Journal of Future Sustainability 5 (2025) 91–106

Contents lists available at GrowingScience

Journal of Future Sustainability

homepage: www.GrowingScience.com/jfs

Municipal solid waste management strategy selection: Multi-criteria decision making under uncertainty

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C H R O N I C L E

Article history:
Received: January 10, 2024
Received in revised format: February 20, 2024
Accepted: April 11, 2024
Available online:
April 11, 2024

Keywords:
Strategy selection
Waste Recycling
Multi-criteria Decision making
Fuzzy DMATEL
Fuzzy ANP
Fuzzy TOPSIS
Dire Dawa city

A B S T R A C T

For decades, due to the increasing generation of waste and its negative environmental impacts, efficient municipal solid waste management (MSWM) has become a major concern of sustainable development. On the other hand, selecting an appropriate strategy remains a critical issue for municipal authorities without applying a multi-criteria decision-making (MCDM) approach. This study aims to select the best MSWM strategy from five potential MSW management strategies under various factors that influence waste strategy selection, such as economic, social, technical, and environmental factors. This study used three fuzzy integrated MCDM methods, namely the Decision-Making Trail and Evaluation Laboratory (DMATEL), the Analytic Network Process (ANP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to select best MSWM strategies. The study used data from a survey of experts who had knowledge of waste management. The survey data was then analyzed using the DMATEL, ANP and TOPSIS methods under a fuzzy environment. The Fuzzy DEMATEL method is used to identify the causal relationships among the criteria and sub-criteria, while ANP is applied to determine the relative weights of MSWM strategy selection sub-criterion. Finally, TOPSIS is used to rank the waste management strategies depending on established sub-criteria. The result of fuzzy TOPSIS demonstrated that recycling of municipal solid waste is the best alternative which has the highest closeness coefficient followed by reuse. Thus, the result of this study revealed that MSWM strategies are ranked as: waste recycling (A1), reuse (A2), reduce (A1), energy recovery (A4), and disposal (A5), with closeness coefficient values of 0.80, 0.61, 0.60, 0.47, and 0.17, respectively.

1. Introduction

Municipal solid waste has emerged as a global issue, and it's growing at a rate faster than urbanization. It is generated due to daily human complex activities in households, institutions, commercial, construction, retailers and shops, road sweeping, industries, etc. The volume of municipal solid waste generated daily grows in lockstep with human living standards. According to Coban et al. (2018), the municipal city's solid waste generation rate is estimated to be 1.42 kg/capita/day by 2025, which means 2.2 billion tons of solid waste will be generated per year. Furthermore, if it is not managed environmentally safely, the total amount is expected to rise to 3.40 billion tons by 2050 (Guo et al., 2021).

Only in Africa, according to Weghmann (2019), since 2015, the annual urban waste generated was 124 million tons, and it is expected to reach 368 million tons by 2040 as rapid growth in urban areas. Less than half of the municipal solid waste generated by African countries is collected, and 95% of it is dumped haphazardly on roadside debris and in uncontrolled areas, frequently on the fringes of urban centers or dispersed throughout the metropolis (Muhammad et al., 2021). According to a world bank report cited by Kaza et al. (2018) from a sub-Saharan African country, Ethiopia has generated more than 6.5 million tons of municipal solid waste annually since 2015.

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ISSN 2816-8151 (Online) - ISSN 2816-8143 (Print)

doi: 10.5267/j.jfs.2025.4.001

Similarly, according to data from the primary source, per capita waste generation rates in Dre Dawa are estimated to be 0.49 kg/capacity/ days, meaning 147 tons of municipal solid waste are generated daily. In the city, the existing solid waste management practice and sorting waste based on waste characteristics is inefficient. The city started a door-to-door waste collection strategy eight years ago. Still, problems like waste segregation, individual carelessness for the environment, sustainable door-to-door waste collection, resource scarcity, temporary storage issues, residents' attitudes toward sorting waste from the beginning, and illegally throwing away bottles and other plastic in open spaces, roadside ditches, and drainage channels are issues unresolved in this city.

However, to improve Dawa City's MSWM strategy, appropriate techniques in line with the UN Sustainable Development Goals are required to bring sustainable solid waste management practices. Significantly one of the UN Sustainable Development Goals for 2030 is to control and monitor waste generation to diminish waste generation through prevention, reduction, recycling, and reuse. The alternative of waste management is prioritized while it is used for circular economy strategy. In 2015 the circular economy strategy (EU commission & Brussels, 2015) argued that waste management based on a waste hierarchy is the most incredible method to get the best overall environmental outcome even while reintroducing valuable materials into the economy. With the advent of sustainable development and its guiding principles, it appears that choosing the best strategy should be based on criteria that consider environmental, economic/financial, social, and technical elements. Several alternatives are important in municipal solid waste management, but several criteria are also essential to select an optimal alternative.

Selecting the most suitable alternative from this waste prevention strategy is no simple task and it requires a complicated multi-criteria decision-making method (MCDM). The goal of MCDM is to assist decision-makers in selecting the best options based on a variety of criteria (Zhou et al., 2019). Additionally, it studies the decision problems in which the decision space is discrete or finite decision space. MADM methods are highly applied to selecting a single option to find the best optimal solution or ranking choices from the most to the least appropriate (Vinogradova, 2019).

Nowadays, numerous techniques for multi-criteria decision-making have emerged. According to the literature reviewed, the most used multi-criteria decision methods are MODM and MADM: distance-based methods, value/utility theory, pairwise comparison process method, outranking methods, metaheuristics, and mathematical programming methods. According to Ghaleb et al. (2020), the selection of MCDM methods evaluation was done depending on the factors: number of alternative processes and criteria, addition or removal of criterion and agility through the process of decision-making, computational complexity, and adequacy in supporting a group decision. Another study by Silva et al. (2021) suggested the selection of a suitable MCDM method is influenced by different factors like time available to decide, the effort that a given strategy will involve, the importance of making an accurate decision, and whether or not the user has to justify their choice to others.

Consequently, the problem in this study is subjected to various MCDM solution selection factors, such as criterion addition or removal, single objective MCDM types, and the need to make an accurate conclusion. Even though there is no generic rule or formality for selecting a specific MCDM method (Coban et al., 2018). This paper adopted the integrational application of MADM under uncertain conditions to prioritize and select the appropriate MSWM alternative because of the following reason.

a) Numerous daily choices involve some level of uncertainty, and they cannot model with accuracy assumption. As an illustration, the data subject to human judgment, such as important/not important, right/wrong, influence/non-influence, yes/no, etc., increase the vagueness in decision-making. Therefore, the Fuzzy integration set with other MCDM methods enables us to get more realistic results in decision-making problems (Kaya et al., 2019).
b) DEMATEL is a powerful MCDM technique that considers the criteria's interrelationships to assess the degree of influence and importance of criteria (Hatefi & Tamošaitienė, 2018).
c) In pairwise comparison, the classification of MADM AHP and ANP are the most frequently used methods. However, AHP is not measuring the possible dependencies among the criteria, while ANP represents the dependencies among criteria or alternatives to solve the problems having dependencies (Agrawal et al., 2020). As a result, ANP is selected for pairwise weight comparison for this research.
d) ANP is formulated in network form to consider nonhierarchical structures, which implies interactions and dependencies among the problem factors are shown in a network to assess the overall influence of these dependencies on the network (Mirahmadi et al., 2018; Agrawal et al., 2020).
e) The ideal solution is the one that excels on all criteria, but decision-makers frequently cannot arrive at the ideal solution. The decision-maker should therefore select the option that comes the closest to providing the ideal solution. Because of this, the Positive Ideal Solution (PIS), which maximizes profit, and the Negative Ideal Solution (NIS), which maximizes cost, are used to find the best alternative. Therefore, TOPSIS is chosen in this study to compare the costs and benefits of appropriate and inappropriate alternatives (Arıkan et al., 2017).

2. Methodological study

From a different stream of MADM method, this paper decided to use three MADM methodologies to select appropriate MSWMin Dire Dawa, Ethiopia's eastern region and segmented it into three stages: The first stage utilizes the Fuzzy DEMATEL method to obtain the critical factors for considering the criteria's interrelationships and to assess the degree of influence and importance of criteria. In the second stage, the Fuzzy Analytic Hierarchy Process is applied to obtain the weights and importance degree of each criterion as the measurable indices of the technologies by fuzzy pairwise comparison matrices. Finally, the Fuzzy TOPSIS technique selects an appropriate sustainable MSWM strategy.

A decision-maker can be an individual or a group of experts (Dire Dawa administration climate change and environmental protection Authority, University staff with various professional profiles and academic backgrounds, Municipal Authority, and risk and disaster management commission) who make the final decision between alternatives.

Besides, the four-step data presentation and analysis process were developed. The first phase involved conducting an extensive literature survey to define the alternative, criterion, and sub-criteria and determine the extent to which the defined alternative, criterion, and sub-criteria are essential and applicable in municipal solid waste management. The second phase was used to determine the influence relationship of criteria to construct a causal and effect diagram by applying the fuzzy DEMATEL approach of MCDM. Using the output of the first phase of DEMATEL, the third phase was introduced for weighing importance comparison of criteria and sub-criteria under fuzzy ANP. The fourth phase of the methodology is to identify the closeness of the selected alternative to the ideal positive solution or furthest from the negative ideal solution with the help of TOPSIS.

2.1 Fuzzy DEMATEL methodology

DEMATEL decision-making was founded in Switzerland at the War Memorial Institute in Geneva. It is a comprehensive structural model creation method, including causal relationships between complex factors (Karimi et al., 2021). The key input data for DEMATEL evaluation is an expert opinion on the relationship and influence among the relevant factors (criteria). The DEMATEL framework and computation procedures include the following steps.

Step- 1 Develop evaluation standards and design a fuzzy linguistic scale.

This step defines an appropriate language scale to gather expert opinions based on fuzzy triangular numbers.

Step-2 Create a fuzzy direct relation matrix by determining the effect of the i, j characteristics depend on expert's opinion.

At this step, decision-makers evaluate the bilateral relationships between the criteria to assess the relationship between them. This pairwise comparison between the i^{th} factor and the j^{th} factor is given by k^{th} expert in the form linguistics variable is transferred to its corresponding triangular fuzzy number denoted as ${Z_{ij}}^{(k)}$ to create a fuzzy direct relation matrix (Z) which is computed as Eq. (1)

$$Z^k = \begin{bmatrix} 0 & \cdots & Z1n^{(k)} \\ Z21^{(k)} & \ddots & Z2n^{(k)} \\ \vdots & .. & \vdots \\ Zn1^{(k)} & \cdots & 0 \end{bmatrix} k = 1 \dots p \tag{1}$$

where: P is an expert to provide their opinions.

Step-3 Normal direct relation fuzzy matrix

By normalizing the initial direct relation fuzzy matrix, the new matrix of direct relation fuzzy matrix X can be obtained as the equation below:

$$xlij = {(xli - minxlij)}\Big/{\Delta_{min}^{max}} \tag{2}$$

$$xmij = {(xmi - minxmij)}\Big/{\Delta_{min}^{max}} \tag{3}$$

$$xuij = {(xui - minxuij)}\Big/{\Delta_{min}^{max}} \tag{4}$$

where $\Delta_{min}^{max} = xijmax - xijmin$

$(xli - minxlij)$

$(xmi - minxmij)$

$(xui - minxuij)$

$\Delta\, max - min$

However, after normalization of the direct fuzzy relation matrix with Eq. (3), the triangular fuzzy number must be converted to a crips number. To acquire crips values, compute the left and right normalized values by applying Eq. (5) and Eq. (6) blow,

$$xlsij^{E1} = {xmijE1}\Big/{(1 + xm^{E1} - xl^{E1})} \tag{5}$$

$$xrsij^{E1} = {xuijE1}\Big/{(1 + xu^{E1} - xm^{E1})} \tag{6}$$

The normalized fizzy relation matrix's left and right value is computed through equations (5,.6) and converted to crips value and total crips value by applying equations 7 and 8, respectively, where it is the end of fuzzy.

$$xj^{crips} = \frac{\mathrm{xLsij^{E1}(1 - xLsij^{E1}) + xRsij^{E1} \times xRsij^{E1}}}{\mathrm{[1 - xRsij^{E1} + xLsij^{E1}]}} \tag{7}$$

$$zij = \min li + xj^{crips} \times \Delta_{min}^{max} \tag{8}$$

Step-4 Establishing total relation fuzzy matrix

From a fuzzy triangular matrix depend on Markov chain theory and the convergence assumptions, the total relation fuzz matrix $\breve{T}$ obtained by the equation below

$$\breve{T} = \sum_{w=1}^{\infty} X^w = X^1 + X^2 + X^3 \dots . X^w \tag{9}$$

$$\breve{T} = X(I - X)^{-1}$$

Step-5 Calculate each factor's influence degree, affected degree, center degree, and cause degree.

To calculate the central degree and cause degree, the sum of each column and row of matrix T are respectively marked as vectors $Di \text{ and } Rj$ in matrix T and calculated as Eq. (10) below

$$\begin{aligned} D &= [Di]1xn \left[\textstyle\sum_{j=1}^{n} tij\right]1xn \\ R &= [Rj]nx1 = \left[\sum_{i=1}^{n} tij\right] \\ Ci &= Di + Ri \,/ i = j \\ Ei &= Di - Ri \,/ i = j \end{aligned} \tag{10}$$

where: $Di, Ri, Ci \text{ and } Ei$ are influence degree, affected degree, center degree, and cause degree, respectively.

Step-6 Set a Threshold Value (α) and build the impact relationship network

To explain the structural relationship between the criteria while maintaining the system's complexity at a manageable level, a threshold value α must be set to filter out some insignificant/negligible effects in the matrix, $\breve{T}$. According to (Yang & Tzeng, 2011), the criteria whose effective relation matrix $\breve{T}$ value greater than the threshold value is chosen and shown in an impact relation network (IRN) for influence, while the values of the criteria effective relation matrix $\breve{T}$ are zero if the value is less than the threshold (α).

The $\alpha - cut$ total direct relation matrix T is formulated as Eq. (11) blow by considering only the components in total relation matrix T whose value is greater or equal to threshold values and setting zero for those below the threshold value.

$$T\alpha = \begin{bmatrix} t_{11} & t_{12} & \cdots & t_{1n} \\ t_{21} & t_{22} & \dots & t_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ t_{n1} & t_{n2} & \cdots & tnn \end{bmatrix} \tag{11}$$

Fuzzy ANP methodology

ANP is an extension of the analytic hierarchy process (AHP) developed to remove the restriction of the AHP method, which has been employed for the selection problems under multiple criteria (Alam-Tabriz et al., 2014). Steps in the Fuzzy ANP process can be divided as follows. Consequently, the impact relation network (IRN) or impact relation map obtained by DEMATEL is the foundation for Fuzzy ANP to design the pairwise comparison between criteria and contraction of the super-matrix.

Step-1 Compare the criteria in the whole system to form an un-weighted super-matrix

In this step, pairwise comparisons were used to determine the importance of the criteria with respect to each other. To evaluate the significance and influence of one criterion concerning another, expert opinion is gathered in the form of linguistic terms and then converted to the corresponding fuzzy numbers (see Eq. (12)).

$$\breve{A} = \begin{bmatrix} 1,1,1 & a_{12} & \cdots & a_{1n} \\ a_{21} & 1,1,1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & 1,1,1 \end{bmatrix} \quad (12)$$

while: $a_{ij} = 1$ if $i = j$ and $a_{ij} = {a_{ji}}^{-1}$ when $i \neq j$

Step-2 Determine Fuzzy aggregated pairwise comparison matrix.

Based on linguistics variables, experts evaluate the degree of importance for each sub-criteria using pairwise comparison. Where $\breve{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ represents a pairwise comparison of criteria i and j which is determined by expert k, the geometric mean of fuzzy comparison value of criterion i to each criterion j is applied to obtain aggregate fuzzy judgment matrix $A*$ as shown in the equation below (Hemmati et al., 2018; Dargi et al., 2014; Wu et al., 2018)

$$A* = (\breve{a}_{ij})n \times n = ({l^*}_{ij}, {m^*}_{ij}, {u^*}_{ij}) \quad (13)$$

where:

$${l^*}_{ij} = \min({l^1}_{ij}, {l^2}_{ij}, \ldots \ldots {l^k}_{ij}) \quad (14)$$

$${m^*}_{ij} = \sqrt[k]{\prod_{k=1}^{k} ({m^k}_{ij})} \quad (15)$$

and

$${u^*}_{ij} = max({u^1}_{ij}, {u^2}_{ij}, \ldots \ldots {u^k}_{ij}) \quad (16)$$

Step-3 Triangular fuzzy weights or local priority weights calculation

After the decision maker's preferences are stated by fuzzy triangular numbers (TFNs), calculations of the local priority weights for these evaluations are derived and arranged into a matrix called $\widetilde{W}_i$. The logarithmic least squares method is implemented as a blow equation to calculate the triangular fuzzy weights from the pairwise comparison matrix (Rekik et al., 2017).

$$\widetilde{W}_i = \frac{\left(\prod_{j=1}^{n} a_{ij}\right)^{1/n}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n} a_{ij}\right)^{1/n}} \quad (17)$$

Step-4: Form un-weighted super-matrix

The output of local priority weights obtained from fuzzy pairwise comparison is used as input in suitable columns of the unweighted constructed super-matrix to obtain the global priorities in a system (Chatterjee et al., 2018)

Sep-5: Determine weighted super-matrix and normalize weighted super-matrix

As a result, the previously extracted super-matrix covers the whole network to calculate the final weights of each criterion, sub-criteria, and alternatives; it's mandatory to be normalized the super-matrix (Hatefi & Tamošaitienė, 2018). Thus, the element pertaining to the $i - th$ row and the $j - th$ column of the normalized super matrix is obtained from dividing the element pertaining to the $i - th$ row and the $j - th$ column of the supermatrix by the sum of the j-th elements of the super matrix.

$$W_i = \frac{w_i}{\sum {w_i}'} \quad (18)$$

Finally, the column stochastic weighted super-matrix is raised to an appropriately large power until it converges. Therefore, according to Eq. (18), the normalized super-matrix to the power of an adequately large odd number, the limited super-matrix, will be obtained (Chatterjee et al., 2018; Hatefi & Tamošaitienė, 2018)

$$W_i = \lim_{k \to \infty} (W_i)^{2k+1} \quad (19)$$

Step-6: Calculation of the consistency index and consistency ratio

$$consistency\ index\ (CI) = \frac{\lambda_{max} - n}{n - 1} \quad (20)$$

where: λ_{max} Is matrixes have their largest eigenvalue, and n is several compared elements. Then from the consistency index, the consistency ration can be computed and checked for each matrix to verify if its value is less than 0.1 according to Saaty's guidelines.

$$consistency\ ratio\ (CR) = \frac{CI}{RI} \tag{21}$$

where: RI is the random index. If the consistency ratio is more than 0.1, an inconsistency has emerged, and the experts will attempt to modify the pairwise comparison values.

Fuzzy TOPSIS methodology

To overcome the concise problem of using the TOPSIS method, fuzzy TOPSIS utilizes cardinal information to analyze undefined issues. The TOPSIS method's main principle is that each chosen alternative should have the shortest distance from the positive ideal solution and the greatest distance from the negative ideal solution in a graph (Uygun & Dede, 2016). The step of computing Fuzzy TOPSIS is as follow (Rani et al., 2020; Sagnak et al., 2021).

Step- 1: Construct the fuzzy decision matrix

There are *n* alternative $A_i = (A_1, A_2, \dots \dots . A_{n)}$ is evaluated with respect to *m* criteria $C_j = (C_1, C_2, \dots \dots . C_m)$ using *k* expert opinion, the fuzzy multi-criteria decision-making problem can be expressed as:

$$\widetilde{DM} = \begin{bmatrix} \tilde{X}11 & \tilde{X}12 & \tilde{X}13 & \dots & \tilde{X}1n \\ \tilde{X}21 & \tilde{X}22 & \tilde{X}23 & \dots & \tilde{X}2n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \tilde{X}m1 & \tilde{X}m2 & \tilde{X}m3 & \cdots & \tilde{X}mn \end{bmatrix} \tag{22}$$

where: $\tilde{X}_{ij} = \frac{1}{k}(l_{ij}, m_{ij}, u_{ij})$, thus,

$l_{ij} = \min\ (lij^k),\ m_{ij} = \frac{1}{n}\sum_{k=1}^{n}(mij^k)$ and $u_{ij} = \max\ (uij^k)$ are the triangular fuzzy number indicates the evaluation rate of ith alternative with respect to jth criteria.

Step-2: Normalize the fuzzy decision matrix**.**

The normalized fuzzy decision matrix $\tilde{R}$ can be computed from the normalized value of benefit-related criteria (B) and cost-related criteria (C) as:

$$\tilde{R} = \left[\tilde{r}_{ij}\right]_{n\times m}, i = 1,2,..n, j = 1,..m \tag{23}$$

where:

$$\tilde{r}_{ij} = \frac{\tilde{x}_{ij}}{u^+{}_j} = \left(\frac{l_{ij}}{u^+{}_j}, \frac{m_{ij}}{u^+{}_j}, \frac{u_{ij}}{u^+{}_j}\right) \tag{24}$$

$$u^+{}_j = \max\left(u_{ij}\right)\ where\ j \in B$$

and

$$\tilde{r}_{ij} = \frac{\tilde{x}_{ij}}{l^-{}_j} = \left(\frac{l^-{}_j}{l_{ij}}, \frac{l^-{}_j}{m_{ij}}, \frac{l^-{}_j}{u_{ij}}\right), \tag{25}$$

$$l^-{}_j = \min\left(\ l_{ij}\right) where\ j \in C$$

Step-4: Compute the weighted normalized fuzzy decision matrix

The weighted normalized fuzzy decision matrix $\tilde{V}$ is computed from the multiplication between normalized decision matrix $\tilde{r}_{ij}$and the weights of the decision criterion W_i extracted from the supermatrix of the fuzzy ANP phase.

$$V = \left(\tilde{v}_{ij}\right)n \times m, i = 1,2,.n\ and\ j = 1,2,..m$$

where:

$$\left(\tilde{v}_{ij}\right) = \tilde{r}_{ij} \times W_i \tag{26}$$

Step-5: Compute the distance of each alternative positive ideal solution (A^+) and negative ideal solution (A^-)

$$A^+ = \{\tilde{v}_1{}^+, \tilde{v}_2{}^+, \dots \dots \dots \tilde{v}_m{}^+\} \tag{27}$$

where:

$$\tilde{v}_j{}^+ = \left\{\max_i\left(v_{ij}\right) if\ j \in B, \min_i\left(v_{ij}\right) if\ j \in C\right\}$$

Similarly, a negative ideal solution is computed as

$$A^{-} = \{\tilde{v}_1^{\ -}, \tilde{v}_2^{\ -}, \dots \dots \dots \tilde{v}_m^{\ -}\} \tag{28}$$

where:

$$\tilde{v}_j^{\ -} = \left\{\min_i\left(v_{ij}\right) \ if \ j \in B, \max_i\left(v_{ij}\right) \ if \ j \in C\right\}$$

Step-6: Calculate the distance of each alternative from A^{+} and A^{-}

Assume any two triangular fuzzy numbers $\tilde{a}$ and $\tilde{b}$ where $\tilde{a} = (a_1, a_2, a_3)$ and $\tilde{b} = (b_1, b_2, b_3)$. The defuzzied distance between them can be determined by using the vertex method (Alam-Tabriz et al., 2014; Cayir Ervural et al., 2018)

$$d\left(\tilde{a}, \tilde{b}\right) = \sqrt{\frac{1}{3}[(a_1 - b_1) + (a_2 - b_2) + (a_3 - b_3)]} \tag{29}$$

Therefore, the distance between each alternative can be calculated as

$$D_i^{\ +} = \sum_{j=1}^{m} d(\tilde{v}_{ij}, \tilde{v}_j^{\ +}); \{i = 1,2, \dots . n\} \tag{30}$$

$$D_i^{\ -} = \sum_{j=1}^{m} d(\tilde{v}_{ij}, \tilde{v}_j^{\ -}); \{i = 1,2, \dots . n\} \tag{31}$$

Step-7: Compute the closeness coefficient CCi for each alternative.

$$CCi = \frac{D_i^{\ -}}{D_i^{\ -} + D_i^{\ +}}, \tag{32}$$

$\{i = 1,2, \dots \dots . n) where \ 0 < CCi < 1$

Step-8 Select the alternative closest to the positive ideal solution or furthest from the negative ideal solution.

3. Results and discussion

3.1 Fuzzy DEMATEL result

The step-by-step procedure presented above is used here to achieve the goal of the fuzzy DEMATEL multi-criteria method, which means building an impact relationship map and analyzing causal relationships between criteria from a direct fuzzy relation matrix. The influence relationship may exist between criteria gathered from experts in the form of linguistic variables, which were expressed as Has no Influence (NO), Very Low influence (VL), Low influence (L), High influence (H), and very high influence (VH). The qualitative data collected from expert opinions in the form of linguistic variables is transformed into the corresponding triangular fuzzy number (TFNS) and normalized using equation through Eqs. (2-4).

Table 1
Normalizing linguistics variable

E1	C1			C1		
	L	m	u	l	M	u
C1	0.00	0.00	0.00	0.00	0.00	0.00
C2	0.50	0.75	1.00	0.50	0.75	1.00
C3	0.75	1.00	1.00	0.75	1.00	1.00
C4	0.50	0.75	1.00	0.50	0.75	1.00
C5	0.75	1.00	1.00	0.75	1.00	1.00
C6	0.75	1.00	1.00	0.75	1.00	1.00
C7	0.50	0.75	1.00	0.50	0.75	1.00
C8	0.25	0.50	0.75	0.25	0.50	0.75
C9	0.75	1.00	1.00	0.75	1.00	1.00
C10	0.50	0.75	1.00	0.50	0.75	1.00
C11	0.25	0.50	0.75	0.25	0.50	0.75
C12	0.25	0.50	0.75	0.25	0.50	0.75
C13	0.75	1.00	1.00	0.75	1.00	1.00
C14	0.50	0.75	1.00	0.50	0.75	1.00
C15	0.25	0.50	0.75	0.25	0.50	0.75
C16	0.50	0.75	1.00	0.50	0.75	1.00
C17	0.50	0.75	1.00	0.50	0.75	1.00
C18	0.75	1.00	1.00	0.75	1.00	1.00
C19	0.50	0.75	1.00	0.50	0.75	1.00
C20	0.50	0.75	1.00	0.50	0.75	1.00

$$xl(71) = {(xl7 - minxl(71))}/{\Delta_{min}^{max}}$$
$$xm(71) = {(xm7 - minxm(71))}/{\Delta_{min}^{max}}$$
$$xu(71) = {(xu7 - minxu(71))}/{\Delta_{min}^{max}}$$

Therefore, the values of criteria C7 with C1 is normalized as:

$$xl(71) = \frac{0.5 - 0}{1} = 0.5$$
$$xm(71) = \frac{0.75 - 0}{1} = 0.75$$
$$xu(71) = \frac{1 - 0}{1} = 1$$

The normalized triangular fuzzy number is minimized to crips values using an equation through Eqs. (5-8), a triangular fuzzy number is converted to total crips values.

Table 2
Total crips values

E1	C1		C1
	$xLsij^{E1}$	$xRsij^{E1}$	xj^{crips}
C1	0.00	0.00	0.00
C2	0.60	0.80	0.73
C3	0.80	1.00	0.97
C4	0.60	0.80	0.73
C5	0.80	1.00	0.97
C6	0.80	1.00	0.97
C7	0.60	0.80	0.73
C8	0.40	0.60	0.50
C9	0.80	1.00	0.97
C10	0.60	0.80	0.73
C11	0.40	0.60	0.50
C12	0.40	0.60	0.50
C13	0.80	1.00	0.97
C14	0.60	0.80	0.73
C15	0.40	0.60	0.50
C16	0.60	0.80	0.73
C17	0.60	0.80	0.73
C18	0.80	1.00	0.97
C19	0.60	0.80	0.73
C20	0.60	0.80	0.73

$$xj^{crips} = {[xLsij^{E1}(1 - xLsij^{E1}) + xRsij^{E1} \times xRsij^{E1}]} \Big/ {[1 - xRsij^{E1} + xLsij^{E1}]}$$

Therefore, the crips values of expert 1 pairwise compression matrix for criteria C7 with C1 is

$$xC1^{crips} = \frac{0.6(1-0.6) + 0.8 \times 0.8}{1 - 0.6 + 0.8} = 0.73$$

And the total crips values is calculated as

$$zij = \min li + xj^{crips} \times \Delta_{min}^{max}$$

Where Δ_{min}^{max} value is 1 and minimum value of respondent is 0 zij is equal with crisp values. Which is

$$C7C1 = 0 + 0.73 \times 1 = 0.73$$

After all expert opinions are reduced to total crips values, aggregating all expert total crips values depend on Markov chain theory and the convergence assumptions and the total de-fuzzified direct relation matrix is obtained (see Tables 1-3).

Table 3
De-fuzzified aggregated crips values

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	Row
C1	0.00	0.66	0.87	0.70	0.91	0.59	0.64	0.33	0.75	0.72	0.20	0.70	0.58	0.81	0.62	0.64	0.62	0.64	0.74	0.76	12.50
C2	0.70	0.00	0.67	0.94	0.90	0.59	0.55	0.56	0.56	0.67	0.42	0.75	0.75	0.72	0.53	0.59	0.66	0.73	0.58	0.69	12.56
C3	0.92	0.78	0.00	0.76	0.92	0.76	0.73	0.55	0.69	0.69	0.44	0.70	0.66	0.83	0.61	0.64	0.72	0.72	0.61	0.72	13.44
C4	0.70	0.97	0.67	0.00	0.79	0.72	0.62	0.61	0.53	0.66	0.41	0.69	0.61	0.76	0.64	0.66	0.66	0.62	0.55	0.76	12.62
C5	0.90	0.95	0.80	0.94	0.10	0.67	0.73	0.62	0.67	0.70	0.61	0.80	0.72	0.70	0.73	0.62	0.72	0.73	0.72	0.87	14.31
C6	0.47	0.58	0.56	0.64	0.62	0.00	0.78	0.59	0.70	0.64	0.64	0.47	0.75	0.47	0.78	0.66	0.62	0.70	0.70	0.76	12.14
C7	0.59	0.70	0.59	0.66	0.71	0.69	0.00	0.64	0.42	0.62	0.69	0.42	0.66	0.48	0.64	0.66	0.67	0.67	0.58	0.72	11.81
C8	0.50	0.59	0.47	0.56	0.67	0.62	0.56	0.00	0.73	0.52	0.56	0.58	0.73	0.45	0.62	0.52	0.56	0.59	0.72	0.64	11.21
C9	0.62	0.62	0.62	0.42	0.61	0.73	0.67	0.56	0.00	0.67	0.42	0.55	0.62	0.34	0.38	0.41	0.28	0.39	0.45	0.67	10.06
C10	0.61	0.50	0.48	0.41	0.59	0.55	0.53	0.61	0.62	0.00	0.72	0.69	0.58	0.48	0.59	0.69	0.69	0.70	0.76	0.76	11.57
C11	0.41	0.52	0.41	0.38	0.40	0.69	0.61	0.45	0.48	0.73	0.00	0.53	0.81	0.36	0.48	0.52	0.52	0.48	0.48	0.75	10.01
C12	0.47	0.62	0.52	0.58	0.60	0.53	0.52	0.44	0.48	0.78	0.58	0.00	0.75	0.73	0.56	0.47	0.47	0.45	0.62	0.56	10.73
C13	0.58	0.48	0.62	0.47	0.66	0.50	0.53	0.48	0.48	0.66	0.76	0.78	0.00	0.58	0.59	0.50	0.56	0.66	0.73	0.73	11.37
C14	0.58	0.66	0.72	0.55	0.73	0.52	0.42	0.27	0.56	0.53	0.56	0.69	0.61	0.00	0.52	0.48	0.34	0.61	0.58	0.62	10.54
C15	0.62	0.64	0.70	0.62	0.70	0.78	0.78	0.47	0.38	0.59	0.64	0.42	0.66	0.47	0.00	0.67	0.76	0.72	0.72	0.80	12.14
C16	0.55	0.62	0.64	0.69	0.64	0.64	0.58	0.47	0.31	0.58	0.47	0.48	0.66	0.44	0.53	0.00	0.75	0.72	0.76	0.73	11.26
C17	0.48	0.58	0.80	0.53	0.64	0.61	0.64	0.47	0.30	0.72	0.55	0.47	0.39	0.52	0.58	0.48	0.00	0.64	0.76	0.62	10.78
C18	0.67	0.70	0.81	0.67	0.76	0.59	0.58	0.33	0.50	0.64	0.62	0.61	0.56	0.70	0.66	0.78	0.56	0.00	0.86	0.69	12.30
C19	0.70	0.72	0.76	0.58	0.66	0.52	0.53	0.53	0.45	0.56	0.62	0.41	0.53	0.58	0.69	0.58	0.62	0.59	0.00	0.70	11.34
C20	0.62	0.64	0.70	0.72	0.74	0.82	0.72	0.57	0.82	0.79	0.65	0.72	0.64	0.75	0.60	0.84	0.80	0.74	0.75	0.00	13.62

Following the aggregated crips values direct relation matrix is obtained by dividing each value in aggregated for the maximum sum values of a row, which means 14.319 to compute the direct relation matrix (*X*). But the total direct relation matrix is calculated from the multiplication between the inverse difference of the identity matrix with the direct relation matrix.

Table 4
Total relation matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	D
C1	0.22	0.27	0.29	0.26	0.30	0.26	0.26	0.20	0.24	0.27	0.21	0.26	0.26	0.26	0.25	0.25	0.25	0.26	0.28	0.30	5.15
C2	0.26	0.23	0.27	0.28	0.30	0.26	0.25	0.21	0.23	0.27	0.22	0.26	0.27	0.25	0.24	0.25	0.26	0.27	0.27	0.29	5.17
C3	0.29	0.30	0.24	0.28	0.32	0.29	0.28	0.22	0.25	0.29	0.24	0.27	0.28	0.28	0.26	0.27	0.27	0.28	0.29	0.31	5.50
C4	0.26	0.29	0.27	0.22	0.30	0.27	0.26	0.22	0.23	0.27	0.22	0.26	0.26	0.26	0.25	0.25	0.26	0.26	0.27	0.30	5.19
C5	0.30	0.32	0.31	0.31	0.28	0.29	0.29	0.24	0.26	0.30	0.26	0.29	0.30	0.28	0.28	0.28	0.29	0.30	0.31	0.34	5.85
C6	0.24	0.26	0.26	0.25	0.28	0.21	0.26	0.21	0.23	0.26	0.23	0.23	0.26	0.23	0.25	0.25	0.25	0.26	0.27	0.29	4.97
C7	0.24	0.26	0.25	0.25	0.28	0.25	0.20	0.21	0.21	0.26	0.23	0.23	0.25	0.23	0.24	0.24	0.25	0.25	0.26	0.28	4.86
C8	0.23	0.24	0.23	0.23	0.26	0.24	0.23	0.16	0.22	0.24	0.21	0.23	0.25	0.21	0.23	0.22	0.23	0.24	0.25	0.26	4.60
C9	0.22	0.23	0.22	0.20	0.24	0.23	0.22	0.18	0.16	0.23	0.19	0.21	0.22	0.19	0.19	0.20	0.19	0.21	0.22	0.24	4.18
C10	0.24	0.24	0.24	0.23	0.26	0.24	0.23	0.20	0.22	0.21	0.23	0.24	0.24	0.22	0.23	0.24	0.24	0.25	0.26	0.28	4.72
C11	0.20	0.22	0.21	0.20	0.22	0.22	0.21	0.17	0.19	0.23	0.16	0.20	0.23	0.19	0.20	0.20	0.20	0.21	0.22	0.25	4.12
C12	0.22	0.24	0.23	0.22	0.25	0.22	0.22	0.18	0.20	0.25	0.20	0.18	0.24	0.22	0.22	0.21	0.21	0.22	0.24	0.25	4.41
C13	0.23	0.24	0.25	0.23	0.26	0.23	0.23	0.19	0.21	0.25	0.23	0.24	0.20	0.22	0.23	0.22	0.23	0.24	0.26	0.27	4.66
C14	0.22	0.24	0.24	0.22	0.25	0.22	0.21	0.17	0.20	0.23	0.20	0.22	0.23	0.17	0.21	0.21	0.20	0.23	0.23	0.25	4.36
C15	0.25	0.26	0.27	0.25	0.28	0.27	0.26	0.20	0.21	0.26	0.23	0.23	0.26	0.23	0.20	0.25	0.26	0.26	0.27	0.29	5.00
C16	0.23	0.25	0.25	0.24	0.26	0.24	0.23	0.19	0.19	0.24	0.21	0.22	0.24	0.22	0.22	0.19	0.24	0.25	0.26	0.27	4.65
C17	0.22	0.24	0.25	0.22	0.25	0.23	0.23	0.18	0.19	0.24	0.20	0.21	0.22	0.21	0.22	0.21	0.18	0.23	0.25	0.25	4.46
C18	0.26	0.27	0.28	0.26	0.29	0.26	0.25	0.19	0.22	0.26	0.23	0.25	0.26	0.25	0.25	0.26	0.25	0.22	0.28	0.29	5.05
C19	0.24	0.26	0.26	0.24	0.27	0.24	0.23	0.20	0.21	0.24	0.22	0.22	0.24	0.23	0.23	0.23	0.24	0.24	0.21	0.27	4.68
C20	0.27	0.29	0.29	0.28	0.31	0.29	0.28	0.23	0.26	0.30	0.25	0.27	0.28	0.27	0.26	0.28	0.28	0.29	0.30	0.26	5.53
R	4.83	5.14	5.10	4.87	5.47	4.96	4.81	3.96	4.32	5.10	4.36	4.71	5.00	4.63	4.68	4.70	4.78	4.98	5.19	5.53	0.254

Depending on total relation matrix, the influence degree, effect degree, central degree, and cause degree are calculated using Eq. (10). As shown in Table 1-5, the influence degree (Di) is calculated as the row sum of the direct relation matrix, where effect degree (Ri) is the column sum of the direct relation matrix. (Di) indicates the effectiveness, and (Ri) demonstrates the effectiveness of each factor.

The degree of central role ($Di + Ri$) and cause degree relation ($Di - Ri$) is thus determined depend on row sum and column sum of the total relation matrix to analyze the causal relationship and degree of influences between the criteria. ($Di + Ri$) Indicates the importance of each system factor on the other hand, ($Di - Ri$) indicate the net effect of each factor. Based on this if the resulting number is positive, the factor falls under the category of causes; if it is negative, it falls under the effect category.

Table 5
Structural correlation

	Di	Ri	$Di + Ri$	$Di - Ri$
C1	5.15	4.83	9.98	0.32
C2	5.17	5.14	10.30	0.03
C3	5.50	5.10	10.61	0.40
C4	5.19	4.87	10.06	0.32
C5	5.85	5.47	11.31	0.38
C6	4.97	4.96	9.93	0.01
C7	4.86	4.81	9.67	0.05
C8	4.60	3.96	8.56	0.64
C9	4.18	4.32	8.49	(0.14)
C10	4.72	5.10	9.83	(0.38)
C11	4.12	4.36	8.48	(0.24)
C12	4.41	4.71	9.12	(0.31)
C13	4.66	5.00	9.65	(0.34)
C14	4.36	4.63	8.99	(0.27)
C15	5.00	4.68	9.68	0.32
C16	4.65	4.70	9.35	(0.05)
C17	4.46	4.78	9.25	(0.32)
C18	5.05	4.98	10.04	0.07
C19	4.68	5.19	9.88	(0.51)
C20	5.53	5.53	11.06	(0.00)

The results in Table 5 revealed, the most extensive ($Di + Ri$) (importance) among the main dimensions is associated with the "Environmental pollution" (C5) dimension, which has a lot of interaction with other dimensions, and the lowest ($Di + Ri$) is associated with the "Job creation" (C11) dimension, which is the lowest interaction with other dimensions. A cause-and-effect diagram is created to convey information about which sub-criteria are most important and which are influenced. It is created by mapping all coordinate sets ($Di + Ri, Di - Ri$) as horizontal and vertical axes. As shown in Fig. 1, the sub-criteria located above $Di + Ri$ (horizontal axis) possess the cause future. In other word, the sub-criteria blow horizontal axis is the effect factor. This means that this sub-criterion cannot be improved on its own; it requires a cause factor to influence improvement.

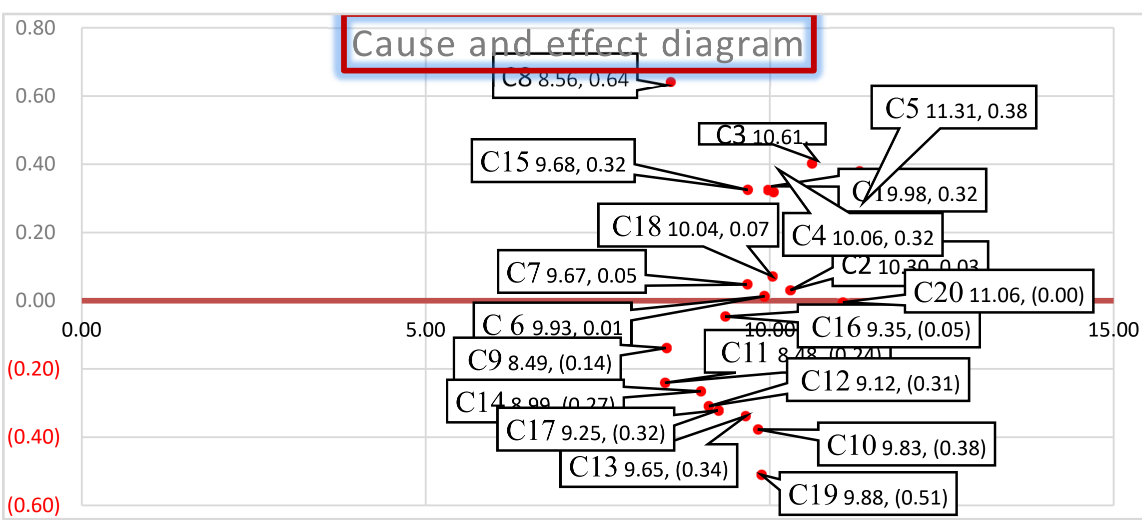

Fig. 1. Cause and effect diagram

At the last step of the DEMATEL analysis, a “threshold value” is created by taking the average of the total relation matrix. Depend on threshold value $\sigma - cut$ relation matrix is created. The value below the threshold value (0.254) in the total relation matrix shown in Table 1-4 is neglected from impact network by replacing the cell values with zero as a minor impact.

3.2 Fuzzy ANP method

Depending on methodology stated in the methodologies section, the step-by-step procedure of fuzzy ANP and the analysis of the fuzzy analytical network started by creating a fuzzy pairwise comparison gathered from experts in the form of linguistic variables. The qualitative linguistics variable is transformed to a triangular fuzzy number (TFN), and the new matrix A is formed as shown in Eq. (12) and aggregated by using Eqs. (13-16).

Table 6
Aggregated pairwise comparison element of social sub-criteria

	C10			C11			C12			C13			C14		
	L	m	u	l	m	u	l	m	u	l	m	u	l	m	u
C10	1.00	1.00	1.00	1.00	1.85	3.00	1.00	1.86	3.00	1.00	1.80	3.00	1.00	1.86	3.00
C11	0.33	0.51	1.00	1.00	1.00	1.00	1.00	1.98	3.50	1.00	1.87	3.00	1.00	1.62	2.50
C12	0.33	0.54	1.00	0.29	0.54	1.00	1.00	1.00	1.00	1.00	2.04	3.50	1.00	1.88	3.00
C13	0.33	0.57	1.00	0.33	0.55	1.00	0.29	0.49	1.00	1.00	1.00	1.00	1.00	1.85	3.50
C14	0.33	0.56	1.00	0.40	0.68	2.00	0.33	0.57	2.00	0.29	0.57	2.00	1.00	1.06	3.00

From the aggregated fuzzy pairwise comparisons, the local priority weight is calculated using either the geometric mean or the matrix logarithmic least squares method (see Eq. (17)). The fuzzy local weight can be calculated from the geometric mean by multiplying the inverse sum of the geometric mean with aggregated fuzzy pairwise comparisons, and the local priority weight of each sub-criteria can be obtained. Then normalizing the average of fuzzy weighted by dividing the average sum of each element for the total sum. For instant, the local weight of C10 in table 1-7 can be calculated as $((0.11 + 0.30 + 0.72)/3)/\ total\ sum\ of\ average\ (1.36)\ = 0.2774$.

Table 7
Local priority weights

	C10			C11			C12			C13			C14			Geometric mean			Fuzzy weight			Local Weight
	l	m	U	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	l	m	u	
C10	1.00	1.00	1.00	1.00	1.85	3.00	1.00	1.86	3.00	1.00	1.80	3.00	1.00	1.86	3.00	**1.00**	**1.63**	**2.41**	**0.11**	**0.30**	**0.72**	**0.2774**
C11	0.33	0.51	1.00	1.00	1.00	1.00	1.00	1.98	3.50	1.00	1.87	3.00	1.00	1.62	2.50	**0.80**	**1.25**	**1.92**	**0.09**	**0.23**	**0.57**	**0.2193**
C12	0.33	0.54	1.00	0.29	0.54	1.00	1.00	1.00	1.00	1.00	2.04	3.50	1.00	1.88	3.00	**0.62**	**1.02**	**1.60**	**0.07**	**0.19**	**0.48**	**0.1805**
C13	0.33	0.57	1.00	0.33	0.55	1.00	0.29	0.49	1.00	1.00	1.00	1.00	1.00	1.85	3.50	**0.50**	**0.78**	**1.28**	**0.06**	**0.15**	**0.38**	**0.1428**
C14	0.33	0.56	1.00	0.40	0.68	2.00	0.33	0.57	2.00	0.29	0.57	2.00	1.00	1.06	3.00	**0.42**	**0.67**	**1.89**	**0.05**	**0.12**	**0.56**	**0.1798**

In forming an unweighted super-matrix, local priority weights obtained from the pairwise comparison are input in appropriate columns of the unweighted super-matrix to get the system's global priorities. Local priority weights are entered into the unweighted super-matrix based on which criteria (rows) influence which criterion (column) was obtained in the fuzzy DEMATEL part, and one (1) is entered if some criteria rely on only one criterion in the same cluster see Table 8 below.

Table 8
Un-weighted super matrix

	Goal	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
Goal	0.000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
C1	0.026	0.0000	0.3103	0.3103	0.3103	0.3103	0.3067	0.3067	0.0000	0.0000	0.2757	0.0000	0.2757	0.2757	0.2757	0.0000	0.0000	0.3077	0.3077	0.3077	0.3077
C2	0.025	0.2764	0.0000	0.2764	0.2764	0.2764	0.2740	0.0000	0.0000	0.0000	0.2493	0.0000	0.2493	0.2493	0.2493	0.0000	0.0000	0.2724	0.2724	0.2724	0.2724
C3	0.023	0.1734	0.1734	0.0000	0.1734	0.1734	0.1695	0.1695	0.0000	0.0000	0.2042	0.0000	0.2042	0.2042	0.2042	0.1750	0.1750	0.1750	0.1750	0.1750	0.1750
C4	0.022	0.1223	0.1223	0.1223	0.0000	0.1223	0.1328	0.1328	0.0000	0.0000	0.1408	0.0000	0.1408	0.1408	0.1408	0.0000	0.0000	0.1270	0.1270	0.1270	0.1270
C5	0.022	0.1176	0.1176	0.1176	0.1176	0.1176	0.1170	0.1170	0.0000	0.1170	0.1301	0.1301	0.1301	0.1301	0.1301	0.1179	0.1179	0.1179	0.1179	0.1179	0.1179
C6	0.018	0.0000	0.3200	0.3200	0.0000	0.3200	0.0000	1.0000	0.0000	0.0000	0.3781	0.0000	0.0000	0.3781	0.0000	0.0000	0.0000	0.0000	0.3466	0.3466	0.3466
C7	0.016	0.0000	0.2629	0.0000	0.0000	0.2629	0.0000	0.0000	0.0000	0.0000	0.2791	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2853	0.2853
C8	0.014	0.0000	0.0000	0.0000	0.0000	0.2264	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2143
C9	0.015	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
C10	0.011	0.0000	0.0000	0.0000	0.0000	0.2692	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.2946	0.2946
C11	0.009	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
C12	0.009	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
C13	0.009	0.0000	0.0000	0.0000	0.0000	0.1354	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1340	0.1340
C14	0.008	0.0000	0.0000	0.0000	0.0000	0.2079	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
C15	0.006	0.0000	0.3017	0.3017	0.0000	0.3017	0.3006	0.3006	0.0000	0.0000	0.2862	0.0000	0.0000	0.2862	0.0000	0.0000	0.0000	0.2225	0.2225	0.2225	0.2225
C16	0.006	0.0000	0.0000	0.0000	0.0000	0.2319	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1993	0.1993
C17	0.005	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1784
C18	0.006	0.1258	0.1258	0.1258	0.1258	0.1258	0.1294	0.0000	0.0000	0.0000	0.1345	0.0000	0.0000	0.1345	0.0000	0.0000	0.1584	0.0000	0.0000	0.1584	0.1584
C19	0.005	0.0000	0.0970	0.0970	0.0000	0.0970	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1281
C20	0.005	0.0697	0.0697	0.0697	0.0697	0.0697	0.0717	0.0717	0.0000	0.0717	0.0888	0.0000	0.0888	0.0888	0.0888	0.1133	0.1133	0.1133	0.1133	0.1133	0.1133

From the unweighted super-matrix, the weighted super-matrix is generated by coherently multiplying the elements of the unweighted super-matrix by the normalized α-cut total relation matrix. Consequently, the weighted super-matrix becomes stochastic and it is normalized the columns to sum one (columns with non-negative entries sum to one). Until the column stochastic weighted super-matrix converges, it is raised to an appropriate large power. This calculation aims to capture the transmission of all influence paths within the network. In order to converge and obtain a long-term, stable set of weights, which is the global priority vector for each element, the weighted super-matrix obtained from the previous step is changed into a limiting super-matrix by raising itself to a limiting power (see Eq. (19)). After thirty-seven (37) iterations the normalized weighted super-matrix has become converged see Table 9.

Table 9
Limited super matrix

		G	C1	C2	C3	C4	………….	C16	C17	C18	C19	C20
A goal	G	0	0	0	0	0	………….	0	0	0	0	0
	C1	0.03544	0.03544	0.03544	0.03544	0.03544	………….	0.03544	0.03544	0.03544	0.03544	0.03544
	C2	0.03394	0.03394	0.03394	0.03394	0.03394	………….	0.03394	0.03394	0.03394	0.03394	0.03394
	C3	0.055599	0.055599	0.055599	0.055599	0.055599	………….	0.055599	0.055599	0.055599	0.055599	0.055599
	C4	0.03504	0.03504	0.03504	0.03504	0.03504	………….	0.03504	0.03504	0.03504	0.03504	0.03504
Environment	C5	0.058544	0.058544	0.058544	0.058544	0.058544	………….	0.058544	0.058544	0.058544	0.058544	0.058544
	C6	0.109689	0.109689	0.109689	0.109689	0.109689	………….	0.109689	0.109689	0.109689	0.109689	0.109689
	C7	0.042736	0.042736	0.042736	0.042736	0.042736	………….	0.042736	0.042736	0.042736	0.042736	0.042736
	C8	0.000155	0.000155	0.000155	0.000155	0.000155	………….	0.000155	0.000155	0.000155	0.000155	0.000155
Economic	C9	0.000045	0.000045	0.000045	0.000045	0.000045	………….	0.000045	0.000045	0.000045	0.000045	0.000045
	C10	0.042608	0.042608	0.042608	0.042608	0.042608	………….	0.042608	0.042608	0.042608	0.042608	0.042608
	C11	0.000025	0.000025	0.000025	0.000025	0.000025	………….	0.000025	0.000025	0.000025	0.000025	0.000025
	C12	0.000225	0.000225	0.000225	0.000225	0.000225	………….	0.000225	0.000225	0.000225	0.000225	0.000225
	C13	0.042606	0.042606	0.042606	0.042606	0.042606	………….	0.042606	0.042606	0.042606	0.042606	0.042606
Social	C14	0.005351	0.005351	0.005351	0.005351	0.005351	………….	0.005351	0.005351	0.005351	0.005351	0.005351
	C15	0.11951	0.11951	0.11951	0.11951	0.11951	………….	0.11951	0.11951	0.11951	0.11951	0.11951
	C16	0.022527	0.022527	0.022527	0.022527	0.022527	………….	0.022527	0.022527	0.022527	0.022527	0.022527
	C17	0.015159	0.015159	0.015159	0.015159	0.015159	………….	0.015159	0.015159	0.015159	0.015159	0.015159
	C18	0.108159	0.108159	0.108159	0.108159	0.108159	………….	0.108159	0.108159	0.108159	0.108159	0.108159
	C19	0.031242	0.031242	0.031242	0.031242	0.031242	………….	0.031242	0.031242	0.031242	0.031242	0.031242
Technical	C20	0.24145	0.24145	0.24145	0.24145	0.24145	………….	0.24145	0.24145	0.24145	0.24145	0.24145

From the limited super-matrix, the global weight of sub-criteria that governs the selection of appropriate MSWM strategy is arranged. And also, it is the input for fuzzy TOPSIS in alternative selection.

Table 10
Final Global Weights

Main Criteria	**Sub-criteria**	**Global weight**	**Priority rank**
Environment	C1	0.03544	10
	C2	0.03394	12
	C3	0.055599	6
	C4	0.03504	11
	C5	0.058544	5
Economic	C6	0.109689	3
	C7	0.042736	7
	C8	0.000155	18
	C9	0.000045	19
Social	C10	0.042608	8
	C11	0.000025	20
	C12	0.000225	17
	C13	0.042606	9
	C14	0.005351	16
Technical	C15	0.11951	2
	C16	0.022527	14
	C17	0.015159	15
	C18	0.108159	4
	C19	0.031242	13
	C20	0.24145	1

3.3 Fuzzy TOPSIS result

From the literature, five alternatives are identified to evaluate their performance in twenty sub-criteria. To perform this, a group of experts were asked to estimate the performance of the MSWM strategy by using linguistic terms ranging from very poor to very good. All respondents are asked for their opinion on performance evaluation of MSWM alternative in direction of evaluation criteria and aggregated by applying the arithmetic means of all experts see Table 11. From an aggregated decision matrix by using Eqs. (23-25) a normalized decision matrix can be calculated, which depends on the sub-criteria's goal.

Table 11
Aggregated fuzzy decision matrix

	A1			A2			A3			A4			A5		
	l	m	U	l	m	u	l	m	U	l	m	u	l	m	u
C1	3.00	7.55	9.00	1.00	6.09	9.00	3.00	7.00	9.00	1.00	4.09	9.00	1.00	3.73	9.00
C2	1.00	5.73	9.00	1.00	5.91	9.00	1.00	4.82	9.00	1.00	6.64	9.00	1.00	4.09	9.00
C3	1.00	6.45	9.00	1.00	6.27	9.00	3.00	7.18	9.00	1.00	5.73	9.00	1.00	3.55	9.00
C4	1.00	6.45	9.00	1.00	5.91	9.00	1.00	5.36	9.00	1.00	6.45	9.00	1.00	3.55	9.00
C5	1.00	8.09	9.00	3.00	8.27	9.00	1.00	7.36	9.00	1.00	7.00	9.00	1.00	4.82	9.00
C6	1.00	6.27	9.00	1.00	5.73	9.00	1.00	5.36	9.00	1.00	3.18	7.00	1.00	6.09	9.00
C7	3.00	6.27	9.00	1.00	5.36	9.00	1.00	4.09	9.00	1.00	3.73	9.00	1.00	6.45	9.00
C8	1.00	5.91	9.00	3.00	6.64	9.00	1.00	5.91	9.00	1.00	5.36	9.00	1.00	4.64	9.00
C9	1.00	7.91	9.00	3.00	8.27	9.00	1.00	7.18	9.00	3.00	7.18	9.00	1.00	3.18	9.00
C10	1.00	7.55	9.00	1.00	4.64	9.00	3.00	6.64	9.00	1.00	6.45	9.00	1.00	4.82	9.00
C11	1.00	4.27	9.00	1.00	6.27	9.00	1.00	7.18	9.00	1.00	7.73	9.00	1.00	4.09	9.00
C12	1.00	6.82	9.00	1.00	5.55	9.00	1.00	6.64	9.00	1.00	5.18	9.00	1.00	4.64	9.00
C13	1.00	5.36	9.00	1.00	5.18	9.00	1.00	5.00	9.00	1.00	5.18	9.00	1.00	5.73	9.00
C14	1.00	6.27	9.00	1.00	5.36	9.00	1.00	5.73	9.00	1.00	4.27	9.00	1.00	2.82	9.00
C15	1.00	5.18	9.00	3.00	6.27	9.00	1.00	5.18	9.00	1.00	3.73	9.00	1.00	4.64	9.00
C16	1.00	4.45	9.00	1.00	5.00	9.00	1.00	5.91	9.00	1.00	5.73	9.00	1.00	4.64	9.00
C17	1.00	5.55	9.00	1.00	5.36	9.00	1.00	7.18	9.00	1.00	5.18	9.00	1.00	5.91	9.00
C18	1.00	6.64	9.00	1.00	6.82	9.00	1.00	7.36	9.00	1.00	5.91	9.00	1.00	6.45	9.00
C19	3.00	6.82	9.00	1.00	6.27	9.00	3.00	7.00	9.00	1.00	6.09	9.00	1.00	6.45	9.00
C20	5.00	8.09	9.00	5.00	7.18	9.00	5.00	8.27	9.00	1.00	5.91	9.00	1.00	3.18	9.00

The sub-criteria are grouped into benefit and cost criteria based on whether the goal is to maximize or minimize. For those criteria classified as a benefit or maximization goal, Eq. (24) is used, while for those criteria classified as cost or minimization goal, Eq. (25) is used to create the general structure of the normalized decision matrix shown in Eq. (23). In this document, four of the twenty sub-criteria are classified as cost, while sixteen are classified as benefit criteria. The normalized decision matrix is shown in Table 12.

Table 12
Normalized decision matrix

	A1			A2			A3			A4			A5		
	l	M	u	l	m	u	l	m	u	l	m	u	l	m	U
C1	0.33	0.84	1	0.11	0.68	1	0.33	0.78	1	0.11	0.45	1	0.11	0.41	1
C2	0.11	0.64	1	0.11	0.66	1	0.11	0.54	1	0.11	0.74	1	0.11	0.45	1
C3	0.11	0.72	1	0.11	0.70	1	0.33	0.80	1	0.11	0.64	1	0.11	0.39	1
C4	0.11	0.72	1	0.11	0.66	1	0.11	0.60	1	0.11	0.72	1	0.11	0.39	1
C5	0.11	0.72	1	0.11	0.66	1	0.11	0.60	1	0.11	0.72	1	0.11	0.39	1
C6	0.11	0.16	1	0.11	0.17	1	0.11	0.19	1	0.14	0.31	1	0.11	0.16	1
C7	0.11	0.16	0.33	0.11	0.19	1	0.11	0.24	1	0.11	0.27	1	0.11	0.15	1
C8	0.11	0.17	1	0.11	0.15	0.33	0.11	0.17	1	0.11	0.19	1	0.11	0.22	1
C9	0.11	0.13	1	0.11	0.12	0.33	0.11	0.14	1	0.11	0.14	0.33	0.11	0.31	1
C10	0.11	0.88	1	0.33	0.92	1	0.11	0.80	1	0.33	0.80	1	0.11	0.35	1
C11	0.11	0.84	1	0.11	0.52	1	0.33	0.74	1	0.11	0.72	1	0.11	0.54	1
C12	0.11	0.47	1	0.11	0.70	1	0.11	0.80	1	0.11	0.86	1	0.11	0.45	1
C13	0.11	0.76	1	0.11	0.62	1	0.11	0.74	1	0.11	0.58	1	0.11	0.52	1
C14	0.11	0.60	1	0.11	0.58	1	0.11	0.56	1	0.11	0.58	1	0.11	0.64	1
C15	0.11	0.70	1	0.11	0.60	1	0.11	0.64	1	0.11	0.47	1	0.11	0.31	1
C16	0.11	0.58	1	0.33	0.70	1	0.11	0.58	1	0.11	0.41	1	0.11	0.52	1
C17	0.11	0.49	1	0.11	0.56	1	0.11	0.66	1	0.11	0.64	1	0.11	0.52	1
C18	0.11	0.62	1	0.11	0.60	1	0.11	0.80	1	0.11	0.58	1	0.11	0.66	1
C19	0.11	0.74	1	0.11	0.76	1	0.11	0.82	1	0.11	0.66	1	0.11	0.72	1
C20	0.33	0.76	1	0.11	0.70	1	0.33	0.78	1	0.11	0.68	1	0.11	0.72	1

Following normalization of the decision matrix by considering the weights of each criterion obtained by the fuzzy ANP part, the weighted normalized decision matrix can be calculated by multiplying the weight of each criterion by the normalized fuzzy decision matrix, as shown in (eq.26). The weighted normalized fuzzy decision matrix with respect to each MSWM strategy sub-factors is constructed. Then, the preference of each alternative from the positive ideal solution (A^{+}) or the negative ideal solution (A^{-}), the alternative preference is calculated using eqs.27 and 28 respectively. The alternative closest to the ideal solution is considered the best alternative, while the alternative furthest away from the ideal solution is considered the worst alternative. After the positive ideal solution and negative ideal solution of each MSWM strategy selection sub-criteria are obtained the distance between each alternative and ideal solution ware computed. To compute the distance between each alternative and FPIS and the distance between each alternative and FNIS Eq. (30) and Eq. (31) were applied respectively, and the result ware presented in Table 13.

Table 13
Distance from positive and negative ideal solutions

Alternative	Distance from positive ideal (D^+)	Distance from Negative ideal (D^-)
A1	0.08278	0.1259
A2	0.08566	0.1320
A3	0.03514	0.1407
A4	0.09657	0.0846
A5	0.15158	0.0303

Table 13 revealed that the smaller D^+ values represent the alternative preference that is closest to the ideal solution, resulting in the best ideal performance, whereas the larger D^+ values represent the alternative that is further away from the ideal solution. Larger D^- values, on the other hand, are the preferred close to ideal solution, which means the best alternative, whereas smaller D^- values are the worst alternative on that specific criterion. Farther more the coefficient of closeness was calculated by applying Eq. (32). The alternative closest to the fuzzy positive ideal solution is chosen as the best alternative, while the alternative farthest from the fuzzy positive ideal solution is designated as the worst alternative. On the other hand, the alternatives that are the furthest away from the fuzzy negative ideal solution and the closest to it are the best and worst. Table 14 displays the results of the closeness coefficient and alternative rank.

Table 14
Closeness coefficient

Alternative	CCi	Rank
A1	0.60	3
A2	0.61	2
A3	0.80	1
A4	0.47	4
A5	0.17	5

The fuzzy TOPSIS result determined that recycling of municipal solid waste is the best alternative in Dire Dawa City, followed by reuse. Depend on results, the MSWM alternatives in Dire Dawa city are as follows: Recycling (A3) > Reuse (A2) > Reduce (A1) > Energy recovery (A4) > Disposal (A5).

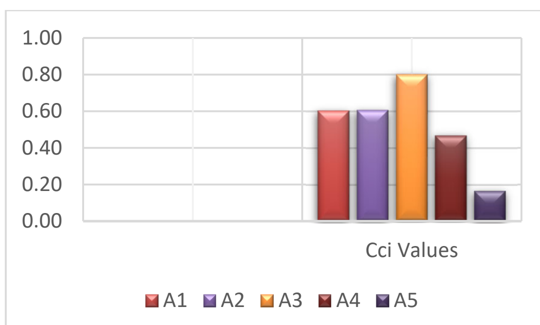

Fig. 2. Closeness coefficient graph

4. Discussion and managerial implementation

As stated in the methodologies sections and the step-by-step procedure presented in the preceding section the extensive literature is reviewed in the first phase to identify MSWM strategy alternatives, the criteria governing the selection of this alternative, and the sub-criteria to be considered when the MSWM strategy is selected.

Depending on the first phase, the second phase Fuzzy DEMATEL utilized to evaluate the influence relationship between sub-criteria. To evaluate the influence relationship between the twenty sub-criteria chosen in phase one, expert opinion is gathered through questionaries. A group of experts agreed to share their opinion on the interaction influence relationship between the identified criteria. Based on expert data, a fuzzy DEMATEL analysis, causal diagram, and IRM were created to depict the interactive relationship between interacting criteria (see Figs. 1-3). Therefore, the municipal authority highly focused on the cause factor as the result of effect factor sub-criterion cannot be improved on its own.

In third phase the fuzzy ANP is implemented to evaluate the local and global weights of sub-criteria depending on influence relationship of sub-criteria obtained in the fuzzy DEMATEL phase. The extensive importance pairwise comparison of sub-criteria and main criteria with respect to goal ware collected from experts depend on IRM obtained in DEMATEL to generate the Fuzzy ANP result, the global weight of sub-criteria. The fuzzy pairwise comparison result is used to rank the sub-criteria based on their global weight, as shown in Tables 1-10.

The fourth phase Fuzzy TOPSIS method concluded that the performance of an alternative was determined by its distance from the negative and positive ideal solutions and the coefficient of closeness. As shown in Table 1-14, the coefficient of closeness and rank alternative as: waste recycling (A1), reuse (A2), reduce (A1), energy recovery (A4), and disposal (A5), with closeness coefficient values of 0.80, 0.61, 0.60, 0.47, and 0.17, respectively. Thus, after extensive analysis, waste recycling has been selected as the best MSWM strategy for Dire Dawa City, as it would improve the city's environmental sustainability more than other alternatives.

Finally, this study makes several significant contributions. Firstly, it introduces a novel fuzzy integrated multi-criteria decision method aimed at identifying the key criteria influencing the selection of MSWM strategies especially fuzzy DEMATEL. Secondly, it employs these identified criteria to determine the optimal alternative considering economic, social, environmental, and human skill factors within the city. Finally, the study presents to municipal authorities the essential factors they need to address to tackle challenges in MSWM effectively. It also outlines actionable steps for implementing waste recycling or selected strategies, providing a comprehensive framework for improving waste management practices at the municipal level. Therefore, municipal authority creates awareness and encourages the growing significance of handmade creations by lowering taxes, providing space and equipment to produce recycled materials, and creating a market for them.

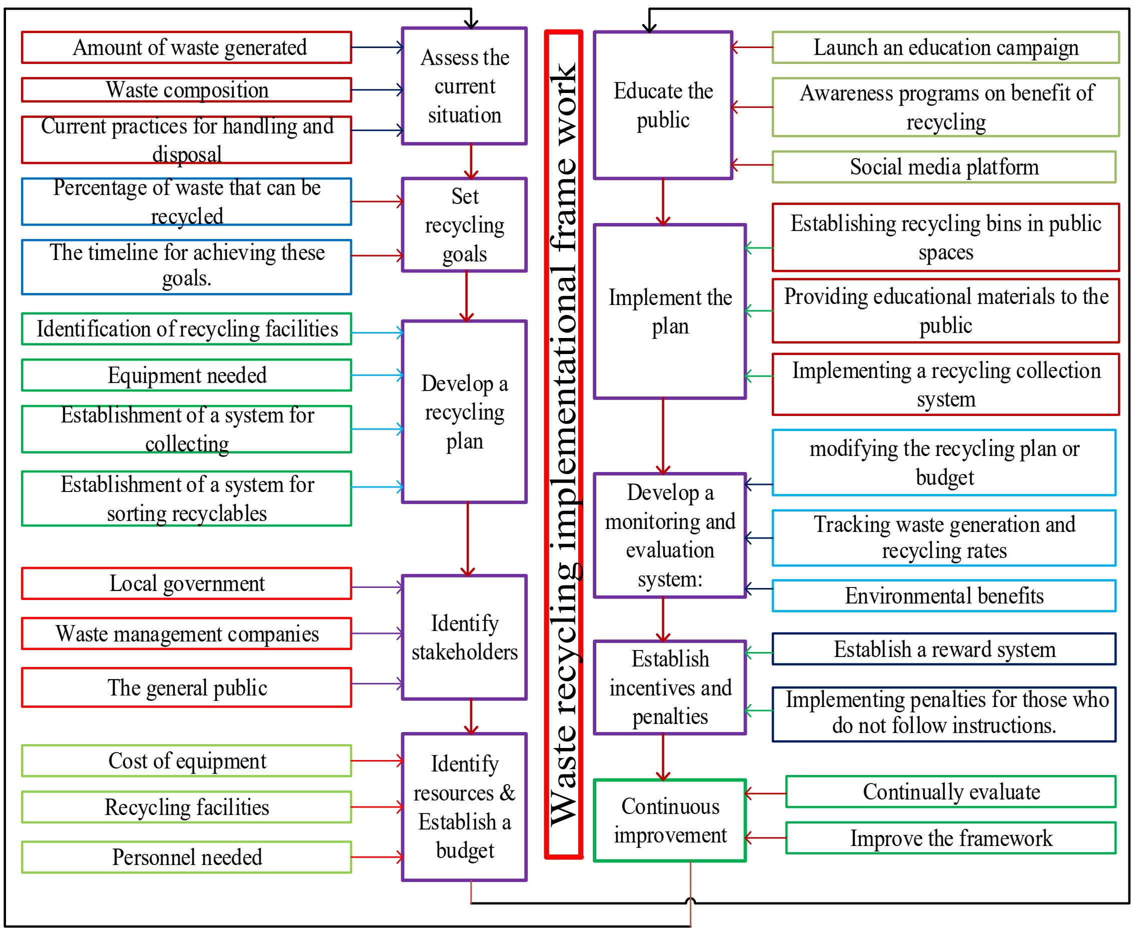

Fig. 3. Waste recycling implementational frame work

5. Conclusion

This study focused on the MCDM approach in the MSWM strategy selection problem. Even though there is no generic rule or formula for selecting a specific MCDM method, and applying a single MCDM in decision-making may result in a wrong decision due to the limitation that method has. Additionally, Numerous selections involve some level of uncertainty, and increase the vagueness in decision-making due to the subjective judgments of respondents. Integration Fuzzy set with other MCDM methods enables us to get more realistic results in decision-making problems. Therefore, this research attempted to apply fuzzy integrated MCDM, specifically fuzzy DEMATEL, ANP, and TOPSIS, to realize the right decision in the Dire Dawa municipal solid waste strategy selection problem.

From the funding of this study, it is concluded that the key MSWM strategy selection criteria and sub-criteria were identified. Thus, it was concluded that four main criteria and twenty sub-criteria are identified as the selection parameters of the city's MSWM strategy selection and waste recycling was selected as the best strategy. On the other hand, the UN concluded waste reduction was the best strategy over recycling. However, depending on specified criteria and environment situation recycling is the best strategy is the best strategy for the city.

Acknowledgement

The authors would like to acknowledge Dire Dawa university for providing the required support for completing this research work.

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