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A Framework for Mathematical Development of a Location-Allocation Model for Recycling Facilities

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Abstract

Unattractive travel distances and poorly located recycling collection points are significant barriers to public participation in recycling and source-separation practices, making effective facility planning essential for improving service accessibility and coverage. This study proposes a capacitated facility location–allocation model that aims to maximize recyclable waste coverage while considering accessibility, fixed facility capacities, and operational constraints on the number of facilities. Building upon an existing facility location framework, the proposed model replaces the busyness-level assumption with fixed capacity levels to better represent standardized recycling container capacities. The problem is formulated as a binary integer programming model on a network graph, in which demand locations are assigned to activated recycling facilities within a predefined travel-time threshold, subject to capacity limitations and an upper bound on facility numbers. Numerical experiments conducted using randomly generated datasets examine the model's behavior under varying travel thresholds, capacity levels, and facility limits. The results reveal clear trade-offs between accessibility, capacity sizing, and facility quantity, demonstrating that increased travel thresholds and capacities improve demand coverage up to saturation points, while stricter facility limits significantly constrain achievable coverage. The study contributes a capacity-based extension to recycling facility location modeling and provides practical decision-support insights for improving recycling accessibility and infrastructure planning.

1. Introduction

Separating waste at the source, especially among households, is critical for establishing a sustainable system [1] and serves as a key component of the recycling process. The need to adapt recycling practices has been recognized for decades, particularly emphasized after the United Nations (UN) introduced the Sustainable Development Goals (SDGs) in 2015. These goals aim to ensure sustainable development, including promoting responsible consumption and production (SDG12). Many countries have voluntarily committed to implementing the SDGs to balance economic growth, social well-being, and environmental protection, including Malaysia. Malaysia currently heavily relies on landfill disposal, with almost 89% of waste collected being sent to a total of 170 landfills [2]. Unfortunately, among these sent waste, 80% are recyclables [3]. Therefore, source separation and recycling, especially within households, are vital for the management of waste. This is increasingly important as population growth directly accelerates waste generation rates [4], as shown in Figure 1.

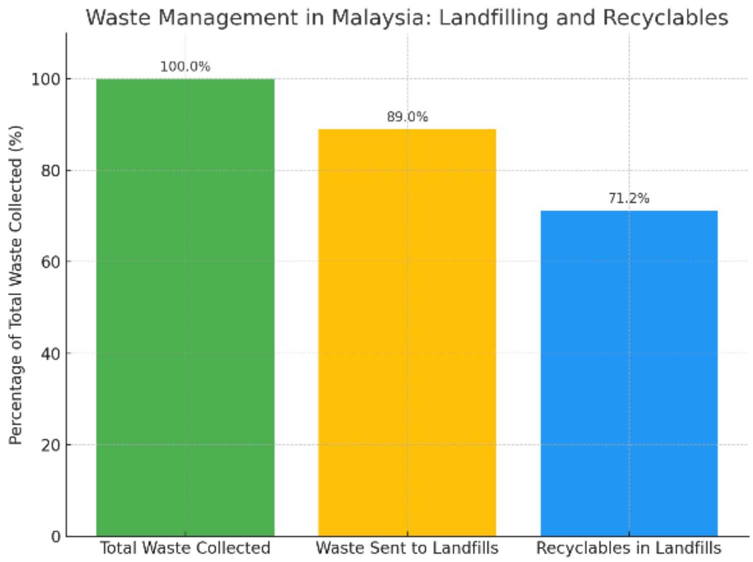

Fig. 1 *Waste management in Malaysia (Source: [4])*

Part of the challenges to promoting recycling practices among households is the lack of accessibility and availability of related infrastructure, i.e., the collection points or the sufficient containers. Several studies have explored the correlation between household recycling practices and the availability and accessibility of recycling infrastructure, including research by [2], [5], and [6]. [2] reported their findings of the study conducted in Perak, where the absence of recycling facilities was also found to be a significant barrier to waste separation and segregation among households in the region. Similarly, [5] discovered that residents of Padang Terap District, Kuala Nerang, Kedah, are aware of source separation activities; however, the lack of recycling facilities in their area results in all generated waste being sent to landfills. [7] also identified that lack of access to such infrastructures as a key factor inhibiting recycling practices among residents in selected areas of Seremban.

Recycling is a sustainable solution that ensures environmental sustainability for future generations by reducing landfill use, conserving resources, and encouraging resource conservation. It is imperative to strategically position recycling facilities to increase accessibility and availability, which would subsequently motivate households to engage in source separation activities. The establishment of well-organized recycling centers is important for the efficient processing and reuse of materials, thereby promoting the sustainable development of the nation [8]. The optimal location of a recycling facility can be determined using mathematical modelling techniques, effectively integrating key variables that enhance and support sustainable recycling practices. These variables include the proximity of users to facility locations, the types of recyclables, the distribution of adequately sized recycling bins, and other relevant factors. Therefore, a comprehensive understanding of these variables is crucial to develop a mathematical model that identifies optimal locations for recycling facilities while optimizing the efficiency of existing resources without causing significant additional costs to the current waste management infrastructure.

This paper presents a framework for developing a mathematical model to determine the minimal number of optimal recycling facility locations and their corresponding capacity levels, aiming to maximize user covering level. The first part of the paper outlines the need for optimal locations of recycling facilities. The remainder of the paper is structured as follows: Section 2 reviews related past studies, Section 3 proposes a gap analysis of the model, Section 4 presents the framework to the improvised mathematical model, and Section 5 concludes with a summary and suggestions for future work.

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1.1 Selected Prior Studies on Facility Location Models with Coverage Levels

Facility location theory originates from early mathematical problems introduced by Fermat, Torricelli, and Cavalieri in the seventeenth century, forming the foundation of modern facility location analysis [9]. In contemporary applications, Facility Location Problems (FLP) focus on identifying optimal facility placements to achieve objectives such as minimizing travel distance or operational cost, or maximizing demand coverage within spatial and operational constraints [10]. Among these objectives, coverage maximization has emerged as a dominant approach, particularly for public service systems where accessibility is a critical performance measure [10], [11].

1.1.1 Coverage Maximization and Probabilistic Service Models

Early coverage-based models, including the Location Set Covering Model (LSCM) and the Maximal Covering Location Problem (MCLP), emphasize ensuring that demand points are served within predefined distance or time thresholds while minimizing the number of facilities required [11]. The Maximum Expected Covering Location Problem (MEXCLP) extends this framework by incorporating facility availability through probabilistic busyness assumptions, allowing coverage to be maximized despite potential congestion or service unavailability [11]. These models reflect a broader research trend toward capturing accessibility and service reliability simultaneously.

Coverage-based FLP models have been most extensively applied in emergency service planning, where response time and service reliability are paramount. Numerous studies apply MEXCLP and its extensions to ambulance location and redeployment, demonstrating that accounting for demand distribution, facility availability, and spatial constraints significantly improves response performance [12], [13], [14], [15], [16], and [17]. Related research integrates covering models with bi-level optimization, simulation, GIS tools, and heuristic algorithms to enhance solution realism and managerial insight in emergency contexts [18], [19], [20], [21], and [22]. Across these studies, service limitations are typically represented using busyness levels or stochastic availability, reflecting the dynamic nature of emergency demand.

1.1.2 Non-Emergency Facility Location Applications

Beyond emergency services, coverage-based FLP models have been applied to a wide range of non-emergency public and commercial facilities, including vehicle routing systems, data centers, postal services, electric vehicle charging stations, and highway rest areas [23], [24], [25], [26], and [27]. In these applications, coverage constraints ensure acceptable accessibility levels, while objectives may vary from operational efficiency to network performance optimization. Unlike emergency facilities, many non-emergency services operate under relatively stable demand patterns and predefined operational limits, highlighting the importance of incorporating capacity considerations more explicitly [25], [26], and [27].

1.1.3 Capacity-Constrained and Cost-Minimization Models in Waste Management

In waste management and recycling planning, facility location models often emphasize either service coverage or cost minimization. Several studies employing mixed-integer linear programming (MILP) focus on minimizing total system costs when locating recycling or waste processing facilities, frequently without explicit coverage constraints [28]. Other works combine MILP with GIS to optimize bin placement and waste collection routes, prioritizing operational efficiency rather than accessibility [29], and [30].

Conversely, coverage-based FLP models have been used to locate and allocate recycling collection bins, particularly in Malaysia, to maximize demand coverage and encourage public participation [31], [32], [33], and [28]. However, these studies often adapt probabilistic concepts such as busyness level from emergency service models to represent service capacity indirectly, typically through the number of allocated containers [31], and [32]. While effective for modeling accessibility, this approach does not fully reflect the fixed physical capacities of recycling containers and collection points.

1.1.4 Research Gaps and Positioning of the Present Study

The reviewed literature reveals a key limitation in existing recycling facility location models: particularly in [31], and [32], while [33] only partially incorporates capacity through service rate constraints [31], [32], and [33]. This creates a mismatch between model assumptions and real-world recycling infrastructure, where container capacities are standardized, fixed, and governed by design and operational regulations. At the same time, cost-minimization models that explicitly consider capacity often neglect accessibility and coverage considerations critical for public participation [28].

Table 1 *Summary constraints of selected articles*

Constraint	Articles			
	[31]	[28]	[32]	[33]
Max. num. of operating facilities	x	x	x	x
Max. num. of containers/bins	x	x		x
Max. Capacity of facility/container/bin	x	x		x
Min. Facility service rate				x

To address these gaps, the present study proposes a capacitated facility location–allocation framework that integrates coverage-based accessibility with fixed capacity levels for operational facilities. Unlike previous approaches that rely on busyness levels to represent service limitations [31], and [32], the proposed model treats capacity as a stable and predefined parameter, aligning the mathematical formulation with the physical and operational realities of recycling containers [33], and [28]. This integration enhances model realism, improves interpretability, and strengthens decision-making relevance for recycling infrastructure planning.

Table 2 *Summary parameters of selected articles*

Definition	Articles			
	[31]	[28]	[32]	[33]
Demand location / Population location	x	x	x	x
Recycling bin location / Potential Recycling Facility Location	x	x	x	x
Distance between demand location and recycling bin location	x	x	x	x
Number of recycling bin location located at each facility location	x		x	x
Busyness level of having bins at each recycling bin location	x		x	
Fixed cost of locating facility at node recycling facility location		x		
Capacity Level of Recycling Facilities		x		x
Overall Service Rate of the Operating Facilities				x

As summarized in Tables 1 and 2, existing models vary considerably in how capacity and service limitations are represented, with most coverage-based approaches relying on indirect indicators rather than fixed facility capacity constraints. A critical comparison of the selected studies reveals fundamental differences in how capacity and service limitations are modelled in recycling facility location problems. Studies [31], and [32] adopt coverage-based formulations that represent service limitations indirectly through busyness levels or container allocations, an approach adapted from emergency service models that does not explicitly reflect the fixed physical limits of recycling facilities. Study [33] partially incorporates service rates within a coverage framework but does not model facility capacity as a stable operational constraint, while [28] explicitly considers capacity within a cost-minimization objective, largely overlooking accessibility and coverage considerations essential for encouraging public participation in recycling. In contrast, the proposed framework integrates coverage-based accessibility with explicitly defined fixed capacity constraints at the facility level, aligning model assumptions with the standardized and physically bounded nature of real-world recycling containers. This integration improves model realism, enhances interpretability for infrastructure planning, and enables a more balanced optimization of accessibility, capacity utilization, and facility deployment. By addressing the limitations of existing approaches, the proposed framework advances the literature by providing a more practical and decision-relevant tool for optimizing the location and allocation of recycling facilities.

2. Materials and Methods

This study extends the model of Rosni et al. (2022) by replacing the busyness level with fixed capacity constraints for each recycling facility. This modification is motivated by the operational reality of recycling infrastructure, where facilities such as public recycling bins and drop-off points are designed with predefined capacity limits determined by container size, collection frequency, and regulatory requirements. Unlike dynamic service systems, recycling facilities cannot continuously adjust their service level in response to short-term demand fluctuations; once capacity is reached, additional demand cannot be accommodated until the next collection cycle. The adoption of fixed capacity constraints therefore provides a more realistic and operationally consistent representation of recycling facilities. Capacity-constrained formulations are also widely used in facility location models for waste management, as they explicitly capture physical and logistical limitations while improving solution

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interpretability. From a planning perspective, this modeling choice enables decision-makers to directly relate model outcomes to tangible actions, such as determining suitable facility capacities, locations, and the number of facilities required. While fixed-capacity assumptions do not capture short-term demand variability, they offer an effective balance between realism and model tractability for strategic planning. Consequently, replacing the busyness level with fixed capacity strengthens the practical relevance and applicability of the proposed recycling facility location–allocation model.

Considers a network of graph G with a set of nodes (N) and arcs (A), i.e., $G = (N, A)$. Let a set of demand location is i = 1, 2, 3, ..., n and a set of facilities j = 1, 2, 3, ..., m. Let the weight for the arcs A or the proximity between set of demand locations and facility locations is defined as t_{ij} where the maximum predefined proximity between these nodes is defined as T. The proposed framework also includes the reachability of a demand location i to a facility location j as s_{ij}, in detail, if $t_{ij} \leq T$, then s_{ij} is valued to 1, otherwise 0. The fixed capacity level of a facility location j is denoted as q_j. With the proposed framework, two decision variables are introduced. First, the x_j that is a binary variable is assigned a value 1 if site j is activated (i.e., a facility is located site j) and 0 otherwise. Second, the y_{ij} that is the binary variable which value is 1 if demand at location i is covered by facility location of j and 0 otherwise.

$$\text{Maximize} \sum_{i}^{n}\sum_{j}^{m} d_i x_j \tag{1}$$

Subject to:

$$\sum_{j=1}^{m} s_{ij} x_j \geq 1; \qquad \forall i = 1,2,\ldots,n \tag{2}$$

$$y_{ij} \leq s_{ij} x_j; \qquad \forall i = 1,2,\ldots,n;\ \forall j = 1,2,\ldots,m \tag{3}$$

$$\sum_{i=1}^{n} y_{ij} \geq x_j; \qquad \forall j = 1,2,\ldots,m \tag{4}$$

$$\sum_{i=1}^{n} d_i y_{ij} \leq q_j x_j; \qquad \forall j = 1,2,\ldots,m \tag{5}$$

$$\sum_{j=1}^{m} x_j \leq \sigma; \tag{6}$$

$$x_j, y_{ij} \in \{0,1\}; \qquad \forall i = 1,2,\ldots,n;\ \forall j = 1,2,\ldots,m \tag{7}$$

Equation (1) represents the objective function, which maximizes the total demand served by activated recycling facilities. Constraint (2) ensures that demand at locations i are served by the nearest activated recycling facility at site j, addressing the accessibility issue. Constraint (3) ensures demand at location i can only visit the operating facility of location j. Also, inequalities (4) ensure that demands are only assigned to the operating facility. Constraint (5) ensures that all operating facility locations have an adequate capacity level. Inequalities (6) sets an upper limit on the total number of activated recycling facilities at most at σ locations. Finally, constraint (7) defines the domains of the decision variables.

2.1 Numerical Experimentation Using Random Generated Dataset

To evaluate the robustness and behavior of the model, this experiment was conducted by varying different parameters. The proposed model was tested using various combinations problem dimensions of demand location (I) and facility location (J). Additionally, factors such as travel times between nodes, demand patterns, fixed facility capacities, and the maximum allowable number of facility locations were randomized to evaluate its performance under different scenarios.

Table 3 illustrates the parameters used for numerical experiments. For testing purposes, the problem dimension was established at 10x10. The maximum travel threshold between these nodes was set between 5 to 10 minutes. The travel time from i to j differs from the travel time from j to i. The demand at each location was randomly assigned a value between 10 and 100 units. The service capacity (q_j) is established to range from 50 to 100 units for each j, increasing by 10 units with each iteration. The maximum allocation for the locations of operational recycling facilities (σ) is set between 1 and 10 units; increase one unit step per iteration. It is important to note that most of these values were randomly chosen for our research, with a deliberate effort to keep them as small as possible. This approach aimed to encourage the proposed model to minimize facility location and allocation while solving the system.

Table 3 *Summary of parameters settings for numerical experimentations*

Problem Dimension ($I \times J$)	Maximum travel times (T)	Recyclable waste generated at each i (d_i)	Service Capacity (q_j)	Operating Recycling Facility (σ)
10x10	5 – 10 minutes	Random between (10,100)	50 – 100 units	1 – 10 units

For this experiment, three tests were performed, which are outlined as follows. Test 1 is maximum travel time thresholds (T) versus objective function values, the total quantity of recyclable waste that can be covered, and the total number of operating facilities. Test 2 is service capacity (q_j) versus objective functions values, total quantity of recyclable waste that can be covered, and the total number of operating facilities. Test 3 is maximum operational recycling facility (σ) versus objective functions values, total quantity of recyclable waste that can be covered, and the total number of operating facilities

3. Results and Discussion

The result is presented according to the three tests made. All the tests were conducted in order to examine the relationship towards objective function values, the total number of operating recycling facilities, and the expected amount of recyclable waste to be collected.

Test 1: Maximum travel time thresholds (T) versus objective function values, the total quantity of recyclable waste that can be covered, and the total number of operating facilities.

Table 4 *Result for test 1*

Service Capacity	Maximum Operational Facilities	Maximum Time Travel	Objective Function	Opearate Facilities (x)
100	10	5	-	-
		6	-	-
		7	1895.6	7 ($x_1, x_2, x_4, x_5, x_7, x_9, x_{10}$)
		8	2437.2	9 ($x_1, x_2, x_3, x_4, x_5, x_7, x_8, x_9, x_{10}$)
		9	2708	10 ($x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}$)
		10	2708	10 ($x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}$)

Table 4 shown the overall, sensitivity analysis helps make informed choices in practical scenarios. The maximum time travel (T) and objective function were increased. That means the maximum time travel was sensitive to the objective function. The table outlines the relationship between the maximum travel time thresholds (T), objective function values, and the number of operating facilities for a service capacity of 100 units and a maximum of 10 operational facilities. As the maximum travel time threshold increases from 5 to 10, the objective function value also rises, indicating improved efficiency or cost-effectiveness. For instance, at $T = 7$, the objective function value is 1895.6, and it increases to 2708 at $T = 10$. Additionally, the number of operating facilities grows with higher travel time thresholds, starting from 7 facilities at $T = 7$ and reaching 10 facilities at $T = 9$ and $T = 10$. Throughout these scenarios, the total quantity of recyclable waste covered remains constant at 100 units. For planners and policymakers, this highlights the importance of considering acceptable travel distances or improving transport connectivity, as modest relaxations in accessibility constraints can substantially enhance recycling system effectiveness without increasing facility capacity.

Test 2: Service capacity (q_j) versus objective functions values, total quantity of recyclable waste that can be covered, and the total number of operating facilities.

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Table 5 *Result for test 2*

Maximum Operational Facilities	Travel Time	Service Capacity	Objective Function	Opearate Facilities (x)
10	10	50	2708	10 $(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10})$
		60	2708	10 $(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10})$
		70	2708	10 $(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10})$
		80	2708	10 $(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10})$
		90	2708	10 $(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10})$
		100	2708	10 $(x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10})$

Overall, sensitivity analysis helps make informed choices in practical scenarios. Table 5 shows that the objective function value remains constant at 2708 as the service capacity increases from 50 to 100 units. This indicates that service capacity is not a binding constraint in this scenario. Since the total demand covered (2708 units) is already fully served under the lowest tested capacity (50 units), increasing the facility capacity does not enable the model to serve additional demand beyond what is already reachable within the travel-time threshold. In other words, the limiting factor in this scenario is not facility capacity, but rather spatial accessibility, defined by the 10-minute travel constraint and the fixed distribution of demand locations, because all demand that can be reached within the allowed travel distance is already covered at the lowest capacity level, raising capacity levels simply provides unused excess capacity without affecting the optimal objective value. This also explains why all ten facilities remain operational in every scenario: they are necessary to cover dispersed demand locations, not because of capacity limitations. These findings suggest that, under the current spatial configuration and travel-time threshold, increasing facility capacity does not enhance system performance. Instead, improvements would require adjustments to travel-time policies, facility placement, or demand distribution rather than expanded capacity.

Table 6 *Total number demand by calibration of* $\boldsymbol{q_j}$

Opearational Facilities (j)	Total i					
	50	60	70	80	90	100
1	2	1	1	3	3	3
2	2	2	1	2	2	1
3	1	1	1	1	1	1
4	2	2	2	2	2	2
5	1	1	1	1	1	1
6	1	1	1	1	1	1
7	1	1	1	1	1	1
8	2	1	1	3	3	3
9	2	1	2	1	1	4
10	1	1	3	3	3	3

Table 6 illustrates the increase in total number (i) as the service capacity (q_j) ranges from 50 to 100 at each fixed operational facility, which is set at 10. This indicates that the sensitivity analysis focuses on service capacity (q_j), as improvements and additional options for the demand location (i) are observed. Consequently, this demonstrates a positive impact from testing the service capacity (q_j) against objective function values, the total quantity of recyclable waste that can be managed, and the total number of operational facilities. In real-world terms, this implies that simply installing larger recycling bins or increasing facility capacity may not significantly improve system performance unless accessibility or facility placement constraints are simultaneously addressed.

Test 3: Maximum operational recycling facility (σ) versus objective functions values, total quantity of recyclable waste that can be covered, and the total number of operating facilities

Table 7 presents data on service capacity, travel time, maximum operational facilities, objective function values, and the specific facilities operated. It starts with a service capacity of 100 and a travel time of 10. The maximum operational facilities range from 1 to 10 units. For each level of operational facilities, the objective function value and the corresponding facilities operated are listed. For instance, with 4 operational facilities, the objective function value is 1083.2 units, and the facilities operated are $x_2, x_5, x_7,$ and x_9. As the number of operational facilities increases, the objective function value also increases, reaching 2708 when all 10 facilities are operated (x_1 through x_{10}). This table helps in understanding the relationship between the number of operational facilities and the resulting objective function values.

Table 7 *Result of test 3*

Service Capacity	Travel Time	Maximum Operational Facilities	Objective Function	Operate Facilities (x)
100	10	1	-	-
		2	-	-
		3	812.4	3 (x_5, x_7, x_9)
		4	1083.2	4 (x_2, x_5, x_7, x_9)
		5	1354	5 (x_1, x_2, x_5, x_7, x_9)
		6	1624.8	6 ($x_1, x_2, x_5, x_7, x_9, x_{10}$)
		7	1895.6	7 ($x_1, x_2, x_4, x_5, x_7, x_9, x_{10}$)
		8	2166.4	8 ($x_1, x_2, x_3, x_4, x_5, x_7, x_9, x_{10}$)
		9	2437.2	9 ($x_1, x_2, x_3, x_4, x_5, x_7, x_8, x_9, x_{10}$)
		10	2708	10 ($x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}$)

Table 7 presents the results of calibrating the maximum number of operational facilities (σ) from one to ten, with a fixed maximum travel time of 10 minutes and service capacities of 100 kg. The outcome indicates an increase in the total number of demand locations (i). For instance, as the number of operational facilities increased from one to ten, significant improvements were observed starting from four operational facilities up to ten. Consequently, the total number of demand locations (i) expanded, offering more options and increased capacity. The sensitivity analysis of the maximum operational facilities provides valuable insights, aiding in making informed decisions in practical scenarios. For decision-makers, this finding provides practical guidance on the minimum infrastructure investment needed to achieve meaningful improvements in recycling coverage.

Table 8 *Total number demand by operational facilities (j)*

Operational Facilities (j)	Total i									
	1	2	3	4	5	6	7	8	9	10
1	0	0	0	0	3	3	3	3	3	3
2	0	0	0	1	1	1	1	1	1	1
3	0	0	0	0	0	0	0	1	1	1
4	0	0	0	0	0	0	2	2	2	2
5	0	0	1	1	1	1	1	1	1	1
6	0	0	0	0	0	0	0	0	0	1
7	0	0	1	1	1	1	1	1	1	1
8	0	0	0	0	0	0	0	0	3	3
9	0	0	4	4	4	4	4	4	4	4
10	0	0	0	0	0	3	3	3	3	3

The sensitivity analyses conducted in Tests 1, 2, and 3 evaluate how changes in key parameters such as travel time, service capacity, and the number of operating facilities affect the performance of the recycling facility location model. The results show that increasing the maximum travel time allows more facilities to be included in the solution, which can improve system efficiency. The service capacity increases, and the objective function values also improves. The better cost-effectiveness or performance, while still maintaining full use of all ten available facilities. This reflects the system's stability and scalability. Moreover, increasing the number of operational facilities (σ) significantly raises the number of demand locations served. These actions indicate that a larger number of facilities creates more coverage, and access can benefit to the demand. In summary, the output behaves this way because each parameter was travelling time, capacity, and facility number, affecting the demand points are matched with facilities. Optimizing these parameters leads to better resource distribution. Overall, the results demonstrate that enhancing accessibility and appropriately scaling facility numbers are key factors for improving recycling system performance, providing actionable insights for planners, facility managers, and policymakers in waste management planning.

4. Conclusion

In conclusion, the analysis of past research and four key articles reveal several significant gaps in the field of recycling facility location-allocation problems using mathematical modeling. Despite the covering location model being established nearly some years ago, there are still a few variants specifically addressing the location of recycling facilities. This paper was reviewed and identified chose four relevant articles, indicating that the proposed model would significantly advance current knowledge and address a notable gap in existing mathematical models for recycling facility locations. Additionally, there is a scarcity of research to improve recycling facilities in Malaysia through mathematical models. There were two articles, by Rosni et al. (2022) and Jamiron et al. (2021), discuss methodologies for establishing recycling facilities in Seremban and Johor Bharu. Implementing the proposed model in Seremban, with broader area coverage than that of Rosni et al. (2022), would fill an application gap in the Malaysian context.

Furthermore, traditional covering models aim to maximize demand location coverage. However, Rosni et al. (2022) proposed an objective function to maximize the number of recyclables collected at designated sites. This paper builds on this by incorporating collected recyclables information as a fixed capacity level to determine the optimal number of recycling bins. Rosni et al. (2022), who based the number of bins on usage likelihood, the model simultaneously determines the number of bins required. This paper provided an overview of the fundamental theory of framework facility location problems and reviewed various application models. It examined decision variables, parameters, objective functions, and constraints based on prior research on recycling facility locations, highlighting existing research gaps. The paper discusses related works on adapting the facility location model to covering problems and elaborates on the data and methods used in this research. Additionally, the results of the numerical experiments demonstrated the effectiveness of the enhanced proposed model. Three distinct tests were conducted, each yielding different outcomes. The sensitivity analysis on fixed service capacities produced realistic results in relation to the paper's objectives. Overall, the proposed model effectively guided the model towards achieving findings aligned with the intended objectives of the study.

For future research, uncertainty factors, particularly variations in waste generation and demand patterns, will be incorporated into the proposed framework using stochastic extensions to further enhance its realism. In addition, the next phase of this study will involve a real-world case study conducted in Seremban, Malaysia, to validate the practicality of the proposed capacitated facility location–allocation model and, specifically, the fixed capacity assumption. The case study will utilize geographic information system (GIS) data, population distribution maps, estimated waste generation rates, standardized recycling container capacities, and local transportation network data. These data sources will enable an empirical assessment of whether fixed facility capacities accurately reflect operational conditions and effectively support demand coverage under realistic spatial and accessibility constraints. By grounding the model in real infrastructure, demographic, and network characteristics, the case study will provide evidence of the framework’s applicability and robustness, thereby bridging the gap between theoretical optimization and practical recycling infrastructure planning.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

Draft manuscript preparation, methodology: *Muhammad Zulhazwan Rosni;* ***writing, reviewing and editing***: *Adibah Shuib, Fitri Maya Puspita, Zati Aqmar Zaharudin.*

References

[1] T. Trushna *et al.*, “Interventions to promote household waste segregation: A systematic review,” *Heliyon*, 2024.

[2] P. L. Yu, N. Ab Ghafar, M. Adam, and H. C. Goh, “Understanding the Human Dimensions of Recycling and Source Separation Practices at the Household Level: An Evidence in Perak, Malaysia,” *Sustainability*, vol. 14, no. 13, p. 8023, Jun. 2022, doi: 10.3390/su14138023.

[3] N. Daim and N. A. Mohamed Radhi, “Separating waste at source to boost recycling rate,” *New Straits Times*, 2023. https://www.nst.com.my/news/nation/2023/03/888284/separating-waste-source-boost-recycling-rate (accessed Dec. 04, 2023).

[4] A. Fazeli, F. Bakhtvar, L. Jahanshaloo, N. A. Che Sidik, and A. E. Bayat, “Malaysia's stand on municipal solid waste conversion to energy: A review,” *Renew. Sustain. Energy Rev.*, vol. 58, pp. 1007–1016, May 2016, doi: 10.1016/j.rser.2015.12.270.

[5] H. Abdul Halim, M. Z. Mohamed Najib, M. Zainal Abideen, H. F. Basri, and K. Muda, “Study of Household Waste Management and Recycling Awareness Between Residential Areas in Kuala Nerang, Kedah, Malaysia,” *Ind. Domest. Waste Manag.*, vol. 2, no. 1, pp. 39–45, 2022, doi: 10.53623/idwm.v2i1.70.

[6] Z. M. Rodzi, A. N. Hazri, N. A. S. Mohd Azri, N. D. F. Sharul Rhmdan, Z. A. Zaharudin, and S. Uttunggadewa, “Uncovering Obstacles to Household Waste Recycling in Seremban, Malaysia through Decision-Making Trial and Evaluation Laboratory (DEMATEL) Analysis,” *Sci. Technol. Indones.*, vol. 8, no. 3, pp. 422–428, 2023, doi: 10.26554/sti.2023.8.3.422-428.

[7] Z. Md Rodzi, Z. A. Zaharudin, and S. Uttunggadewa, “Unlocking the Barriers of Household Waste Recycling in Seremban, Malaysia,” *Environ. Proc. J.*, vol. 8, no. SI15, pp. 241–247, 2023, doi: 10.21834/e-bpj.v8isi15.5069.

[8] P. Nnonyelu and N. Dongjie, “Strategies for Enhancing Solid Waste Management Practices in Urban Secondary Schools in Developing Countries,” *Eur. J. Theor. Appl. Sci.*, vol. 2, no. 4, pp. 770–786, 2024, doi: 10.59324/ejtas.2024.2(4).66.

[9] V. Marianov and H. A. Eiselt, “Fifty Years of Location Theory - A Selective Review,” *Eur. J. Oper. Res.*, vol. 318, no. 3, pp. 701–718, 2024, doi: 10.1016/j.ejor.2024.01.036.

[10] G. Bruno, A. Genovese, and C. Piccolo, “Capacity management in public service facility networks: a model, computational tests and a case study,” *Optim. Lett.*, pp. 975–995, 2016.

[11] M. S. Daskin, “Maximum Expected Covering Location Model: Formulation, Properties and Heuristic Solution.,” *Transp. Sci.*, vol. 17, no. 1, pp. 48–70, 1983, doi: 10.1287/trsc.17.1.48.

[12] P. Sorensen and R. Church, “Integrating expected coverage and local reliability for emergency medical services location problems,” *Socioecon. Plann. Sci.*, vol. 44, no. 1, pp. 8–18, Mar. 2010, doi: 10.1016/j.seps.2009.04.002.

[13] A. Shuib and Z. A. Zaharudin, “TAZ_OPT: A goal programming model for ambulance location and allocation,” in *2011 IEEE Colloquium on Humanities, Science and Engineering*, Dec. 2011, no. Chuser, pp. 945–950. doi: 10.1109/CHUSER.2011.6163878.

[14] Z. A. Zaharudin, N. A. M. Nordin, H. M. Tahir, C. W. R. A. C. W. Kamal, N. H. A. Ghani, and N. H. A. Halim, “An application of MEXCLP model: A case study for mobile ambulance location,” in *2012 IEEE Colloquium on Humanities, Science and Engineering (CHUSER)*, Dec. 2012, pp. 539–543. doi: 10.1109/CHUSER.2012.6504372.

[15] C. J. Jagtenberg, S. Bhulai, and R. D. van der Mei, “An efficient heuristic for real-time ambulance redeployment,” *Oper. Res. Heal. Care*, vol. 4, pp. 27–35, Mar. 2015, doi: 10.1016/j.orhc.2015.01.001.

[16] S. Nilsang, C. Yuangyai, S. Buatongkue, and C.-Y. Cheng, “Allocation strategy for an ambulance base under traffic congestion,” *MATEC Web Conf.*, vol. 192, p. 01026, Aug. 2018, doi: 10.1051/matecconf/201819201026.

[17] J. Zhao and G. Y. Ke, “Optimizing Emergency Logistics for the Offsite Hazardous Waste Management,” *J. Syst. Sci. Syst. Eng.*, vol. 28, no. 6, pp. 747–765, Dec. 2019, doi: 10.1007/s11518-019-5429-5.

[18] R. Sitepu, F. M. Puspita, S. Romelda, A. Fikri, B. Susanto, and H. Kaban, “Set covering models in optimizing the emergency unit location of health facility in Palembang,” *J. Phys. Conf. Ser.*, vol. 1282, no. 1, p. 012008, Jul. 2019, doi: 10.1088/1742-6596/1282/1/012008.

[19] S. A. Hassan, K. Alnowibet, P. Agrawal, and A. W. Mohamed, "Optimum Location of Field Hospitals for COVID-19: A Nonlinear Binary Metaheuristic Algorithm," *Comput. Mater. Contin.*, vol. 68, no. 1, pp. 1183–1202, 2021, doi: 10.32604/cmc.2021.015514.

[20] Y. Deng, Y. Zhang, and J. Pan, "Optimization for Locating Emergency Medical Service Facilities: A Case Study for Health Planning from China," *Risk Manag. Healthc. Policy*, vol. Volume 14, pp. 1791–1802, Apr. 2021, doi: 10.2147/RMHP.S304475.

[21] S. Doungpan, S. Moryadee, C. U-tapao, and Z. Laokhongthavorn, "Analysis of Three Emergency Medical Location Models: A Case Study of Thailand," in *2018 International Conference on System Science and Engineering (ICSSE)*, Jun. 2018, pp. 1–6. doi: 10.1109/ICSSE.2018.8520208.

[22] M. Grot, T. Becker, P. M. Steenweg, and B. Werners, "Enhanced coverage by integrating site interdependencies in capacitated EMS location models," *Health Care Manag. Sci.*, vol. 25, no. 1, pp. 42–62, Mar. 2022, doi: 10.1007/s10729-021-09562-4.

[23] A. Maneengam and A. Udomsakdigool, "Solving the collaborative bidirectional multi-period vehicle routing problems under a profit-sharing agreement using a covering model," *Int. J. Ind. Eng. Comput.*, vol. 11, pp. 185–200, 2020, doi: 10.5267/j.ijiec.2019.10.002.

[24] S. Kheybari, M. Davoodi, H. Farazmand, and J. Rezaei, "Sustainable Location Selection of Data Centers: Developing a Multi-Criteria Set-Covering Decision-Making Methodology," *Int. J. Inf. Technol. Decis. Mak.*, vol. 19, no. 03, pp. 741–773, May 2020, doi: 10.1142/S0219622020500157.

[25] H. Yu and W. D. Solvang, "A Comparison of Two Location Models in Optimizing the Decision-making on the Relocation Problem of Post Offices at Narvik, Norway," in *IEEE International Conference on Industrial Engineering and Engineering Management*, Dec. 2019, vol. 2019-Decem, pp. 814–818. doi: 10.1109/IEEM.2018.8607606.

[26] O. Arslan, "The location-or-routing problem," *Transp. Res. Part B Methodol.*, vol. 147, pp. 1–21, May 2021, doi: 10.1016/j.trb.2021.02.010.

[27] Y. Kakimoto and Y. Shimakawa, "Rest-Area Location Model for Time-Driven Demands To the Expend Buffer Time of Freight Vehicles," *Int. J. Innov. Comput. Inf. Control*, vol. 18, no. 1, pp. 15–28, 2022, doi: 10.24507/ijicic.18.01.15.

[28] H. Yu and X. Tong, "Producer vs. local government: The locational strategy for end-of-life photovoltaic modules recycling in Zhejiang province," *Resour. Conserv. Recycl.*, vol. 169, no. February, p. 105484, Jun. 2021, doi: 10.1016/j.resconrec.2021.105484.

[29] P. Rathore, S. P. Sarmah, and A. Singh, "Location–allocation of bins in urban solid waste management: a case study of Bilaspur city, India," *Environ. Dev. Sustain.*, vol. 22, no. 4, pp. 3309–3331, Apr. 2020, doi: 10.1007/s10668-019-00347-y.

[30] D. H. Utku and S. Erol, "The hazardous waste location and routing problem: an application in Marmara Region in Turkey," *SN Appl. Sci.*, vol. 2, no. 2, p. 299, Feb. 2020, doi: 10.1007/s42452-020-2107-7.

[31] N. F. H. Jamiron, N. A. S. Sarif, N. S. Abdul Rahman, and Z. A. Zaharudin, "Establishing Recycling Bins Location and Allocation for Sustainable Urban Municipalities of Johor Bahru in Malaysia," *Int. J. Acad. Res. Econ. Manag. Sci.*, vol. 10, no. 3, pp. 459–472, Sep. 2021, doi: 10.6007/IJAREMS/v10-i3/11344.

[32] M. Z. Rosni, M. I. Ishak, A. Z. Mohd Shah, and Z. A. Zaharudin, "Location-Allocation Model of Recycling Facilities – A Case Study of Seremban, Malaysia," *Int. J. Acad. Res. Econ. Manag. Sci.*, vol. 11, no. 1, pp. 51–62, 2022, doi: 10.6007/IJAREMS/v11-i1/12119.

[33] Z. A. Zaharudin, A. Shuib, R. Hadianti, and Z. M. Rodzi, "Towards Sustainable City: A Covering Model for Recycling Facility Location-allocation in Nilai, Malaysia," *Sci. Technol. Indones.*, vol. 8, no. 4, pp. 570–578, 2023, doi: 10.26554/sti.2023.8.4.570-578.