JCRINN Journal of Computing Research and Innovation e-ISSN : 2600-8793

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Journal of Computing Research and Innovation 11(2) 2026

Journal of Computing Research and Innovation

Optimizing Provisional Urban Waste Cooking Oil Collection: A Literature Review of MCDM and Set Covering Models

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ARTICLE INFO

Article history:
Received 26 October 2025
Revised 10 February 2026
Accepted 27 February 2026
Online first
Published 1 September 2026

Keywords:
Waste Cooking Oil Management
Multi-Criteria Decision Making
Set Covering Model

DOI:
10.24191/a3rwxv13

ABSTRACT

As urban populations grow, the amount of waste cooking oil (WCO) generated by households also increases. This WCO creates more environmental pollution if not handled properly. Small and Medium Enterprises (SMEs) are responsible for collecting WCO from households but face difficulties due to limited support and poorly planned collection systems. This study focuses on the optimal placement of provisional WCO collection points in urban areas. It uses a two-stage decision-making framework which are combining Multi-Criteria Decision Making (MCDM) and the Set Covering Model (SCM). A systematic literature review is conducted to evaluate the use of MCDM and SCM for WCO collection and facility location planning. However, the review finds no existing research combine MCDM and SCM for WCO collection from households. This represents a critical research gap, especially for planning provisional facilities in dynamic urban settings. To address this, the study proposes a future research direction that uses a two-stage decision-making framework to support better decision-making and improve operational efficiency in urban WCO collection systems.

1. INTRODUCTION

Households use cooking oil regularly, and it is important for daily cooking activities. After use, many people throw waste cooking oil (WCO) into drains, sinks or rivers, which causes water pollution and blocked pipes (Alwi et al., 2022). Studies show that each Malaysian household produces about 0.14 to 0.25 kilograms of WCO every day (Rahman et al., 2024). A lot of this WCO is not properly recycled, especially in urban areas where WCO generation is consistently increasing (Foo et al., 2022). Urban areas are growing

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https://doi.org/10.24191/a3rwxv13

rapidly, which puts pressure on existing waste management systems. Many residential areas in cities do not have enough space or proper facilities for permanent WCO collection. Because of this, Small and Medium Enterprises (SMEs) help collect and recycle WCO through informal method. However, provisional collection systems are not well planned. Despite their contribution, this makes it difficult for SMEs to operate efficiently.

Designing a good WCO collection system is difficult because every stakeholder wants different things and has different priorities (Anna et al., 2025). Households want disposal places that are nearby and easy to use. SMEs want collection routes that are cost-effective and easy to manage (Gultekin et al., 2020). Local governments want full area coverage, compliance with regulations, and protection of the environment for the future. Because of these different needs, it is important highlight to have a decision-making system that includes every perspective and balance what each group wants. This research uses a qualitative method through a systematic literature review. It reviews academic studies from 2020 to 2025 on urban WCO management using decision-making tools. The review focuses on studies that integrate Multi-Criteria Decision Making (MCDM) with Set Covering Model (SCM). The results show that no study combines these two methods for planning provisional WCO collection in urban settings. Even though sustainable waste management is important, there are still few studies on this topic. This lack of research highlights the importance of this study.

To address this issue, this study proposed a two-stage decision-making method. First, it uses the Adaptive Utility Ranking Algorithm (AURA) under the MCDM method. This step helps score and rank collection site options based on what stakeholders consider important. Second, it uses an SCM to find the best number and locations of provisional collection points that cover all areas and use resources efficiently. The next parts of this paper will explain the relevant literature, identify the research gap, and demonstrate how the proposed method can help improve WCO collection in cities.

2. STRUCTURED REVIEW OF PAST STUDIES ON MCDM AND SCM RELATED TO RECYCLING FACILITIES

WCO from households is a major problem because many people dispose of it improperly, which can harm the environment. To solve this problem, some researchers use decision-making tools to help plan better WCO collection systems. Two commonly used methods are MCDM and SCM models. This part of the paper reviews past research that uses MCDM and SCM to help improve household WCO collection and management in urban areas.

2.1 Multi-Criteria Decision Making (MCDM) for facility location problem

MCDM methods like AHP, TOPSIS, VIKOR, and fuzzy logic are often used to solve complex environmental planning problems. These methods combine technical, financial, and social factors, which makes the approach suitable for selecting sites for waste management. However, many studies that use MCDM only focus on permanent buildings or systems. These studies do not consider the flexible plans needed for collecting WCO in fast-changing cities.

MCDM is a useful method for planning WCO collection because it can handle many different and conflicting factors. This method includes technical, environmental, social, and economic factors when choosing the best location. In urban areas, planning must consider easy access for households, cost efficiency for SMEs, and long-term goals set by the local government. Some studies show that MCDM works well, such as university site selection in Turkey using TOPSIS, WASPAS and MULTIMOORA by Miç et al. (2021) and the use of AHPTOPSIS for optimal gas station siting in New York by Shaikh et al. (2021). For WCO, Boyacı et al. (2021) and Zulkifli et al. (2023) used MCDM to select collection points

https://doi.org/10.24191/a3rwxv13

from household WCO. However, these studies did not use mathematical optimization, so their models are not suitable for large-scale or low-cost WCO management.

Many MCDM methods have been used in planning, such as AHP, fuzzy logic, BWM, and TOPSIS. AHP is often used independently or in combination with other methods, like AHP-TOPSIS in studies in online grocery hub by Özder (2025), business location by Shaikh et al. (2021) and bakery facility by Aljohani (2023). WASPAS was used by Yanık (2024) to help in selecting healthcare facility sites when the data is unclear. Zandi et al. (2025) used TOPSIS, COPRAS and WASPAS with mapping tools to plan solar plant development in Iran. MCDM TOPSIS methods are also used for transport and warehouse location, such as in smart cities used TOPSIS by Hajduk (2021) and in logistics by Tarigan et al. (2023). These examples show that MCDM is flexible, but for WCO problems, it is still not fully integrated with mathematical models.

Specifically for household WCO, the use of MCDM methods is still not common. Existing studies by Boyacı et al. (2021) and Zulkifli et al. (2023) used simple methods like MULTIMOORA and AHP but did not combine with advanced optimization models like SCM. Moreover, traditional MCDM methods like standard TOPSIS use fixed weights and do not work well in cities where conditions change frequently. To solve this problem, the AURA method was introduced by Zaman et al. (2025). It can adjust the weight of each factor depending on new data and feedback from users. AURA supports better and more accurate decisions, especially for planning provisional WCO collection in areas with rapid changes. According to Zaman et al. (2025), AURA shows good results, but it has not been tested in actual WCO collection planning. By merging AURA and SCM, this study offers an improved and more adaptable model for household WCO collection in urban areas.

Table 1. Selected MCDM Methods with Corresponding Applications

Authors (year)	Type of MCDM						Applications
	AHP	COPRAS	TOPSIS	WASPAS	MULTI MOORA	AURA	
Boyacı et al. (2021)					x		WCO collection box siting
Hajduk (2021)			x				Urban Transport Location
Miç et al. (2021)			x	x	x		University Location
Shaikh et al. (2021)	x		x				Business Location
Aljohani (2023)	x		x				Bakery Facility
Tarigan et al. (2023)			x				Warehouse Location
Zulkifli et al. (2023)	x						WCO collection centers
Yanık (2024)				x			Healthcare Facility Location
Özder (2025)	x		x				Online Grocery Hub
Zaman et al. (2025)						x	Malaysia Microfinance
Zandi et al. (2025)		x	x	x			Solar Photovoltaic Power Plant

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2.2 Set Covering Model (SCM) for facility location problem

The FLP models like SCM are useful to identify the best locations to construct building facilities that are cost-effective and wide service coverage. The SCM method improve location planning by using mathematical tools such as Linear Programming (LP), Integer Linear Programming (ILP), and Mixed-Integer Linear Programming (MILP). These models are useful for balancing objectives such as reducing costs, good service coverage, and improved delivery routes. In waste management studies, many researchers use these models to find the best locations for collection points and achieve efficient resource allocation. These models perform successfully solve even for complex problems by providing clear and reliable solutions. For example, Claudia et al. (2022) used an ILP model to decrease both expenses and time required for household WCO collection in Bogotá. Geng et al. (2021) developed a MILP model to reduce transport expenses for commercial WCO collection in China. Quintana et al. (2020) also used MILP model for WCO collection planning across Latin America, resulting in substantial cost reductions. Several studies have also employed LP and ILP models. Julia et al. (2024) used ILP models to choose fire station locations in Indonesia, while Musa (2025) applied LP to select factory sites in Africa. In Malaysia, Rosni et al. (2022) and Zaharudin et al. (2023) used MILP to create low-cost and wide-coverage recycling networks. These examples show that SCM and mathematical models help make better and smarter decisions for facility construction and planning.

Table 2. Selected mathematical modelling with objective functions and application areas

Authors (year)	Mathematical Modelling			Objective Function			Applications	Case Study Area
	LP	ILP	MILP	Cost	Service Coverage	Transportation Efficiency		
Quintana et al. (2020)			x	x			WCO Vehicle Routing	Latin, America
Geng et al. (2021)			x	x		x	WCO-to-Biodiesel Supply Chain	Yangtze River Delta, China
Claudia et al. (2022)		x				x	WCO Vehicle Routing	Bogota, Colombia
Rosni et al. (2022)			x	x	x		Recycling Facility	Seremban, Malaysia
Julia et al. (2024)		x		x	x		Fire Station	Pekanbaru, Indonesia
Musa (2025)	x			x			Optimal Processing Plant	Sub-Saharan, Africa
Zaharudin et al. (2023)			x		x		Recycling Facility	Nilai, Malaysia

2.3 Integration of MCDM and Mathematical Model in Provisional Facility Location

New studies use hybrid MCDM methods for location ranking and mathematical models for better planning. However, most research do not include opinions from stakeholders such as SMEs, especially for provisional collection sites. Many previous studies focus more on permanent buildings and not on provisional systems needed in busy cities. Mathematical models are good at finding the best locations using

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data and numbers, so they are often used for long-term planning. Despite their strengths, these models do not always include qualitative factors such as public opinion, community acceptance, and environmental concerns. Some studies used combined tools, such as GIS with MCDM by Zandi et al. (2025) and Hajduk (2021), but these were still focused only on permanent facilities. The integration of decision-making methods and mathematical optimization into a single system framework is still uncommon, which limits the flexibility and real-world effectiveness of many proposed models. This makes many models less flexible or useful in real life, especially when fast decisions are needed. Provisional collection points must be easy to adjust when the city grows or conditions change. Quintana et al. (2020) and Aidoo et al. (2025) started addressing this issue but did not use MCDM to consider the needs of all stakeholders. To address this gap, this study proposes a new solution by combining the AURA method with the SCM framework. This new method allows for flexible and accurate planning of household WCO collection in fast-growing urban areas.

Table 3. Integration of MCDM and mathematical model in provisional facility planning

Authors (year)	Integration Method		Facility Location		Applications
	MCDM	SCM	Permanent	Provisional	
Zandi et al. (2025)	x		x		Solar Photovoltaic Power Plant
Hajduk (2021)	x		x		Urban Transport Location
Aidoo et al. (2025)		x		x	Waste Management
Quintana et al. (2020)		x		x	WCO

2.4 Identified gap and proposed approach

Current studies on WCO collection mainly focus on mathematical models like LP, ILP, and MILP for permanent waste collection facilities. However, there is limited attention on provisional collection points that can adapt to rapid changes in urban population density, infrastructure, and waste generation patterns. Similarly, MCDM methods such as AHP, TOPSIS, and WASPAS are often applied independently to evaluate multiple criteria but are rarely integrated with location optimization models like SCM to identify the most cost-effective and geographically suitable sites. This reveals three clear gaps:

(i) current methods lack advanced adaptive MCDM methods like AURA for dynamic urban decision-making,

(ii) SCM is rarely used for provisional facility location planning, and

(iii) there is no integrated framework that combines AURA’s stakeholder-based ranking with SCM’s optimization strength.

To address these gaps, this study proposes a two-stage approach. First, it applies AURA to evaluate and rank potential collection locations according to specific stakeholder priorities. Then, it applies SCM to determine the best number and locations for provisional WCO collection points. This approach ensures both adaptability and cost-effectiveness in rapidly changing urban areas. Hence, this gap will be addressed using the following framework for provisional WCO collection locations.

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3. TWO STAGE MATHEMATICAL MODELLING APPROACHES USING AURA AND MILP MODEL FOR DETERMINING PROVISIONAL WCO COLLECTION LOCATION

This study proposes a two-stage decision-making framework to optimise provisional WCO collection in urban areas by integrating the AURA with a MILP for the SCM. The process of integrating the AURA model with the MILP for determining optimal provisional WCO collection locations is illustrated in Fig. 1. In this process, user preferences are ranked using the AURA model, while the mathematical model is modified to incorporate authority perspectives. The integration of these two components generates provisional WCO collection locations that balance both user needs and regulatory requirements. The detailed methods are presented in Section 3.1 for the AURA model and Section 3.2 for the MILP model.

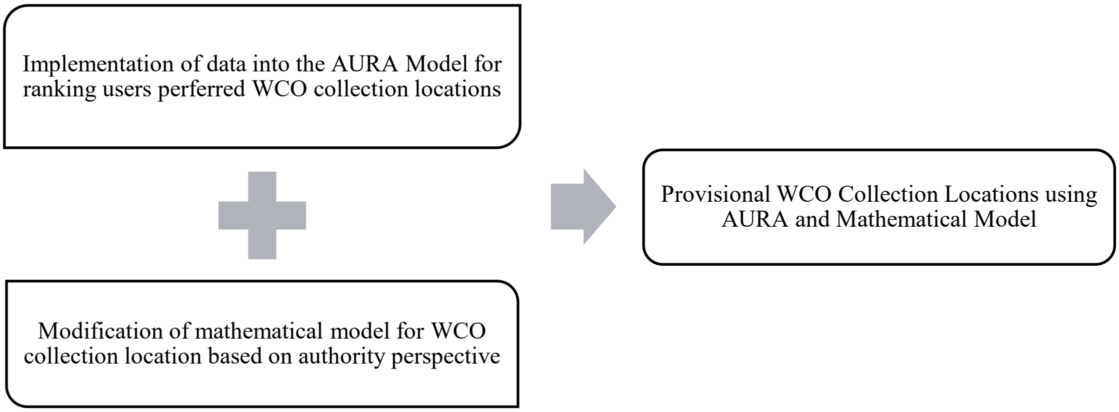

Fig. 1. Framework for determining provisional WCO collection locations using AURA and mathematical modelling

3.1 AURA: Adaptive utility ranking algorithm

In the first stage, the AURA method of Zaman et al. (2025) is applied to household inputs to prioritise residential preferences for potential WCO collection sites. Household data are assessed using quantitative criteria such as accessibility and coverage, and qualitative factors including convenience and community acceptance. The method constructs a decision matrix, normalises criteria values, and evaluates each location’s proximity to ideal, anti-ideal, and average solutions. Its flexible weighting enables adaptation to stakeholder priorities and dynamic data, ensuring transparency in ranking outcomes. The novelty lies in introducing AURA that is previously unused in WCO collection planning to support short-term facility siting in rapidly changing urban contexts.

3.1.1 Model Formulation of AURA Method

Step 1: Construct the Decision Matrix

Decision matrix is developed using alternatives, denoted by $i = 1,2, \dots m$ and criteria, denoted by $j = 1,2, \dots n$ selected based on stakeholder input.

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \tag{1}$$

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Step 2: Normalize the Decision Matrix

To fairly compare different criteria with different units, normalization of the decision matrix A is carried out. The normalized value for each element is calculated using the following formula:

$$\psi_{ij} = 1 - \frac{\left|a_{ij} - k_j\right|}{h_j} \tag{2}$$

This formula ensures that higher normalized value, ψ_{ij} correspond to better performance for benefit criteria, while adjusting all values to the same scale $[0,1]$. Where k_j is a reference value for criterion j and h_j is the range for criterion j where $h_j = \left(\max\left(a_j\right) - \min\left(a_j\right)\right)$.

Step 3: Weighted Normalized Decision Matrix

After the normalization step, the importance of each decision criterion is applied by constructing the weighted normalized decision matrix Δ_ω. This ensures that criteria with higher weightages influence the final ranking. The weighted normalized decision matrix is shown as Δ_ω:

$$\Delta_\omega = \left[\omega_j \times \psi_{ij}\right]_{m\times n} \tag{3}$$

where ω_j shows the weight for each criterion j, and it suggests its relative importance with $\sum_{j=1}^{n} \omega_j = 1$. The resulting weighted matrix is denoted as $V = \left[v_{ij}\right]$ where $v_{ij} = \omega_j \times \psi_{ij}$. The weights ω_j can be decided using expert opinions, mathematical methods like entropy, or both together. Including these weights in AURA, these adds stakeholder priorities and ensures all criteria are treated equally for the final ranking.

Step 4: Determine the Positive Ideal Solution (PIS), Negative Ideal Solution (NIS), and Average Solution (AS)

The weighted normalized decision matrix is made by multiplying each normalized value by its important weight. Then, the benchmark solutions for each criterion are computed as follows:

$$PIS = S_j^+ = \max_i\left(v_{ij}\right), \forall_j = 1, \dots, n \tag{4}$$

$$NIS = S_j^- = \min_i\left(v_{ij}\right), \forall_j = 1, \dots, n \tag{5}$$

$$AS = S_j^a = \frac{\sum_{i=1}^{m}\left(v_{ij}\right)}{m}, \forall_j = 1, \dots, n \tag{6}$$

AURA compares each options using three reference points which are the best, worst and average possible outcomes.

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Step 5: Compute the Distances from the Benchmark Solutions

The distance of each alternative i, $d_i(S)$ from a selected benchmark, S_j such as best (PIS), worst (NIS) and average (AS) is calculated using the following equation:

$$d_i(S) = \left(\sum_{j=1}^{n} \left|v_{ij} - S_j\right|^{p}\right)^{\frac{1}{p}} \tag{7}$$

The parameter, p is used to control the influence of big differences in values, keeping the distance measurement stable. Furthermore, AURA method also uses a correction coefficient, σ to calculated the distances:

$$\sigma = max\big(d_i(S)\big) - min\big(d_i(S)\big) \tag{8}$$

The correction coefficient, $D_i(S)$ is included into the distance formula like this:

$$D_i(S) = d_i(S) + \ \sigma \cdot d_i(S)^2 \tag{9}$$

By using this, AURA show slight and significant differences between alternatives. It helps that alternatives that are close or far from benchmarks are recognized.

Step 6: Rank the Alternatives

This step is important to build a strong and clear ranking score, dR_i at the final stage.

$$dR_i = \frac{\alpha \ \cdot \ \big(D_i(S^+) - D_i(S^-)\big) + (1-\alpha\ ) \ \cdot \ D_i(S^a)}{2} \tag{10}$$

A smaller dR_i means the option is better. After calculating dR_i for all options, the alternatives are ranked from best to worst.

3.2 SCM: Set Covering Model

In the second stage, the mathematical approach builds on the SCM of Zaharudin et al. (2023) and extends it through a MILP formulation with a cost-minimisation objective. This refined model balances financial feasibility and service quality by considering major costs, including site establishment and workforce requirements, while ensuring full coverage of household demands within a defined travel radius. By incorporating decision variables such as facility location, SME container allocation, and household assignment—together with constraints on capacity, service levels, and zoning—the model generates cost-efficient, scalable, and adaptable solutions. Solved using CPLEX, it enables decision-makers to optimise resources, maintain high operational performance, and respond effectively to the challenges of dynamic and densely populated urban environments. The model is shown as follows:

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Notation – Sets, Indices, Input Parameters, and Decision Variables:

Sets	i	:	Demand locations
	j	:	Location of facility
	k	:	Number of containers or collection units
Input Parameters	d_i	:	Demand amount of waste generated at location i
	t_{ij}	:	Travel distance (in minutes) between location i and j
	T	:	Maximum travel distance (in minutes) between location i and j
	s_{ij}	:	Binary parameter, 1 if $t_{ij} \leq T$, 0 otherwise
	Q	:	Maximum capacity of a container for recyclables
	δ	:	Maximum total number of permissible facility locations
	ε	:	Maximum total possible allocations for recyclable containers
	τ	:	Minimum service level for the recycling system
Decision Variables	x_j	:	Binary variable, values to 1 if a facility is operating at location j and 0 otherwise
	y_{kj}	:	Binary variable, values to 1 if facility at location j is allocated with k containers
	q_{ij}	:	Amount of demand served at location i using the facility at location j

Mathematical model:

$$max\left(\sum_{j=1}^{m}\sum_{i=1}^{n} q_{ij}\right) \tag{11}$$

subject to:

$$\sum_{j=1}^{m} s_{ij}\, x_j \geq 1; \forall_i = 1,2,\dots,n \tag{12}$$

$$\sum_{j=1}^{m} x_j \leq \delta; \tag{13}$$

$$\sum_{j=1}^{m}\sum_{k=1}^{K} k y_{kj} \leq \varepsilon; \tag{14}$$

$$\sum_{k=1}^{K} y_{kj} \leq x_j; \forall_j = 1,2,\dots,m \tag{15}$$

$$\sum_{i=1}^{n}\sum_{j=1}^{m} q_{ij} \geq \tau \sum_{i=1}^{n} d_i\,; \tag{16}$$

$$\sum_{j=1}^{m} q_{ij} \leq d_i; \forall_i = 1,2,\dots,n \tag{17}$$

$$\sum_{i=1}^{n} q_{ij} \geq x_i; \forall_j = 1,2,\dots,m \tag{18}$$

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$$\sum_{i=1}^{n} q_{ij} \leq \sum_{k=1}^{K} kQy_{kj}\,; \forall_j = 1,2,\dots,m \quad (19)$$

$$x_j, y_{kj} \in \{1,0\}; \forall_j = 1,2,\dots,m; \forall_i = 1,2,\dots,n; \forall_k = 1,2,\dots,K \quad (20)$$

$$q_{ij} \geq 0; \forall_j = 1,2,\dots,m; \forall_i = 1,2,\dots,n \quad (21)$$

The mathematical model is explained from equation (11) till equation (21). The goal of this model, shown in equation (11), is to collect the maximum amount of waste using the drop-off collection facilities. The constraints of the model are shown in equations (12) till (21). Equation (12) ensures that each demand point at location i has at least one nearby recycling facility within a reasonable travel time. Equations (13) and (14) set limits related to budget and container capacity. Equation (13) explains that the total number of recycling sites in the area cannot be more than a certain number, δ. Equation (14) limits the total number of containers used in the area to a maximum value, ε. But, if there are no limits on budget or capacity, these two constraints can be removed. Equation (15) ensures that each demand point i is only served by a facility that is working at location j. Equation (16) ensures that at least τ percent of the total demand is served, and also shows whether location i can access a working facility at location j. Equation (17) ensures that each demand point is connected to at least one facility. Equation (18) makes sure that demand from location i is only assigned to a facility that is open and working. Equation (19) checks the total amount of demand from all locations and ensures that it does not go over the total container capacity. Lastly, equations (20) and (21) explain the rules for the decision variables in the model.

The study of Zaharudin et al. (2023) is limited because the model prioritizes accessibility through wide coverage but neglects the critical objective of minimizing costs. This narrow focus likely reduces its practical usefulness, especially in urban settings where financial constraints are critical. A proposed modification is to expand the framework by directly integrating cost minimization as an additional objective. By adding this objective, the framework provides both flexibility and cost efficiency, making it highly suitable for urban areas where demographics, infrastructure, and waste generation patterns are dynamic and continuously evolving.

3.3 Expected output

3.3.1 Expected output from AURA

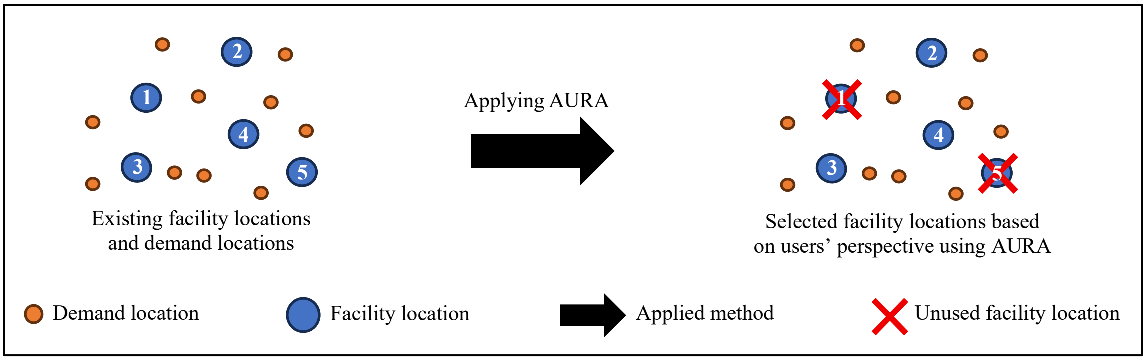

Fig. 2. Expected output from AURA

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Fig. 2 shows the existing facility locations are refined using AURA method. On the left, the diagram shows several existing facility locations surrounded by multiple demand points. In this stage, all facilities are considered potential candidates to serve the surrounding demand. After applying AURA, facility locations 1 and 5 are identified as unused, indicating they are less preferred by users. The outcome shows the remaining active facilities are assigned to cover the surrounding demand locations. This highlights the AURA method enables facility location strategy that considers users' needs, ensures all demand is served, and avoids opening unnecessary facilities.

3.3.2 Expected output from SCM

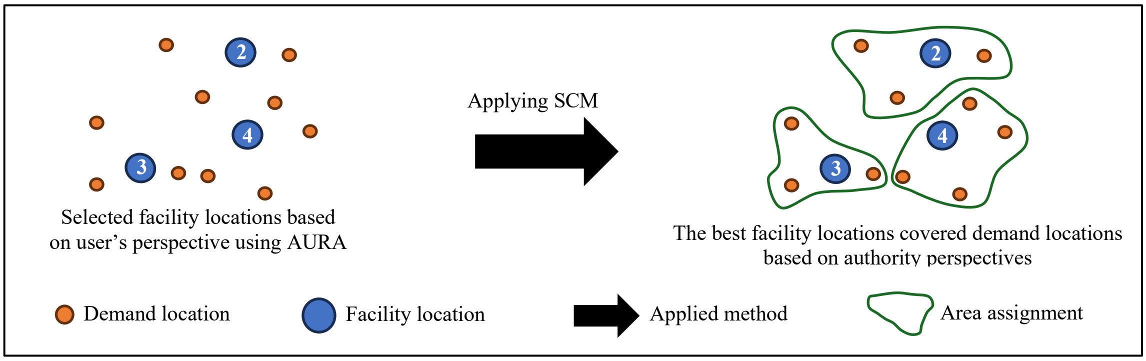

Fig. 3. Expected output from SCM

Fig. 3 continues by showing the expected outcome of applying SCM. The process begins with the pre-selected facility locations using AURA. Then, SCM method is applied which carried out from the authority's perspective and focuses on systematically identifying the minimum number of facilities required to cover all demand locations. On the right, the result shows the chosen facilities, each surrounded by a green boundary that represents its service area. Every demand point is now assigned to a facility within its zone, creating a clear and efficient allocation. Hence, this illustrates how SCM ensures complete coverage of all demand locations while defining service areas in a structured way, balancing efficiency with authority decision-making.

4. CONCLUSION AND FUTURE WORKS

This review highlights a critical gap in past research on WCO collection, particularly in urban contexts where most studies have focused on permanent systems or single-method approaches. To address this, a two-stage framework combining AURA and SCM is proposed to identify provisional collection sites by integrating stakeholder input with quantitative optimisation. The novelty of this approach lies in its adaptability, balancing community needs with analytical rigour to support decision-making in dynamic urban environments. This provides a more complete and practical solution for WCO problems in fast-changing urban areas. Despite the conceptual promise of this approach, the review reveals this approach remains untested in real-world case studies. This highlights the need for further research to implement and validate the proposed framework in actual urban settings.

Future research should focus on real-world validation of the framework using case studies with actual data. This includes testing its cost-effectiveness across diverse urban areas, incorporating real-time data for dynamic planning, and evaluating cultural and systemic differences to assess broader applicability. Practical implementation is particularly needed to ensure scalability for both households and SMEs. The approach also aligns with the UN Sustainable Development Goals (SDG 11 and SDG 12) by promoting sustainable

https://doi.org/10.24191/a3rwxv13

urban systems, preventing improper WCO disposal, and supporting circular economy applications such as biodiesel production.

5. ACKNOWLEDGEMENTS/FUNDING

The authors would like to acknowledge the support of Universiti Teknologi MARA, Malaysia for providing the facilities on this research.

6. CONFLICT OF INTEREST STATEMENT

The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

7. AUTHORS' CONTRIBUTIONS

Nurul Falah Mohd Razali: Conceptualisation, methodology, formal analysis, investigation and writing-original draft; **Zati Aqmar Zaharudin**: Conceptualisation, validation, supervision, writing- review and editing, methodology, and formal analysis; **Zahari Md Rodzi**: Conceptualisation, formal analysis, methodology and validation.

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