weighted values for each criteria calculated by Entropy method

3. Calculate the summation for beneficial criteria and non-beneficial criteria using

$$\mathcal{S}_{+\mathrm{i}} = \sum_{\mathrm{j}=1}^{\mathrm{n}} \mathcal{Y}_{+ij} \qquad \text{for beneficial} \quad (8)$$

$$\mathcal{S}_{-\mathrm{i}} = \sum_{\mathrm{j}=1}^{\mathrm{n}} \mathcal{Y}_{-ij} \qquad \text{for non- beneficial} \quad (9)$$

4. Calculate the overall score for each alternative by

$$\mathcal{RI}_i = \sqrt[2+\,\mathcal{S}_{-\mathrm{i}}]{2 + \mathcal{S}_{+\mathrm{i}}} \quad (10)$$

5. Finally, Ranking alternatives based on the value of $\mathcal{RI}_i$ as the bigst value of $\mathcal{RI}_i$ the higher priority of its alternatives. It usually that small gab between the overall score of $\mathcal{RI}_i$ value as results are very close to each other so they cannot be ranked. To Solve this problem we must equalize the $\mathcal{RI}_i$ value to be in the range of [0,1] and normalized it using min-max normalization method.

4 | Case Study

4.1 | Problem Definition

As we discussed above, one of the problems facing smart cities is the use of unclean energy, as well as how to manage the smart waste management system, as this system is considered one of the most important systems that must be available in smart cities, as the waste management system has many aspects as well as many advantages, and with the overlap technology has become more important, as we also mentioned that the use of fuel cell vehicles (FCEVs) is one of the most important elements of the waste management system, as it leads to a reduction in noise pollution as well as to the absence of greenhouse gas emissions. It is believed that these vehicles have the potential to be one of the most sustainable transportation alternatives because they are powered by a clean, reliable, safe, and environmentally friendly energy source, especially hydrogen, as it does not produce any emissions during movement. Egypt has become one of the countries that seeks to provide smart cities for its citizens to improve the quality of life. In this paper, we propose manufacturing vehicles that operate on fuel cells for use in transporting garbage in the smart waste management system.

4.2 | Definition of Criteria and Alternatives

One of the most famous companies in Egypt that helps the country develop smart cities and also has the ability to manufacture vehicles that operate on fuel cells, as it has manufactured cars that operate with the same idea, so there are 3 alternatives (Alt1 , Alt2 , Alt3).

According to the TreeSoft approach, criatria and sub-criteria are structured as hierarchical form to achieve the TreeSoft's goals. So, criateris will be devided as follow:

1. $\mathcal{C}_1$: Economic criterion taking into account that it is a beneficial criateria which includes three sub-criateria.
   a) $\mathcal{C}_{11}$: Project costs: (beneficial) The costs required to produce cars and the infrastructure for hydrogen production stations, as well as government funding to manage the project.
   b) $\mathcal{C}_{12}$: (beneficial) Logistics costs: include design, manufacturing, installation, transportation, and other expenses
   c) $\mathcal{C}_{13}$: (non-beneficial) Staff and labor costs : are relative to the experience and skills of each person.
2. $\mathcal{C}_2$: Environmental criterion defined as beneficial criteria, it includes two sub-criateia :

a) $\mathcal{C}_{21}$: (beneficial) Impact on the environment: The possibility of high-risk conditions and serious effects arising from handling hydrogen if the necessary precautions are not taken.
b) $\mathcal{C}_{22}$: (non-beneficial) Use of renewable energies: to maintain the concept of the smart city and the absence of any harmful emissions to the environment.

3. $\mathcal{C}_3$: Technical criterion which defined as non-beneficial criteria. It includes two sub-criateria :
a) $\mathcal{C}_{31}$: (beneficial) Project structure: It includes the components and materials used, in addition to the types of modern technology used to improve the performance of FCEVs.
b) $\mathcal{C}_{32}$: (non-beneficial) Logistics efficiency: Providing the necessary technologies and methods to manage and manufacture FCEVs in the best way.

The problem is represented as hierarchy form as Figure 2, it's consist of attributes of level one then these attributers branched into sub attributes as level 2.

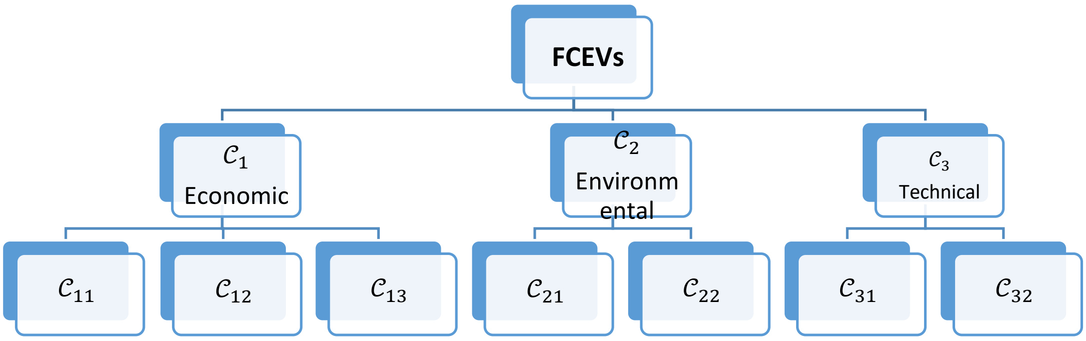

Figure 2. Modelling criteria and sub-criteria into tree-soft.

4.3 | Experiment and Results

After the alternatives and criteria have been defined, decision makers can easily express their opinions to obtain the decision matrix to each level.

First, calculate weights using Entropy Method for level one from tree-soft as Figure 2 .So, need to calculate first weights for $\mathcal{C}_1, \mathcal{C}_2$ and $\mathcal{C}_3$ the decision matrix fist level in Table 1.

Step 1: Apply Eq. (2) to get normalized decision matrix $\boldsymbol{\mathcal{P}_{ij}}$ represented in Table 2.
Step 2: Apply Eq .(3) to calculate entropy value for each criterion $\boldsymbol{E_j}$ as Table 3.
Step 3: Apply Eqs. (4, 5) to get final weights for first level $\mathcal{W}_j$ as shown in Table 4.
Step 4. Applying previous step on sub-criteria of criterion $\mathcal{C}_1$ second level to get method So, decision matrix is represented in Table 5 then results of the steps will be in Table 6.
Step 5: applying previous step on sub-criteria of criterion $\mathcal{C}_2$ second level to get method So, decision matrix is represented in Table 7 then results of the steps will be in Table 8.
Step 6: applying previous step on subcriteria of criteria $\mathcal{C}_3$ second level to get method So, decision matrix is represented in Table 9 then results of the steps will be in Table 10.

Table 1. decision matrix fist level.

	$\mathcal{C}_1$	$\mathcal{C}_2$	$\mathcal{C}_3$
Alt_1	0.68	0.98	0.38
Alt_2	0.78	0.46	0.82
Alt_3	0.94	0.83	0.5

Table 2. normalized decision matrix

$\mathcal{P}_{ij}$	$\mathcal{C}_1$	$\mathcal{C}_2$	$\mathcal{C}_3$
Alt_1	0.28333333	0.431718062	0.223529412
Alt_2	0.325	0.202643172	0.482352941
Alt_3	0.39166667	0.365638767	0.294117647

Table 3. entropy value for each criterion.

	$\mathcal{C}_1$	$\mathcal{C}_2$	$\mathcal{C}_3$
E_j	0.9919098	0.959382386	0.952567127

Table 4. final weights for first level.

	$\mathcal{C}_1$	$\mathcal{C}_2$	$\mathcal{C}_3$
$\mathcal{W}_j$	0.306219	0.343033704	0.350747254

Table 5. decision matrix for sub-criteria of criterion 1.

	$\mathcal{C}_{11}$	$\mathcal{C}_{12}$	$\mathcal{C}_{13}$
Alt_1	0.105	0.93	0.75
Alt_2	0.131	0.701	0.35
Alt_3	0.57	0.532	0.46

Table 6. Weights for sub-criteria of criterion 1.

	$\mathcal{C}_{11}$	$\mathcal{C}_{12}$	$\mathcal{C}_{13}$
$\mathcal{W}_j$	0.14415256	0.0778648	0.084202

Table 7. decision matrix for sub-criteria of criterion 2.

	$\mathcal{C}_{21}$	$\mathcal{C}_{22}$
Alt_1	0.49	0.78
Alt_2	0.38	0.62
Alt_3	0.93	0.56

Table 8. Weights for sub-criteria of criterion 2.

	C_{21}	C_{22}
w_j	0.188360552	0.154673153

Table 9. decision matrix for sub-criteria of criterion 3.

	C_{31}	C_{32}
Alt_1	0.75	0.61
Alt_2	0.42	0.93
Alt_3	0.36	0.82

Table 10. Weights for sub-criteria of criterion 3.

	C_{31}	C_{32}
w_j	0.166780445	0.183966809

Now, we get all weights for all levels of tree using Entropy method to get finial weights for each criteria in the tree it's represented in Figure 3.

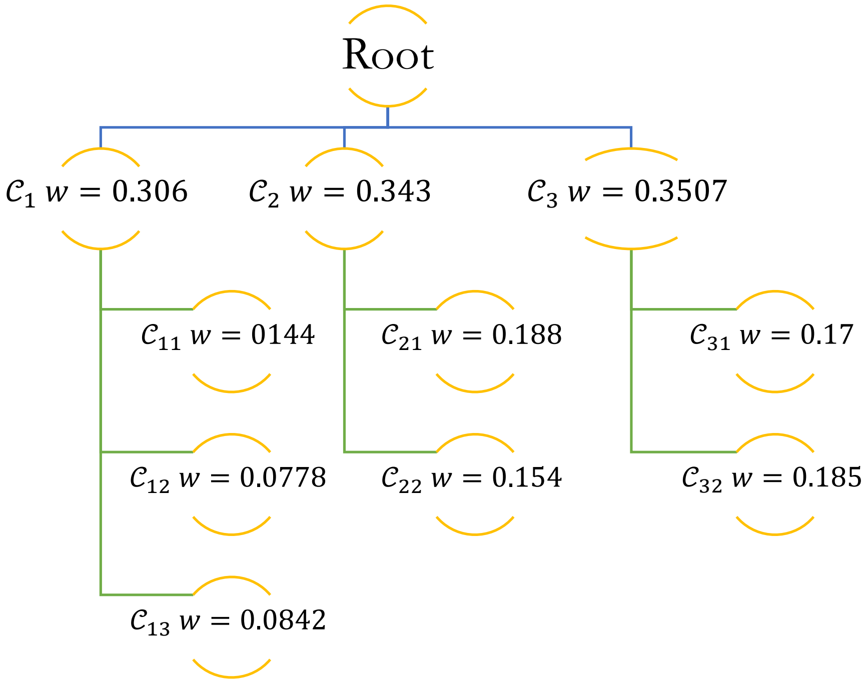

Figure 3. Final weights for criteria and sub-criteria.

Second Stage is ranking alternatives based on weights using RAM Method as following Steps: First Rank alternatives for first level C_1, C_2 and C_3 using the following steps :

Step 1: Normalize decision matrix using Eq. (7) to get Table 11.

Step 2: calculate the weighted normalized matrix using Eq. (8).

Step 3: calculate the sum of weighted normalized matrix for all alternative using Eqs. (9,10). As shown the result of S_+ *and* S_- will be in Table 14 then using Eq. (11) to get $\mathcal{RI}_i$ to rank alternatives based on the first level of tree. After calculate $\mathcal{RJ}_i$ we used min –max normalization to be able to rank alternatives as the values of $\mathcal{RJ}_i$ was too close to each other the result also displayed in Figure 4.

Table 12.

r_{ij}	C_1 +	C_2 +	C_3 −
Alt_1	0.28333333	0.431718062	0.223529412
Alt_2	0.325	0.202643172	0.482352941
Alt_3	0.39166667	0.365638767	0.294117647

Table 13. Weighted normalized matrix.

y_{ij}	C_1 +	C_2 +	C_3 −
Alt_1	0.08676206	0.148093846	0.078402327
Alt_2	0.09952119	0.069513438	0.16918397
Alt_3	0.11993579	0.125426421	0.103160957

Table 14. Ranking of alternatives.

	S_+	S_-	$\mathcal{RJ}_i$	Normalized $\mathcal{RJ}_i$	Rank
Alt_1	0.052257821	0.04048156	1.433	0.068965517	2
Alt_2	0.048664238	0.018891395	1.431	0	3
Alt_3	0.121095338	0.02482869	1.46	1	1

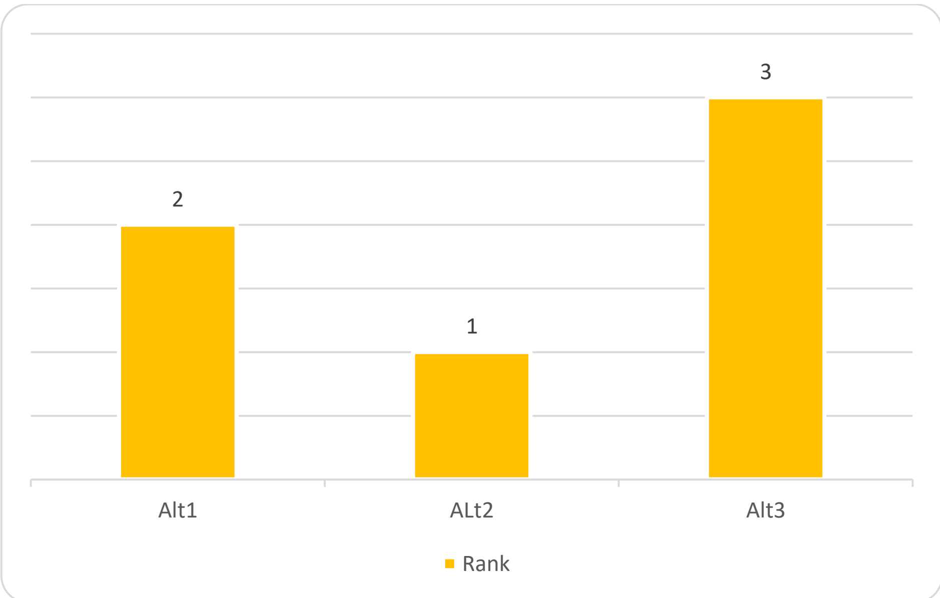

Figure 4. Ranking of alternatives based on main criteria.

Table 15. normalized decision matrix.

	$\mathcal{S}_+$	$\mathcal{S}_-$	$\mathcal{RJ}_i$	Normalized $\mathcal{RJ}_i$	Rank
$\boldsymbol{Alt_1}$	0.1494778	0.179439	1.466	0.26087	2
$\boldsymbol{Alt_2}$	0.1159216	0.142631	1.454	0	3
$\boldsymbol{Alt_3}$	0.2837028	0.128828	1.5	1	1

Repeat the previous step for the second level of $\mathcal{C}_1$ and rank alternatives based on $\mathcal{C}_{11}, \mathcal{C}_{12}$ and $\mathcal{C}_{13}$ the normalized decision matrix in represented in Table 15 and other steps will displayed in Table 16.

Table 16. Ranking of alternatives.

	$\mathcal{C}_{11}$ +	$\mathcal{C}_{12}$ +	$\mathcal{C}_{13}$ −
$\boldsymbol{Alt_1}$	0.13027295	0.4299584	0.480769
$\boldsymbol{Alt_2}$	0.16253102	0.3240869	0.224359
$\boldsymbol{Alt_3}$	0.70719603	0.2459547	0.294872

The penultimate step here is to rank level two of $\mathcal{C}_2$ and rank alternatives based on $\mathcal{C}_{21}$ and $\mathcal{C}_{22}$ by repeat the previous steps, the normalized decision matrix in represented in Table 17 and other steps will displayed in Table 18.

Table 17. Normalized decision matrix.

	$\mathcal{C}_{21}$ +	$\mathcal{C}_{22}$ −
$\boldsymbol{Alt_1}$	0.2722222	0.397959
$\boldsymbol{Alt_2}$	0.2111111	0.316327
$\boldsymbol{Alt_3}$	0.5166667	0.285714

Table 18. Ranking alternatives.

	$\mathcal{S}_+$	$\mathcal{S}_-$	$\mathcal{RJ}_i$	Normalized $\mathcal{RJ}_i$	Rank
$\boldsymbol{Alt_1}$	0.051275928	0.061553602	1.432	0.4	2
$\boldsymbol{Alt_2}$	0.039765005	0.048927222	1.42	0	3
$\boldsymbol{Alt_3}$	0.097319618	0.044192329	1.45	1	1

The penultimate step here is to rank level two of $\mathcal{C}_3$ and rank alternatives based on $\mathcal{C}_{31}$ and $\mathcal{C}_{32}$ by repeat the previous steps, the decision matrix in represented in Table 19 and other steps will displayed in Table 20.

Table 19. Normalized decision matrix

	$\mathcal{C}_{31}$ +	$\mathcal{C}_{32}$ −
$\boldsymbol{Alt_1}$	0.3370166	0.5050505
$\boldsymbol{Alt_2}$	0.2099448	0.3131313
$\boldsymbol{Alt_3}$	0.4530387	0.1818182

Table 20. Ranking alternatives.

	$\mathcal{S}_+$	$\mathcal{S}_-$	$\mathcal{RJ}_i$	Normalized $\mathcal{RJ}_i$	Rank
Alt_1	0.0562078	0.0929125	1.434	0.7	2
Alt_2	0.0350147	0.0576058	1.42	0	3
Alt_3	0.075558	0.0334485	1.44	1	1

5 | Conclusion

Fuel cell vehicles, operating on hydrogen, are introduced into the smart waste management system. Their use aims to improve environmental performance by reducing emissions associated with traditional fossil fuel vehicles. MCDM Methods Multi-Criteria Decision-Making (MCDM) methods are employed to evaluate alternatives and criteria in the decision-making process. The RAM (Root Assessment Method) is selected as the preferred method due to its accuracy and reliability in providing results. The TreeSoft approach is applied to structure the decision problem into hierarchical levels, making it easier to analyze and solve. This approach helps in organizing the criteria and alternatives hierarchically, facilitating a systematic evaluation process. Based on the results of the MCDM analysis using the RAM method and the TreeSoft approach, Alt1 emerges as the preferred alternative for integration into the smart waste management system. This decision is made considering its superior performance across the identified criteria and hierarchical levels. Based on the evaluation, Alt3 is consistently identified as the best alternative across multiple levels, while Alt2 is consistently rated lower in performance. Overall, by combining MCDM methods such as RAM with structured problem-solving approaches like TreeSoft, decision-makers can systematically evaluate alternatives and criteria to make informed decisions, such as selecting the most suitable alternative for integrating fuel cell vehicles into a smart waste management system in smart cities.

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Author Contributaion

All authors contributed equally to this work.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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