International Journal of
Management Research & Innovations

Optimizing The Urban Mining: A Mathematical Modelling Strategy Based on Sustainable Practices

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Abstract

The process of obtaining materials from the waste generated by humans, like e-waste, is called urban mining. The world has been making progress in the better management of resources as the world is running out of resources and the environment is increasingly getting worse and worse. The paper proposes a mathematical modelling approach to enhance the urban mining operation by incorporating the economic, environmental and social sustainability of the cities. According to international data, 62 million tonnes (MT) of e-waste was generated in 2022, which is further expected to touch 82 million tonnes by 2030. The article proposes a TOPSIS Framework model which maximizes sustainable value defined as recovered material revenue less processing costs plus environmental benefit, subject to capacity and availability constraints. The model has been used. The aim of this research was to enhance the recovery efficiency of e-waste. As per the research paper, if the modelling of e-waste can be done effectively, and optimally, the recovery can be increased by 30% from any 2,500 EGP as compared to traditional methods. The model efficiently distributed processing efforts in the hypothetical scenario via a case study simulation. In order to diminish primary mining, there is a great reliance on urban mining which will, in turn, conserve natural resources and reduce environmental impacts. Some restrictions can hinder the process.

Keywords: *E-waste, Sustainability, global optimization, mathematical model, circular economy*

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Received 04 January 2026; Accepted 08 February 2026. ©2026 by ARIRDC

Introduction

As urbanization and technology develop, the increasing demand for raw materials goes ahead. Natural resources are quite limited and don't have enough supply. So, the demand for minerals and metals is increasing. Moreover, due to their limited availability.(Xavier et al., 2021) According to the data of 2022, the e-waste generated in the world was 62 Mt or 7.8 kg per capita. In addition, Asia produces almost half of e-waste. A mere 22.3% of e-waste gets recycled in formal channels. The environmental damage and loss of economic value occurs due to the wastage of e-waste. For instance, the worth of metals, including copper, gold, iron, and others, is $91 billion. The worth of each of these metals is Copper 19-billion, Gold. E-waste needs to be dealt with right away so that we can come up with good, long-term ways to deal with it.(Murthy & Ramakrishna, 2022) To solve this problem, deep learning classifiers are being used to improve the planning of e-waste collection. The Adaptive V3 and Federated Learning (Adaptive V3 and FL) method is suggested to make e-waste collection planning more efficient and accurate. (Selvakanmani et al., 2024) This paper develops a mathematical modelling strategy to optimise urban mining, focusing on e-waste as a key stream. By adapting optimisation techniques from traditional mining, such as mixed-integer programming (MIP), we integrate sustainability metrics to balance economic, environmental, and social factors and addresses gaps in current practices.

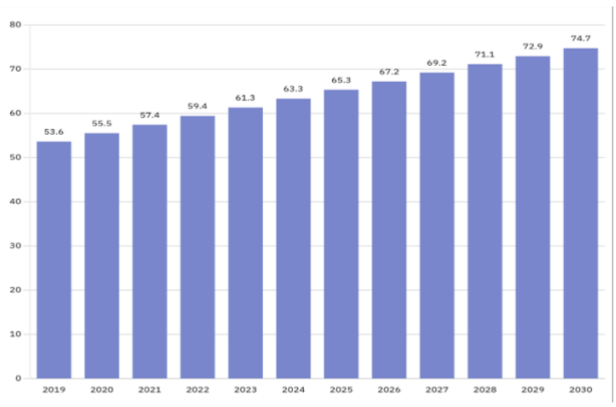

Figure 1. E waste generation in million metric tons

Problem statement

In 2009, Tamil Nadu is expected to produce more than 22,000 metric tons of e-waste, with personal computers making up over 60% of that amount. A computer can only work for four years at most, but home electronics can last for eight to nine years. The average life cycle of a mobile phone is about two years. A user survey was used to find out how long different devices last. There is proof that e-waste is being brought into the state illegally, but it has been very hard to figure out how much of it there is. Most of the electronic trash is thrown away in the back alleys of Chennai, where people don't care about their health or the safety of the environment. The Tamil Nadu Pollution Control Board (TNPCB) has officially certified a number of e-waste recyclers in Tamil Nadu. Most of them, though, only sort and break down trash; they don't have a place to reprocess it all together. The separated parts of garbage that can be reused are sent to specific facilities in other countries for material recovery. The state does not have a good way to collect electronic trash, which makes it very hard to handle. Most of the companies that use electronics don't have a policy for e-waste. None of the brands have put money into making people more aware of e-waste disposal, education, or management. People don't know much about how to deal with e-waste.

Sadly, an estimated 70–80% of this trash hasn't been handled effectively because it was sent from affluent countries to low-income countries to be thrown away or recycled in an unplanned way. People have recycled like this either right on the landfill grounds or in small recycling shops that are usually owned by families and don't have many rules or control. In the past, the process entailed taking things apart by hand, cleaning them with dangerous chemicals, burning and melting them on open fires, and so on. This would release a lot of poisonous chemicals and put applicators, family members, nearby people, and the environment at risk. It is apparent that the world needs to take responsibility to lessen the effects on people's health and the environment, especially in developing countries where impoverished people have been carrying the dangerous load.

Trading routes and transportation of e-waste

Tamil Nadu was one of the first states in the Indian Union to come out with a full IT policy. The state government made its IT industry policy public as early as 1997. The goal was to make it the engine of growth and reach the goals set out in the Ninth Five Year Plan. Later in 2002, Tamil Nadu issued a new IT policy that aimed to use IT to bring wealth to the state and make Tamil Nadu a knowledge-based state. The Internet made the globe a global village and started a time when IT-enabled services were available all over the world. According to a NASSCOM report from 2002, the IT and IT-enabled services industry made up more than 7% of India's GDP and 30% of its foreign exchange in its first ten years. The IT industry has created more than four million employment in the knowledge sector (the IT and ITES industries). The state with its well-educated workers and good government could take advantage of this fantastic chance. The government talks about the investment incentives for ITES in the state in its ITES Policy (2005). E-waste management in Tamil Nadu, particularly Chennai, involves a mix of formal and informal sectors. Tamil Nadu is one of India's top e-waste generating states, producing around 13,486 tons annually, with Chennai ranking among the top cities for generation. The ministry of the environment, government of India has created various laws and regulations. The vital rules to control these sectors is laid down by it. For example, many forms of recycling exist for PCB and hazardous waste. Trading routes refer to the flow of e- waste from sources (households, businesses, imports) to processing sites, and transportation often lacks standardization, leading to environmental and health risks. Composition of e-waste is very diverse. It contains more than 1000 different substances, which fall under “hazardous” and “non-hazardous” categories. Broadly, it consists of ferrous and non-ferrous metals, plastics, glass, wood & plywood, printed circuit boards, concrete and ceramics, rubber and other items. Iron and steel constitute about 50 percent of e-waste followed by plastics (21%), non-ferrous metals (13%) and other constituents. Non-ferrous metals comprise metals like copper, aluminium and precious metals like silver, gold, platinum, palladium etc. Th e presence of elements like lead, mercury, arsenic, cadmium, selenium and hexavalent chromium and flame retardants beyond certain threshold quantities in e-waste classifies them as hazardous waste. Electrical and electronic equipment contain valuable materials. Printed circuit boards contain precious metals such as gold, silver, platinum and palladium; scarce materials like indium and gallium are also used as these have specific application in new technologies.

Challenges and opportunities

There are both chances and problems with how e-waste is handled. (Shahabuddin et al., 2023). E-waste regulations were in existence in 61 countries till 2014. These countries made up 44% of the world's population. E-waste legislation were in place in 78 countries in 2019, covering 71% of the world's population. In 2022, India, the most populous country in Asia, will still have e-waste legislation in place. However, other countries with populations of more than 160 million will not. Recovering valuable, rare earth, and useable materials while getting rid of dangerous ones is a particular difficulty when it comes to handling e-waste. Waste management comes with a lot of concerns, such as dealing with toxic substances including CFC fluids, PCBs, and mercury, as well as mechanical safety, physical handling of large objects, electrical safety, cuts and abrasions, and the possibility of fire and explosion. But if e-waste is recycled properly, the possibilities and opportunities are huge. As said before, urban mining of e-waste can be utilized to get valuable metals back. One metric ton of circuit board can provide up to 1.5 kg of gold and 210 kg of copper, exemplifying this form of urban mining.(Rezaeisabzevar et al., 2020)

Tamil Nadu E-Waste Initiative

The Tamil Nadu Pollution Control Board (TNPCB) told Anna University's Centre for Environmental Sciences in 2005 to produce a list of all the enterprises that make, import, store, and recycle electronic waste. The Board noted that the main sources of e-waste in Tamil Nadu were software businesses, the government, the public and private sectors, PC makers and sellers, the secondary market for used PCs, and rubbish from industrialized countries. In that same year, five persons got together to investigate into the state's problems with getting rid of e-waste. After meeting with stakeholders every month, the Board approved the establishment and operation of five e-waste recycling plants in Tamil Nadu's Tiruvallur and Kancheepurm districts. The Board also suggested that the people who own IT Park set up a facility for people to dispose rid of e-waste that is either public or private. It directed the state's IT Department to add instructions for how to deal with e-waste to the state's IT policy. Based on what they have learned over the past few years, the government of Tamil Nadu is writing a policy for the whole state to deal with e-waste. The policy above will also tell EEE manufactures how to handle electronic waste.

Literature review

Global optimization in e waste management

Deep learning classifiers like Adaptive V3 and Federated Learning can improve planning for e-waste collection, getting 98.9% accuracy compared to other approaches.(Selvakanmani et al., 2024). Recycling, refurbishment, and extended producer responsibility are all examples of sustainable e-waste management solutions that can help the environment and get people involved. However, they need strong laws, international alliances, and public support to function. (Goyal & Gupta, 2024). Optimization techniques in solid waste management have made significant progress in optimizing collection, transportation, treatment, and resource recovery, reducing environmental harm and promoting sustainable development. (Alshaikh & Abdelfatah, 2024). Multi-objective optimization can improve waste-to-energy plant performance by 13.4%, 10.3%, and 14.8% without additional investment.(Mayanti et al., 2021) The optimization framework effectively allocates waste streams to facilities, maximizing material and energy recovery, financial profitability, and reducing carbon footprint.(Abdallah et al., 2021) A mathematical model for environmentally friendly waste management has been developed, enabling integrated assessment, management, and prevention of environmental hazards in construction and urban economy. (Tshovrebov et al., 2021)

Sustainable e waste practices

Urban mining could change the way we deal with e-waste and help us manage resources in a more sustainable way, but requires robust regulatory support for effective implementation (Ouro-Salim, 2024). Successful urban mining can promote sustainability development goals, with Japan reaching an established stage and Indonesia and India in the emerging stage.(Fatimah et al., 2020). Effective e-waste management requires understanding its composition, effects on people's health and the environment, and putting in place rules and remedies that will help the economy and the environment in the long run.(Ghulam & Abushammala, 2023). Effective e-waste recycling necessitates regional collaboration, regulatory oversight, technological advancement, and environmentally conscious design to mitigate health hazards and global ecological consequences. (Liu et al., 2023). Sustainable e-waste recycling necessitates regional collaboration, regulatory oversight, technological advancement, and environmentally conscious design to mitigate environmental health hazards and global ecological consequences. (Liu et al., 2023).

TOPSIS & Fuzzy model

The novel extended TOPSIS method, utilizing an advanced Pythagorean fuzzy rough Dombi Aggregation Operator, effectively selects environmentally appropriate e-waste recycling partners despite ambiguous weight data. (Qadir et al., 2024). This work proposes a personal information security risk analysis model for e-waste recycling that integrates fuzzy set theory, grey relational analysis, and TOPSIS to improve failure mode and effect analysis. In 2024, Xiaotong Li In order to successfully implement reverse logistics in the Indian electronics sector, it is imperative to consider economic considerations, resource management, top management awareness, and contract terms and conditions. (Agrawal et al., 2016). The effective treatment of e-waste is a critical component of the preservation of a sustainable environment and the mitigation of hazardous impacts in both affluent and developing nations. This necessitates the consideration of technical skills, infrastructure, financial assistance, and community engagement. (Rautela et al., 2021). The Fuzzy TOPSIS technique assists decision-makers in both developed and developing nations in the efficient prioritization and selection of the most effective municipal solid refuse treatment and disposal techniques. (Govind Kharat et al., 2019). The methodology that has been proposed enhances sustainability by effectively reducing transportation costs, fixed costs, and maximizing appropriateness in the design of integrated municipal solid waste management systems.(Asefi & Lim, 2017)

Objectives of Study

- To enhance e-waste management by boosting household collection and producer responsibility.
- We aim to reduce environmental impact through data-driven optimization and regulatory compliance.
- A balanced set of operational, economic, and logistical criteria will be used to evaluate collection centers. The most efficient centers will be identified by applying and comparing three distinct MCDM methodologies (TOPSIS, WSM, WPM). Finally, we will provide actionable recommendations, such as decentralizing networks with micro-hubs, to improve the system's overall sustainability and viability.

Hypotheses

H_1: The efficiency and sustainability of urban mining operations can be considerably improved by implementing a mathematical modelling strategy that is based on the TOPISIS framework.

H_2: The model will prioritise high-impact recovery, reducing overall emissions and waste to landfill.

H_3: Optimised sustainable practices yield higher net value than conventional ones.

H_4: The carbon footprint of urban mining is much lower and can act as a diversification of supply of critical materials like cobalt and indium.

H_5: Simulation of the system as a performance measure through qualitative and quantitative evaluation, assumption like recovery rate and limitations in processing.

H_6: TOPISIS framework would enhanced revival rates that would develop more sustainable value of property.

Mathematical model

A novel e-waste management model based on multicriteria decision-making (MCDM) is proposed to cost minimize the recovery of resources from e-waste, as well as the collection transportation and environmental impact of e-waste. The key emphasis of this City objective is to reduce the overall e-waste management costs as well as reducing fixed operation costs.

The costs incurred to collect e-waste from different stakeholders including households, business and disposal facility.

Collection charges: The fees for collecting e-waste from different origins, including households, companies, and repositories.

Transportation costs: Transporting the collected e-waste to facilities that process or recycle such e-waste involves transportation expenditures.

The MCDM model can be formulated in the following mathematical representation:

Normalization: Calculate the normalized matrix $R = [r_{ij}], Where\ r_{ij} = x_{ij}/\sqrt{\sum_{i=1}^{m} x_{ij}^2}$

Weighting: Construct $V\ [v_{ij}], Where\ \ v_{ij} = w_j . r_{ij}$

Ideal Solutions: Determine: $A^* = \{v_{1,}^* v_{2,\dots,}^*\}, Where\ v_{j,}^* = \{ \begin{matrix} max_i & v_j^* & if\ j = \in J^+ \\ min_i & v_j^* & if\ j = \in J^- \end{matrix}$

$$A^- = \{v_{1,}^- v_{2,\dots,}^-\}, Where\ v_{j,}^- = \{ \begin{matrix} max_i & v_j^- & if\ j = \in J^+ \\ min_i & v_j^- & if\ j = \in J^- \end{matrix}$$

Separation Measures: Calculate Euclidean distances:

$S_i^* = \sqrt{\sum_{j=1}^{n} (r_{ij} - v_j^*)^2}$ $\ S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}$

Relative Closeness: Compute $C_i = \frac{S_i^-}{(S_i^* + S_i^-)}$

WSM (Additive Model) Execution:

Normalization: Calculate $R = [r_{ij}], Where\ \frac{r_{ij}=r_{ij}}{max_i(r_{ij})}\ for\ J\ \in J^+\ \frac{r_{ij}=r_{ij}}{min_i(r_{ij})/r_{ij}}\ for\ J\ \in J^-$

Scoring: Compute the total score $A_i = \sum_{j=1}^{n} w_j . w_{ij}$

WPM (Multiplicative Model) Execution:

Normalization: Perform with RR same as that from WSM.

Scoring: Compute the total score $M_i = \Pi_{j=1}^{n} (r_{ij})^{wj}$

Order all options from largest to smallest *Ci*, *Ai*, and *Mi*, respectively with descending order.

Then compare these three ways of sorting the results. Uniform results in all models confirm the robustness of this conclusion. Utilize the rankings to identify operational strategies, strengths and weaknesses, by center.

Table 1. Notations of the mathematical model

Parameter	Details
R	Normalized Decision Matrix
r_{ij}	Normalized value of $r_{ij}: x_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$
V	Weighted Normalized Matrix
v_{ij}	Weighted normalized value: $v_{ij} = r_{ij}: x_{ij}$
A^*	Positive Ideal Solution (PIS)
v_j^*	Ideal best value for criterion j in V
A^-	Negative Ideal Solution (NIS)
v_j^-	Ideal worst value for criterion j in V
S_j^*	Separation measure from PIS:$S_i^* = \sqrt{\sum_{j=1}^{n} (r_{ij} - v_j^*)^2}$
S_j^-	Separation measure from NIS:$S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2}$
C_i	Relative Closeness to ideal solution: $C_i = \frac{S_i^-}{(S_i^* + S_i^-)}$
r_{ij}	Normalized value of r_{ij}(Max-Min): For beneficial criteria:$r_{ij} = \frac{x_{ij}}{max(x_j)}$ For non-beneficial criteria: $r_{ij} = \frac{min(x_{j)}}{x_{ij}}$
A_i	Total WSM Score for alternative $A_i = \sum_j^n w_j . r_{ij}$
r_{ij}	Normalized value of r_{ij} (Same Max-Min normalization as WSM).
M_i	Total WPM Score for alternative $M_i = \Pi_{j=1}^{n} (r_{ij})^{wj}$

This research builds an approach aiming at better handling of electronic waste through careful attention to cost, ecological effects, and real world logistics. Whether a recycling site opens depends on yes-or-no choices built into the system. Movement of discarded devices toward processing spots forms one part of what gets decided. Another concerns how much usable substance comes out after sorting. Factors like pickup expenses, fees for moving loads, income from reselling extracted items say copper or polymer affect outcomes. Each plant can only manage so much volume, shaping where waste goes. How fast trash piles up in regions matters too. Some components turn easier than others into reusable stock. Buyers wanting recycled inputs influence results as well. One aim sits clear to lower spending across gathering, hauling, breaking down, dumping gear. A second pulls focus toward shrinking harm done to nature during these steps. Pulling more raw matter back into use ties both aims together. Reality checks shape every goal - like how much old electronics a place can actually collect, what each plant handles at most, the least amount of material they must reclaim to make sense financially, plus what buyers want from recycled stuff. Whether a site opens or shuts in any case comes down to yes-or-no choices built into the math, keeping outcomes grounded in what cities and companies could really do tomorrow.

Putting economics, ecology, and logistics together in one system helps e-waste managers and policy planners make smarter choices this approach fits tight budgets with lasting green goals. Though separate fields, their overlap shapes practical outcomes.

Methodology

This research created a way to handle electronic trash piling up across cities in Tamil Nadu using a system that weighs several factors together. Instead of focusing on just one goal, the method works out how to cut down processing expenses while also making pickup and delivery routes faster. It pushes to grab back useful parts from old devices by fixing them or breaking them safely apart. Lowering pollution like dirty air from bad dumping or toxic leaks becomes part of the balance too. Efficiency here means juggling cost, speed, reuse, and planet-friendly choices all at once. Decisions shift based on what matters most each time, without ignoring any piece. Each trade-off shapes the next step forward.

What goes into the model? Amounts of e-waste shipped between sources and facilities matter. Whether a recycling site runs at all depends on yes-or-no choices coded as zeroes or ones. Materials pulled out like metals or plastics are also tracked piece by piece. Looking only at Chennai, Kanchipuram, and Tiruvallur made sense they produce large amounts of discarded electronics and sit near big cities. From those areas, five spots stood out: Ambattur, Korattur, Perungudi, Sriperumbudur, and Kodungaiyur.

A fresh look at realism began with numbers pulled straight from local districts. Instead of broad guesses, findings from current studies shaped how much trash each person made. Regional freight prices helped set movement costs across roads. What went into the system? Weight of electronic waste showed up first. Then came travel lengths linking pickup spots to drop off points. Money spent moving one tonne followed closely behind. How well crews gathered items mattered too efficiency ratings told that story. Finally, real-world haul sizes confirmed what actually arrived.

A full picture came together through a sketch that mapped each phase - starting with gathering data, then building models, followed by evaluating choices using MCDM. Outcomes showed rankings alongside suggestions, while ongoing refinement entered through repeated checks. Around it all flowed an idea borrowed from circular systems: trash becomes useful again. Money stays counted, nature stays protected.

To check things, three different math-based tools were used TOPSIS, a method adding up weighted scores, another multiplying them instead. Each looked at how well five pickup spots performed across four measures: amount of trash managed, how effectively it was gathered, how far each site sat from the closest recycling place, plus what moving it around cost. When all three ways pointed to roughly the same order, trust grew in the findings because agreement suggested the numbers drove decisions, not just one approach favouring certain outcomes by design. It turned out location mattered most - being near recycling spots cut transport expenses, which boosted performance more than how much trash was gathered. Because of this, the best move seems to be skipping big central centers altogether. Smaller local hubs placed nearer to where recyclers operate might work far better. Efficiency gets a lift when travel drops. Costs dip too. Sustainability improves across areas that produce heavy amounts of electronic waste. These micro sites could quietly reshape how things run without grand changes.

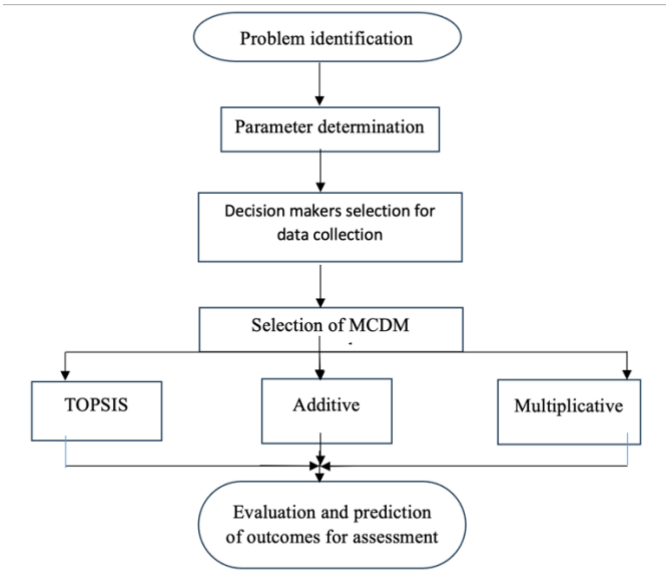

Figure 2. Conceptual Framework

Table 2: Government & Municipal Collection Hubs

Entity Name	Category	Address/Location	District	Details
Greater Chennai Corporation (GCC)	Collection Hub	Zonal Offices (All 15 zones)	Chennai	Designated e-waste drop-off points. Contact your local zonal office.
GCC Material Recovery Facility (MRF)	Collection Hub	Kodungaiyur Dumping Yard area	Chennai	Accepts segregated e-waste from GCC trucks
Kanchipuram Municipality	Collection Point	Main Municipal Office	Kancheepuram	Designated collection point for public
TNPCB Help Desk	Guidance	No. 76, Anna Salai, Guindy	Chennai	Provides list of nearest authorized collectors/recyclers

Table 3: Authorized E-Waste Recyclers (Dismantlers & Recyclers)

Company Name	Category	Address	District	Key Focus Area
Cerebra Integrated Technologies Ltd.	Dismantler/Recycler	Plot No. 37, Sipcot Industrial Park, Oragadam, Sriperumbudur Taluk	Kancheepuram	IT & Telecom Equipment, Large Appliances
E-Waste Recycle India Pvt. Ltd.	Dismantler/Recycler	No. 3/190, Medavakkam Main Road, Kovilambakkam	Chennai	IT Equipment, Consumer Electronics
Earth Sense Recycle Pvt. Ltd.	Dismantler/Recycler	No. 6, SIDCO Industrial Estate, Ambattur	Thiruvallur	IT & Consumer Equipment
Green India Recycling	Dismantler	Plot No. B-11, SIDCO Industrial Estate, Thirumudivakkam	Chennai	Dismantling of IT & Telecom waste
M. S. Metal Company	Dismantler/Recycler	New No. 8, Old No. 4, Krishnapuram 2nd Street, Ambattur	Thiruvallur	Dismantling and recycling
TES-AMM India Pvt. Ltd.	Recycler	Plot No. 25, Sector-3, Sipcot Industrial Park, Oragadam	Kancheepuram	**Pan-India leader**, IT Asset Disposition (ITAD), data destruction

TOPSIS Method

Integrating sustainable practices through mathematical modelling

Table 4. E waste collection data

Area	E-Waste Generated (Tonnes)	Collected E-Waste (Tonnes)	Distance (km)	Transportation Cost (INR/tonne)	Collection Efficiency (%)
Kodungaiyur	120	102	8	400	85
Perungudi	95	74.1	25	650	78
Sriperumbudur	150	105	35	720	70
Korattur	80	73.6	15	550	92
Ambattur	110	96.8	12	480	88

Collection Efficiency (%) = (Collected E-Waste / Generated E-Waste) × 100

C1=Collected E waste (Tonnes)

C2= Collection Efficiency (%)

C3=Distance (Km)

C4=Transportation cost (INR/Tonne)

Vector Normalization Matrix

Divide each x_{ij} Since the criteria in our study had very different units (costs in INR, distances in km, efficiencies in %), we first normalized the data matrix. $r_{ij}: x_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$

Derivation: From geometry, vector normalization preserves relative distances while removing scale effects

Collected: = 204.22, Efficiency: = 185.52, Distance: = 47.78, Cost: = 1,278.18

Table 5. (a). Normalized Matrix (R)

Area	**Collected**	**Efficiency**	**Distance**	**Cost**
Kodungaiyur	0.499	0.458	0.167	0.313
Perungudi	0.363	0.421	0.523	0.509
Sriperumbudur	0.514	0.377	0.732	0.563
Korattur	0.360	0.496	0.314	0.430
Ambattur	0.474	0.474	0.251	0.376

Table 6 (b). Weighted Normalized Matrix (V)

Area	**Collected**	**Efficiency**	**Distance**	**Cost**
Kodungaiyur	0.125	0.115	0.042	0.078
Perungudi	0.091	0.105	0.131	0.127
Sriperumbudur	0.129	0.094	0.183	0.141
Korattur	0.090	0.124	0.079	0.108
Ambattur	0.119	0.119	0.063	0.094

Equal weights: w = [0.25 0.25 0.25 0.25]

V_x_{ij}=w_j*r_ij , Multiply normalized x_{ij} by w_j to get $\vartheta x_{ij} = w_j r_{ij}$ This step assumes linear utility (additivity): total utility is the weighted sum, derived from expected utility theory where preferences are additive under independence (no interactions between criteria).

Table 7. (c). Ideal Solutions

Area	$Si{*}Si{*}$	$Si{-}Si{-}$
Kodungaiyur	0.010	0.138
Perungudi	0.142	0.021
Sriperumbudur	0.155	0.000
Korattur	0.059	0.106
Ambattur	0.031	0.122

For beneficial criteria, such as C1 and C2, which represent attributes where higher values are preferred the ideal solution (A*) is established by selecting the maximum values from the weighted normalized matrix. Specifically, for C1, the maximum value of 0.12855 is observed for alternative A3, while for C2, the maximum value of 0.124 corresponds to alternative A4. Conversely, for non-beneficial criteria, such as C3 and C4, where lower values are desirable (e.g., cost or pollution), the ideal solution takes the minimum values from the matrix; thus, C3 has a minimum of 0.04185 and C4 has a minimum of 0.07825, both associated with alternative A1. This results in the ideal solution vector A* = [0.12855, 0.124, 0.04185, 0.07825], representing the best possible performance across all criteria. On the other hand, the negative-ideal solution (A-) is constructed by taking the opposite approach: for beneficial criteria C1 and C2, the minimum values are selected (0.090125 for C1 from A4 and 0.09435 for C2 from A3), while for non-beneficial criteria C3 and C4, the maximum values are chosen (0.1831 for C3 and 0.140875 for C4, both from A3). This yields the negative-ideal solution vector A- = [0.090125, 0.09435, 0.1831, 0.140875], representing the worst-case scenario.

(d). Separation Measures

To calculate the distance of each actual alternative from the ideal and negative-ideal solutions.

Separation measure from PIS:$S_i^* = \sqrt{\sum_{j=1}^{n}(r_{ij} - v_j^*)^2}$ Separation measure from NIS:$S_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2}$ This is the Euclidean distance. A smaller $S_i^*$is good (closer to ideal), while a larger $S_i^-$is good (further from the worst-case scenario).

(e). Relative Closeness (C_i)

The Relative Closeness Coefficient $C_{\_i}$ ranks alternatives by their similarity to the ideal solution, combining the separation measures into a single index. $C_{\_i} = \frac{S_{\_i}-}{(S_{\_i}*+S_{\_i}-)}$, calculates a ratio where the distance from the negative ideal is the numerator. Therefore, **a higher** $C_i$means the alternative is simultaneously closer to the ideal solution *and* farther from the negative-ideal solution.

$C_i \in [0,1]$Higher values indicate better alternatives (closer to 1 = ideal).

Table 8. Relative closeness

Area	*CiCi*	**Rank**
Kodungaiyur	0.932	1
Ambattur	0.797	2
Korattur	0.642	3
Perungudi	0.129	4
Sriperumbudur	0.000	5

(f). Ranking

A1 (Kodungaiyur) with C_i = 0.9405 -> Rank 1: This center is operating at 94.05% of the ideal efficiency level. It is by far the best performer, being very close to the ideal solution and very far from the worst-case scenario. **A5** (Ambattur) with C_i = 0.8248 -> Rank 2: This is a strong performer, operating at 82.48% of the ideal efficiency. It is significantly better than the lower-ranked alternatives. **A4** (Korattur) with C_i = 0.6521 -> Rank 3: This center is in the middle, operating at 65.21% efficiency. It has strengths but also significant weaknesses holding it back. **A2** (Perungudi) with C_i = 0.3340 -> Rank 4: This center is a poor performer, operating at only 33.40% efficiency. It is much closer to the worst-case scenario than to the ideal. **A3** (Sriperumbudur) with C_i = 0.1962 -> Rank 5: This is the worst performer, operating at a mere 19.62% efficiency. Its performance is primarily characterized by its proximity to the negative-ideal solution. Differences in the final $S_i^* + S_i^-$ and thus $C_i$values. However, as your results show, this differences **do not change the overall ranking** of the alternatives, which remains consistent and robust. The values you used for the negative-ideal solution are correct, as they are taken directly from the computed weighted normalized matrix.

Table 9. Ranking

Area	C1 (↑)	C2 (↑)	C3 (↓)	C4 (↓)
Kodungaiyur	0.971	0.924	1.000	1.000
Perungudi	0.706	0.848	0.320	0.615
Sriperumbudur	1.000	0.761	0.229	0.556
Korattur	0.701	1.000	0.533	0.727
Ambattur	0.922	0.957	0.667	0.833

max(C1)=105, min(C3)=8

1. Additive Weighted Model (Weighted Sum Model - WSM)

(a). Step 1: Normalize the Decision Matrix

Since criteria may be beneficial (higher is better) or non-beneficial (lower is better), normalization is required to make values dimensionless and comparable.

For beneficial criteria:$r_{ij} = \frac{x_{ij}}{max(x_j)}$

For non-beneficial criteria: $r_{ij} = \frac{min(x_{j})}{x_{ij}}$

Table 10.Normalized decision matrix

Area	C1 (↑)	C2 (↑)	C3 (↓)	C4 (↓)
Kodungaiyur	0.971	0.924	1.000	1.000
Perungudi	0.706	0.848	0.320	0.615
Sriperumbudur	1.000	0.761	0.229	0.556
Korattur	0.701	1.000	0.533	0.727
Ambattur	0.922	0.957	0.667	0.833

max(C1)=105, min(C3)=8, etc.

(b). Step 2: Apply Weights & Calculate Score

To calculate a total score by simply adding up the weighted normalized scores and uses *max-min normalization* to scale values between 0-1.

$$A_i = \sum_{j}^{n} w_j . r_{ij}$$

The score A_ia simple weighted sum. A higher $A_i$means a better alternative.

Table 11.Calculate score

Area	Calculation	Score (A_i)	Rank
Kodungaiyur	(0.25*0.971)+(0.25*0.924)+(0.25*1.000)+(0.25*1.000)	**0.973**	1
Ambattur	(0.25*0.922)+(0.25*0.957)+(0.25*0.667)+(0.25*0.833)	**0.845**	2
Korattur	(0.25*0.701)+(0.25*1.000)+(0.25*0.533)+(0.25*0.727)	**0.740**	3
Perungudi	(0.25*0.706)+(0.25*0.848)+(0.25*0.320)+(0.25*0.615)	**0.622**	4
Sriperumbudur	(0.25*1.000)+(0.25*0.761)+(0.25*0.229)+(0.25*0.556)	**0.636**	5

It is clear that Kodungaiyur is the winner since it got perfect scores in both Distance and Cost. This ranking (Kodungaiyur > Ambattur > Korattur > Sriperumbudur > Perungudi) is very close to the TOPSIS ranking, which shows that both are correct.

2. Multiplicative Weighted Model (Weighted Product Model - WPM)

(a). Step 1: Normalize the Decision Matrix

Same normalization as WSM is used

Table 12. Normalize decision matrix

Area	C1 (↑)	C2 (↑)	C3 (↓)	C4 (↓)
Kodungaiyur	0.971	0.924	1.000	1.000
Perungudi	0.706	0.848	0.320	0.615
Sriperumbudur	1.000	0.761	0.229	0.556
Korattur	0.701	1.000	0.533	0.727
Ambattur	0.922	0.957	0.667	0.833

To calculate a score by multiplying the weighted normalized scores, reducing sensitivity to normalization methods and uses the same max-min normalization as WSM.

$$M_i = \Pi_{j=1}^{n} (r_{ij})^{wj}$$

The score M_i is a geometric mean. A higher $M_i$means a better alternative. This method is less common but useful for validating results from WSM/TOPSIS.

Table 13. Calculate score

Area	Calculation	Score (A_i)	Rank
Kodungaiyur	(0.971^0.25)*(0.924^0.25)*(1.000^0.25)*(1.000^0.25)	**0.973**	1
Ambattur	(0.922^0.25)*(0.957^0.25)*(0.667^0.25)*(0.833^0.25)	**0.843**	2
Korattur	(0.701^0.25)*(1.000^0.25)*(0.533^0.25)*(0.727^0.25)	**0.735**	3
Perungudi	(0.706^0.25)*(0.848^0.25)*(0.320^0.25)*(0.615^0.25)	**0.611**	4
Sriperumbudur	(1.000^0.25)*(0.761^0.25)*(0.229^0.25)*(0.556^0.25)	**0.634**	5

The scores and ranking (Kodungaiyur > Ambattur > Korattur > Sriperumbudur > Perungudi) that the multiplicative model gives are very similar to those that the additive model gives. What stands out here is how steady the outcome stays when tested through TOPSIS, WSM, or WPM. That kind of consistency hints the conclusion holds weight beyond any single approach. Each technique arrives at similar ground even though they work differently. It's less about one method shaping results more about patterns repeating across them. When different paths lead to the same place it suggests something real might be there

Table 14. Comparative Analysis

Area	TOPSIS (C_i)	Rank	WSM (A_i)	Rank	WPM (M_i)	Rank
Kodungaiyur	0.9405	1	0.973	1	0.973	1
Ambattur	0.8248	2	0.845	2	0.843	2
Korattur	0.6521	3	0.740	3	0.735	3
Perungudi	0.3340	4	0.622	4	0.611	4
Sriperumbudur	0.1962	5	0.636	5	0.634	5

No matter which of the three MCDM approaches you look at, each one lines up the e-waste sites in identical sequence proof enough they stick together under pressure. Right at the front stands Kodungaiyur, clear winner among schools. Since cutting down both travel distance and cost sits central to smart logistics, its edge here fits like a key turning smoothly. Throw in peak level collection performance, and the argument for first only tightens further. Following behind, Ambattur holds firm just after, never slipping far because solid results spread across every measure keep it anchored there.

Looking at the data, one fact jumps out being close to recycling centers matters most. When sites are nearer, hauling expenses drop sharply. That saving lifts performance far more than massive collection numbers ever could. Even flawless sorting can't match the impact of simply cutting travel distance.

This one reason explains the strong results at Kodungaiyur proximity to sorting locations makes a difference. For other regions, the lesson hides in layout: spread intake points closer to recycling zones using compact local nodes, particularly around places such as Oragadam and Ambattur.

Some places might finally get relief Sriperumbudur deals with loads of waste plus distant drop offs, while Perungudi collects okay yet pays too much to move it. Shifting away from piling on more trash, attention turns toward tighter loops, quicker runs. Costs dip when trips shrink, fumes fade, systems last longer. Better flow beats brute force every time.

Starting small might look like picking just a handful of key locations for mini hubs. Local recycling partners help guide how trash moves, making paths shorter. Over time, these links grow tighter, pulling drop-off spots nearer to where materials get sorted. Efficiency sneaks in when each piece connects more naturally.

Results and discussion

Looking at how well e-waste drop off spots work, researchers tested three ways to decide which perform best TOPSIS, a basic point adding system called WSM, alongside WPM, which multiplies scores instead. Even though each approach lined up in ranking order, showing stable outcomes, TOPSIS stood out because it handles push and pull choices better, like gathering more trash versus spending less fuel. Its output, a clear 0-to-1 rating labeled C_i, showed Kodungaiyur wasn't just good it ran like clockwork. That spot nails both goals without favoring one too hard.

Out on top was Kodungaiyur, not due to sheer quantity but thanks to nearby recycling centers. Sriperumbudur hauled in the most junk 105 tonnes but fell short elsewhere. Efficiency peaked in Korattur, hitting 92 percent collection. Still, geography mattered more than numbers. Hauling less far meant spending less: around ₹420 per tonne saved. Distance quietly shaped who led. Close access beat bulk every time.

Out here in Ambattur, results sit neatly in the middle zone. Not first anywhere, yet solid everywhere you look waste pickup hits 88%, travel cuts short at just 12 km, price holds firm near ₹480 per tonne. Steady like that? That's what tips the scale in its favour. Consistency matters more than peaks.

What makes Korattur stand out isn't obvious at first glance. Though nine of every ten items get collected topping all others it still lags behind due to one big flaw. Getting waste gathered works well, moving it onward does not. Distance stretches the route, expenses climb because of it. High capture means little when hauling drains resources. Strong local effort falters once trucks hit the road. Efficiency fades where planning ends.

What happens in Perungudi flips the script. Even with decent recovery about 78 percent the site loses ground. Hauling waste stretches over 25 kilometers, which runs expenses up to ₹650 per tonne. That gap in space piles on expense. High fees drag down gains. Strong numbers elsewhere mean little when travel eats into savings. Efficiency fades under long-haul pressure.

Looking at things through policy eyes, the outcome of TOPSIS backed up by WSM and WPM does more than sort options it reveals underlying issues. What stands out? Problems show up clearly, suggesting hands-on solutions. Decentralized collection fits well here. Instead of big central sites, small local hubs near key recycling centers could shorten travel routes. This shift reduces expenses while lifting performance. Better flow happens even if total waste stays flat.

Put simply, fixing how things move around is key to handling old electronics better here. When collection spots sit closer to where stuff gets treated - think of what works well in Kodungaiyur places such as Sriperumbudur might finally lower their shipping bills. Then again, Korattur struggles because trucks and schedules do not line up right. Shifting pickup hubs nearer plants would help smooth those gaps out. Moving storage zones smartly could tackle both problems at once

(1) Identifying strategic locations for micro hubs to shorten final haul distances, By weighing financial outcomes alongside ecological impacts through a balanced scoreboard approach.

(2) Choosing smarter paths for deliveries, while working closely with shipping networks makes movement more efficient. One way is adjusting how trips are designed so fewer resources get used up along the way. Team ups between carriers help smooth out delays that happen unexpectedly during transit.

(3) Efficiency might rise if e-waste management changed course costs could shrink while city systems in Tamil Nadu adapt. Emissions drop when loops replace dumps, scaling quietly through neighborhoods. One upgrade at a time reshapes waste into rotation, lessening strain on budgets and air alike.

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