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Review of Optimisation Models for Split Pickup and Delivery Problem in Solid Waste Collection System

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Waste management typically involves technical, climatic, environmental, demographic, socio-economic, and legislative parameters. Such complex nonlinear processes are challenging to model and optimise using fundamental methods. This article reviews optimisation methods for municipal waste collection, concentrating on the Split Pickup and Delivery Problems (SPDP). Throughout our review, a final list of twenty-eight (28) related articles was extracted and investigated to generate new knowledge in the domain of study, which examined several optimisation methods in terms of objectives and constraints related to time, vehicles, and route services, with most variants employed. Based on the review, existing studies have focused on single objective methods with a ratio of 75%, whereby only 25% focused on solving multi-objective problems. Furthermore, the evaluation of optimisation methods to define the knowledge gap, identify the challenges, and provide recommendations were presented by authors that will aid the researchers and serve as a guide for their work. Overall, it is necessary to use real-world data for a more realistic evaluation of SPDP and provide optimal estimation techniques of the uncertain parameter, especially in symmetric and bounded random variables in demand.

Keywords: Solid waste collection; optimisation methods; split of pickup; delivery problem

V. INTRODUCTION

Municipal Waste Management (MWM) is a waste collection, transportation, treatment, and disposal phase (Babaee Tirkolaee *et al.*, 2016; Abdel-Shafy & Mansour, 2018). The priorities for these activities are outlined in the European Union Waste Framework Directive 2008/98/EC (Bertanza *et al.*, 2018). Solid waste management is a great challenge for most nations due to the rapidly increasing population and flourishing industries (Al-Jubori & Gazder, 2012).

In addition, the generation of municipal waste would have drastically grown from 1.3 to 2.2 billion metric tonnes per year (Hoang & Louati, 2016). The waste collection service costs higher expenditures, around 50 to 70% of municipal service expenses (Boskovic *et al.*, 2016). Therefore, finding an effective waste collection strategy and protecting the environment is necessary. In a study introduced by Armington and Chen (2018), the waste collection challenge is related to the traditional Vehicle Routing Problems (VRP) and scheduling for urban-scale networks, which refers, in turn, to combinatorial optimisation difficulties (Montoya-Torres *et al.*, 2015).

In recent years, Solid Waste Collection (SWC) has attracted the attention of researchers worldwide. A comprehensive review was carried out by Hannan *et al.* (2020b). Though they defined the objective and limits of optimisation approaches for efficient SWC in terms of economic, environmental, and social considerations, this study did not consider the mechanism for evaluating the performance of

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proposed optimisation methods. Sahib *et al.* (2022) assessed distinct meta-heuristic methodologies employed for solving VRPs with their aims, limitations, and most distinct versions used in the municipal garbage collecting system. They suggested assessing the constraints and objectives analytically and highlighting most of the research gaps.

Meanwhile, Ramos *et al.* (2018) and Jatinkumar *et al.* (2018) investigated the problem of vehicle routing, relying on collecting real data that represents the level of solid waste in containers and collecting data dynamically by employing sensors inside the containers. The goal is to increase the amount of waste collected and reduce transportation costs periodically, which is worth noting. However, this hypothesis was implemented in a simulated environment only. Sulemana *et al.* (2018) reviewed several studies on mathematical programming with a Geographic Information System (GIS) approach for addressing SWC. This study recommended future studies to optimise the fleet's routes by considering information related to traffic conditions.

In Liang *et al.* (2021), the authors focused on the heuristic and metaheuristic optimisation methods associated with the SWC problem, and some approaches combined GIS with heuristic methods. The results concentrated on the total travelling distance and travel time as main constraints. Likewise, Han and Cueto (2015) reviewed the optimisation approaches with their waste type strategies, whether residential, commercial, or industrial.

The classical Vehicle Routing Problems (VRP) can be extended to Time Window (VRPTW) or add the capacitated to the classical VRP to be (CVRP) whereby the volume and weight capacity addressed by each vehicle per trip does not exceed the capacity of vehicles (François *et al.*, 2016; Akpinar, 2016; Babaee Tirkolaee *et al.*, 2018; Guo *et al.*, 2020). Moreover, Periodic with VRPs (PVRP) can be incorporated when waste collection problems are scheduled. Similarly, the VRP could work with single or multiple depots (it is not necessary to return the vehicle to the starting depot) and Dynamic VRP (DVRP), in which routes can change dynamically (Wongsinlatam & Thanasate-angkool, 2021).

Before going in-depth into the details of the research methodology, we must have an insight into the following problems for more clarity. It is well known that the Pickup and Delivery Problem (PDP) is one of the CVRPs, and the Split Delivery VRP (SDVRP) is a certain vehicle that could visit each node once or more than once. Furthermore, the demands can be split, and every route starts and ends at the depot (Ray *et al.*, 2014; Silva *et al.*, 2015). Our review focused on the Split Pickup and Delivery Problem (SPDP), which differs from the existing review problems in delivering waste to transfer stations. The review of this perspective is the main contribution of this paper as, to our knowledge, it is yet available in the literature, and the review on this topic is significant concerning multi-objectives and variants involved. VRP variants with the highlighted part of the SPDP are illustrated in Figure 1.

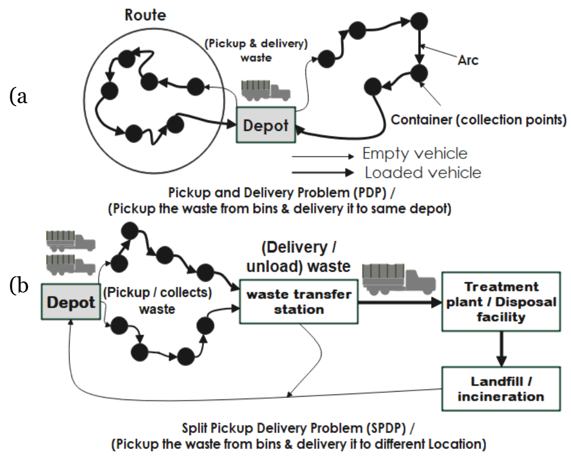

Figure 1. Comparison study between (a) PDP and (b) SPDP

For more explanation about SPDP, the vehicle does not empty its garbage into the same depot where it originated (Huang *et al.*, 2015; Wongsinlatam *et al.*, 2021), as evidenced by comparing the PDP and SPDP in Figure 2.

PDP involves a sequence of collection points (CPs) and arcs linked together, whereas each vehicle departs the depot with no load to service the bins and back to the same depot, as shown in Figure 2(a). Meanwhile, Figure 2(b) highlights SPDP, which comprises a sequence of CPs, arcs for linking CPs, a waste transfer station, a treatment plant, and a landfill area. In this scenario, the vehicles leave the depot empty toward the transfer stations (Yadav *et al.*, 2016; Jia *et al.*, 2022) or multiple transfer stations (Son & Louati, 2016). Next, consider a suitable location for unloading their waste (waste dumping in large yards to turn it into larger vehicles) or directly delivering it to the landfill (Przydatek & Kanownik, 2019). Finally, some cases go to the treatment plant, and eventually, the vehicles return to the same depot.

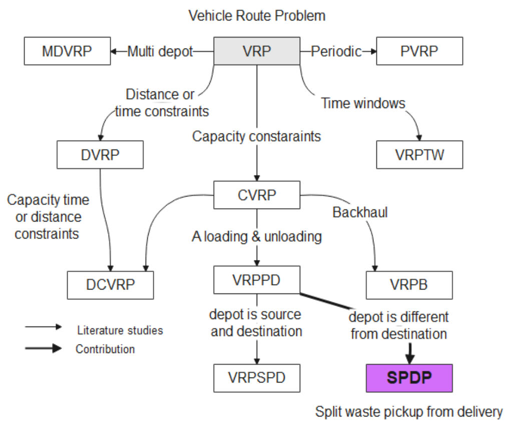

Figure 2. Variants of the VRP (Montoya-Torres *et al.*, 2015)

This paper aims to review the optimisation methods for solving the Split Pickup and Delivery Problems (SPDP) in SWC tasks, including variant models and the characteristics of optimisation algorithms in terms of exact, heuristic, metaheuristics, and hybridisation, as well as the evaluation methods with existing benchmark datasets provided by researchers. Moreover, it illustrates the criteria that affect optimisation methods' results and discusses research gaps in previous studies. Eventually, it highlights the crucial future directions and some recommendations that benefit researchers. Consequently, the contributions of our research are summarised in the four steps follows:

1. Present a Literature Review (LR) on a framework with a classification of optimisation algorithms and their constraints for addressing SPDP in the SWC system.
2. Provide simplified practical processes and theories for conducting LR studies to equip other waste collecting and transportation industry researchers with sufficient knowledge for writing LR.
3. Present a table of simplified mathematics of previous research for the most variants linked to the study's scope.
4. Clear description and analysis of the benchmark instances with comparison-related methodologies.

VI. REVIEW METHODOLOGY

This paper introduced a literature review (LR) to identify the most relevant studies on the Vehicle Routing Problems (VRP) with Split Pickup and Delivery Problem (SPDP) in Solid Waste Collection (SWC) with both single-objective and multi-objective functions of optimisation methods. The methodology has been divided into two steps:

A. *Source of Articles*

The results of an exhaustive search of five databases characterised by originality and reputation included Scopus, ScienceDirect, IEEE Xplore, Taylor & Francis, and Web of Science. These databases enable the discovery of published materials in journals, conference proceedings, grey literature, and book chapters. In addition, each article's full text was reviewed to eliminate studies irrelevant to the SPDP. Hence, based on this analysis, twenty-eight (28) relevant articles were selected for analysis, as illustrated in Figure 3.

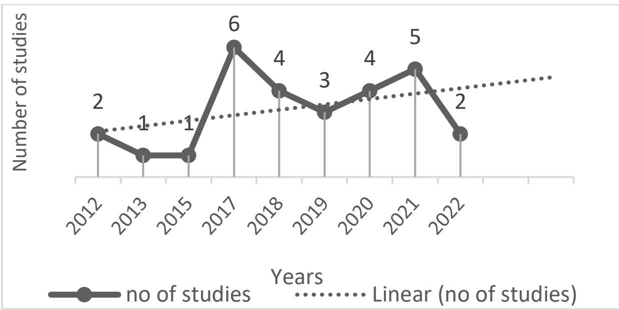

Figure 3. Distribution of the publications (2012-2022)

B. *Search Process*

The databases allow authors to research journal articles, conference proceedings, and book chapters. Their reliability and dependability led us to choose them as a resource for our research. Based on the keyword search features, the keywords related to the field of study were chosen: "heuristic method" OR "heuristic algorithm" AND "waste collection" OR "garbage collection" OR "rubbish collection". Following a search of relevant publications, 128 papers were found in various databases. The documents were divided as follows: 93 from ScienceDirect, 13 from Taylor & Francis, 8 from Scopus, 8 from Web of Science, and 6 from IEEE Xplore. We narrowed the research scope to 28 papers that were analysed for classification. The LR method was implemented based on guidelines published in computer science and software engineering research adopted by Alyasiri *et al.* (2022).

III. RELEVANT OPTIMISATION METHODS

In recent decades, waste collection in several countries was implemented without considering optimisations, leaving the selection of optimal routes to the drivers. Therefore, the increase in the urban population will impact the collection system's effectiveness. Consequently, there should be a method for maximising a solution's general acceptance. It is worth noting that there are numerous methods have been developed, each focusing on a different objective function, such as cost, number of collection vehicles, and route length (Han *et al.*, 2015). The objective function will either be a single objective or multiple objectives for solving optimisation methods (Mat *et al.*, 2017; Han & Cueto, 2015). Each optimisation method is classified according to its objective function in the following subsections.

A. Single Objective Methods

In this section, the Split Pickup and Delivery Problems (SPDP)-related research articles listed in Table 1 are divided into two main headings, including the constraints and approach of an optimisation method regarding exact, heuristic, metaheuristic, and hybrid methods.

1. Exact

Recent studies focused on solving SPDP using well-known mathematical models, which was 14%, less than the number of studies that focused on employing heuristic algorithms. Meanwhile, other studies were concerned with finding the optimal path and implementation time to reduce transportation costs (Monzambe *et al.*, 2021). Typically, the mathematical models involve Integer Linear Programming (ILP) and Mixed Integer Linear Programming (MILP).

In the literature, a study used the exact method reported by Özceylan *et al.* (2020). They formulated MILP for resolving SPDP, which considers the constraint of time with one exception related to the constraints of the vehicle in terms of speed and the distance covered; both were never used. On the other hand, Jia *et al.* (2022) proposed a model for the selection and adjustment of existing transfer stations for the minimum cost of total distance, which includes the sum of distances from the collection points (CPs) to the candidate transfer station and from the latter to the waste treatment plant (WTP) concerning the vehicle capacity, transfer station capacity, and waste treatment plant capacity.

2. Heuristic

This section briefly describes some of the most significant works on the SPDP problem. The rate of the heuristic method is 10%, used together with other optimisation techniques to solve problems. Historically, the heuristic method was proposed to determine the optimal routes within a set of systematic rules by designers (Belien *et al.*, 2014). Most variants in the literature applied to heuristic algorithms have been discussed.

Based on the homogeneous vehicle fleet and the route service constraints presented by Mat *et al.* (2017), the waste collection and disposal are separated using the Nearest Greedy (NG) algorithm as a heuristic approach to construct the initial solution. The results have proved that NG gives the optimal vehicle routes with a reduction rate of 11.07% of the current total distance routes. Similarly, a study proposed by Mat *et al.* (2018) implemented the constraint of a homogeneous vehicle fleet and the route service constraints. This study also reduced the travel distance of vehicles by 12% as well. Through investigating multiple heuristic algorithms derived from previous research to solve the waste collection problem, such as NG, savings approach, sweep algorithm, and different initial customer (DIC), the results of the computations demonstrate that the DIC outperforms other heuristic algorithms.

3. Metaheuristic

For other NP-hard combinatorial optimisation problems, numerous studies have utilised metaheuristic approaches effectively for solving SPDP, and the rate of these studies reached 61% from other approaches. Other than that, the constraints related to the vehicle in terms of homogenous fleet and route service constraints in split delivery are observed. A study carried out by Buhrkal *et al.* (2012) proposed an Adaptive Large Neighbourhood Search Algorithm (ALNSA) for attempting to solve the Waste

Collection VRP with Time Window (WCVRPTW). Two data sets have been used to evaluate the collection system. Another study attributed to Assaf and Saleh (2017) reduced the total cost and travel distance to reach CPs by considering the time constraints, homogenous vehicle fleet, and vehicle capacity. The study constructed and improved the optimal routes using the Genetic Algorithm (GA) and Nearest Neighbor Algorithm (NNA), respectively. The proposed algorithms used the vehicle's speed to determine the arrival time at the CPs.

Table 1. Reviewed papers focusing on the single objective SPDP in the SWC system

Ref.	**Constraints**								
	TC	**Capacitated based on**		**Constraints related to vehicles**			**Routes service constraints**		
		Bin	**Vehicle**	**Homogenous**	**Speed**	**Distance covered**	**Split delivery**	**Periodic waste collection**	**Undirect graph**
Exact methods									
(Hannan *et al.*, 2020b)	×	√	√	√	×	×	√	×	√
(Özceylan *et al.* , 2020)	√	×	√	√	×	×	×	×	√
(Jia *et al.*, 2022)	×	×	×	×	×	×	√	√	×
Heuristic methods									
(Mat *et al.*, 2017)	×	×	√	√	×	×	√	×	×
(Mat *et al.*, 2018)	×	×	√	√	×	×	√	×	×
Metaheuristic methods									
(Buhrkal *et al.*, 2012)	√	×	√	√	×	×	√	√	×
(Wy *et al.*, 2013)	√	×	×	×	×	×	√	×	×
(Akhtar *et al.*, 2017)	×	√	√	√	×	×	×	√	×
(Assaf & Saleh, 2017)	√	×	√	√	√	×	√	√	×
(Gajpal *et al.*, 2017)	×	×	√	×	×	×	×	×	×
(Anagnostopoulou *et al.*, 2017)	√	×	√	×	×	×	√	√	×
(Hannan *et al.*, 2018)	√	√	√	√	×	×	×	√	×
(Adedokun *et al.* , 2018)	×	√	√	√	×	×	×	×	×
(Raflesia & Pamosoaji, 2019)	√	√	×	×	√	×	×	×	×
(Marković *et al.*, 2019)	√	×	√	√	√	×	√	×	×
(Fermani *et al.*, 2021)	√	×	√	√	×	×	-	×	×
(Rossit *et al.*, 2021)	×	×	√	√	×	×	-	×	×
(Seçkiner *et al.*, 2021)	×	×	√	√	×	×	√	×	√
Hybrid methods									
(Kuo *et al.*, 2012)	√	×	√	×	-	×	×	√	×
(Jorge *et al.*, 2022)	√	√	√	√	√	×	×	√	√
(Babaee Tirkolaee *et al.*, 2018)	√	×	√	×	√	×	×	√	×
∑ studies	52%	24%	86%	62%	24%	0%	48%	43%	19%

√ constraints covered by study**;** × constraint not covered; **TC**: Time constraints

Most metaheuristic algorithms also utilised simulated annealing algorithms in the studies (Fermani *et al.*, 2021; Rossit *et al.*, 2021). Other studies focused on the Ant Colony System (ACS), as proposed by Gajpal *et al.* (2017) and Seçkiner *et al.* (2021). Daily distance is decreased by 28% to maintain a clean environment while minimising labour costs. In contrast, Raflesia and Pamosoaji (2019) focused on designing a dynamic system with a novel ant colony system to predict when a vehicle will arrive at a disposal site within a given schedule to avoid vehicle accidents. A similar approach suggested by Hannan *et al.* (2018) applied the dynamic system. The authors employed a modified Particle Swarm Optimisation (PSO) to measure the level of bins in real-time data by the Threshold Waste Level (TWL) technique. The objective is to reduce the vehicle's distance to save economic and social sustainability.

The same technique was utilised by Akhtar *et al.* (2017), in which the objective of the modified Backtracking Search Algorithms (BSA) for CVRP is to minimise the number of bins to be emptied by identifying the optimal range and thereby reducing the distance. The computational results indicated a 36.80% reduction in route distance for 91.40% of the total waste collection on four days, which increased the average waste collection efficiency by 36.78% and decreased fuel consumption, fuel cost, and CO_2 emissions by 50%, 47.77%, and 44.68%, respectively. In addition, the proposed algorithm was compared against Hybrid Discrete Particle Swarm Optimization (HDPSO) and PSO.

In addition, Adedokun *et al.* (2018) focused on a homogenous fleet's vehicle and bin capacities. The authors proposed the Firefly Algorithm (FFA) for optimising the route using the dynamic data collection from CPs. The route distance constraint has been considered (all vehicles must not exceed the total distance travelled). The comparison was made between Unified Hybrid Genetic Search (UHGS), Iterated Local Search with Set Partitioning (ILS-SP), and Branch and Cut Price (BCP), in addition to comparing the standard FFA with PSO (Uchoa *et al.*, 2017; Hannan *et al.*, 2018).

A study by Anagnostopoulou *et al.* (2017) has decreased the total distance travelled by waste vehicles, energy consumption, and CO_2 emissions by 8.4%, 9%, and 8.66%, respectively, when employing a metaheuristic algorithm referred to as Tabu Search (TS). The technique is enhanced by relocating the edge-exchange neighbourhood structures to discover the search space iteratively in terms of construction solutions and improvement. Similarly, Wy *et al.* (2013) employed a strategy of iterative heuristics for collecting a large amount of waste from commercial and industrial sites using large containers. They proposed Large Neighborhood Search (LNS) construction methods with an improved algorithm. The data collection is based on a real case study.

Subsequently, a study introduced by Marković *et al.* (2019) considered a homogenous fleet of vehicles to minimise the total distance travelled and reduce the total working with heuristic and metaheuristic algorithms, employing a saving algorithm (Clarke & Wright algorithm) for the construction of the initial solution, and improve the solution in two ways: first by applying local search heuristic iteratively. Meanwhile, a metaheuristic algorithm called the Improved Harmony Search Algorithm (IHSA) implemented the stochastic demands for expectation and variants for estimating the normal distribution of waste amount under time constraints. Concerning the periodic SPDP, a few studies demonstrated a metaheuristic algorithm as can be referred for example, in Buhrkal *et al.* (2012), Akhtar *et al.* (2017), Assaf *et al.* (2017), Hannan *et al.* (2018) and Anagnostopoulou *et al.* (2017).

4. Hybrid

Typically, hybrid metaheuristics are widely used to solve VRP, such as the Capacitated VRP (CVRP), the VRP with Time Windows (VRPTW), the Multi-depot MDVRP, the Heterogeneous VRP (HVRP), and the VRP with Simultaneous Pickup and Delivery (VRPSPD). Combining swarm algorithms with the local search heuristic algorithm (Abdulkader *et al.*, 2015) or combining a different algorithm from the same swarm-inspired method are common ways to hybridise artificial intelligence (AI) algorithms (Jorge *et al.*, 2022).

From other studies, only 14% dedicated to improving SPDP efficiency in applying a waste collection system were hybrid studies. Some researchers, like Kuo *et al.* (2012), used the Hybridized Particle Swarm Optimization Genetic Algorithm (HPSOGA). The authors combined the mutation and crossover of GA with the best solution of the one particle to ensure the proposed algorithm always generated a new solution. The proposed method was evaluated by comparing the results with Discrete Particle Swarm Optimization (DPSO), GA, and Simulated Annealing (SA).

Another hybridised study by Jorge *et al.* (2022) combined the Simulated Annealing with Neighborhood Search (SANS) algorithms to maximise the profitable routes per collection day for the capacity constraints of vehicles and bins. Besides that, the proposed system is subject to the periodic Solid Waste Collection (SWC) problem. A similar study combines the SA algorithm with a constructive heuristic algorithm to generate the initial solution for developing a MILP model that considers crew working time and driver availability. The objective is to minimise the number of vehicles which employ Periodic Capacitated Arc VRP (PCARP) (Babaee Tirkolaee *et al.*, 2018).

B. Multiple Objective Methods

Real-world enterprise logistics problems are distinguished because decision-makers must frequently balance multiple objectives simultaneously. These objectives are sometimes inconsistent (e.g., minimising the number of vehicles and maximising service level). The literature on the SPDP contains a few papers that consider multiple objectives: approximately 25% of the papers reviewed here. This proportion corresponds to seven papers reviewed in this article, as shown in Table 2.

Regarding time constraints, several studies have modelled two evolutionary algorithms for implementing cases with multiple objectives. The work of Hashemi (2021) formulated a multi-objective case with a comparative study of the Non-dominated Sorting Genetic Algorithm (NSGA-II) and the Bee Colony Algorithm (BCO). The motivation for using NSGA-II was to achieve good resolution and spacing metric time, whereas using BCO was to explore and extract the area to find a near-optimal solution. The results are compared based on self-generation.

A comparative study by Huang and Lin (2015) presented an Ant Colony Optimization (ACO) algorithm for the multi-trip Split Delivery and Pickup VRP in the context of periodic and time constraints. The goal is to decrease the number of vehicles and total distance travelled to serve particular CPs. This study eliminates the constraints of visiting each node only once. Likewise, a study proposed by Farrokhi-Asl *et al.* (2017) modelled an NSGA-II with different evolutionary objectives named Multi-Objective Particle Swarm Optimization (MOPSO). In this case, a heterogeneous vehicles fleet with multi-compartment capacity will start servicing the CP from the depot after the load capacity moves directly to disposal centres to unload its waste and then return to the same depot. However, the vehicle with a single-compartment system outperformed the others in reducing the number of routes based on a study by Zbib and Wohlk (2019).

Alternatively, Wongsinlatam and Thanasate-angkool (2021) proposed two meta-heuristic algorithms: first by combining the Intelligence Hybrid Harmony Search Algorithm (IHHS) and second by the Standard Harmony Search Algorithm (SHS). In this study, the execution time for algorithm efficiency was not considered. Other than that, Babaee Tirkolaee *et al.* (2019) carried out a design for solving the Capacitated Arc VRP (CARP). The objective is to minimise the long distance of the vehicle's route and the total cost. The important factor is to find the longest allowable route for the vehicle. Correspondingly, the authors developed a Multi-Objective Invasive Weed Optimization (MOIWO) algorithm for solving this problem under uncertain demands and used the ε constraints method in the General Algebraic Modeling System (GAMS) software, which is a high-level modelling system for mathematical optimisation with small-sized and medium-sized problems.

On the other hand, Blazquez and Paredes-Belmar (2020) considered the average speed of vehicles beside bins capacity with a homogenous fleet of vehicles to service the bin in the network. This study employed the Large Neighborhood Search (LNS) algorithm for large-scale problems and MILP models for small-scale problems to minimise the total travel distance and the cost of bin location at the chosen collection site. In addition, Delgado-Antequera *et al.* (2020) also concentrated on the SPDP time constraints by calculating the constraints of vehicle speed and capacity. The study aims to minimise distance and duration differences between long and short routes. The proposed algorithm is Iterated Greedy–Variable Neighbourhood Search (IG-VNS), which has been compared to NSGA-II and Strength Pareto evolutionary algorithm 2 (SPEA2). According to studies on the periodic SPDP, few works with a multi-objective algorithm as the solution approach appear in the literature. We have identified only those works by Farrokhi-Asl *et al.* (2017), Wongsinlatam *et al.* (2021) and Blazquez and Paredes-Belmar (2020).

Table 2. Reviewed papers focusing on the multi-objective SPDP in the SWC system

Ref.	Constraints								
	TC	Capacitated based on		Constraints related to vehicles			Routes service constraints		
		Bin	Vehicle	Homogenous	Speed	Distance covered	Split delivery	Periodic waste collection	Undirect graph
Exact methods									
(Blazquez & Paredes-Belmar, 2020)	√	√	√	√	√	√	√	√	×
Heuristic methods									
(Delgado-antequera *et al.*, 2020)	√	×	√	×	√	×	√	×	×
Metaheuristic methods									
(Huang & Lin, 2015)	√	×	√	√	√	×	√	√	√
(Farrokhi-Asl *et al.*, 2017)	√	×	√	×	×	√	√	×	×
(Babaee Tirkolaee *et al.*, 2019)	√	×	√	×	×	√	√	×	×
(Hashemi, 2021)	√	×	√	√	√	×	√	×	×
Hybrid methods									
(Wongsinlatam & Thanasate-angkool, 2021)	×	×	√	√	×	×	√	√	√
# studies	86%	14%	100%	57%	57%	43%	100%	43%	29%

√ constraints covered by study**;** × constraint not covered; **TC**: Time constraints

IV. VARIANTS IN SPDP

Vehicle Routing Problems (VRP) have several variants for each original constraint, such as fuzzy service time windows, longest route, hard, soft, pickup and delivery, and more (Montoya-Torres *et al.*, 2015). For more diving into the variant of time, time constraints of VRPs include vehicle arrival time at collection points (CPs), service time at CPs, lunchtime, fuel time, and more (Refer to Table 4, Appendix A). This section will discuss variants in mathematical models to time constraints and the vast majority of other constraints used in Split Pickup and Delivery Problems (SPDP) literature.

Typically, most variants consist of vehicle capacity, trash transfer station capacity, treatment facility capacity, and container capacity. A study conducted by Fermani *et al.* (2021) indicated that the waste collected should not exceed the waste capacity of the vehicle (Equation 1), and vehicles were assigned one-time service for each container based on Equation 2. In a close study presented by Huang *et al.* (2015), the frequency of vehicles collecting waste from each container should be calculated based on Equation 3. Alternatively, Hashemi (2021) confirmed that the vehicle's capacity, weight, and volumetric capacity are not exceeded when waste is collected from CPs (Equation 4 and Equation 5). Here, all strategies are subjected to periodic constraints (Equation 6).

Regarding bin capacity, Hannan *et al.* (2020a) proposed that the bin's fill level cannot exceed the Threshold Waste Level (TWL) for variable route optimisation according to Equation 7. Similarly, Blazquez and Paredes-Belmar (2020) recommended that the number of bins should be less than or equal to collection sites by keeping a minimum distance between the collection points as a fixed characteristic of the collection site (Equation 8). Additionally, Jia *et al.* (2022) state that the waste received from transfer stations should not exceed the treatment plate's capacity (Equation 9) and gradually descend with the same approach related to the capacity of the transfer station, which must not be violated by vehicles that unload the waste inside it (Equation 10).

Adedokun *et al.* (2018) adopted a total travel distance, whereas all waste vehicles are prohibited from exceeding the limit (Equation 11). Furthermore, Huang *et al.* (2015) confirmed that maximum working time (Equation 12) and average speed play significant roles in the efficacy of waste collection systems (Equation 13). Nevertheless, Hannan *et al.* (2020a) believe it is necessary to eliminate sub-tours when resolving the routing problem in the waste collection system; doing so will reduce route service costs (Equation 14). Furthermore, a few studies have eliminated sub-tours. Therefore, comparing waste collecting systems with and without a sub-tour approach is necessary. In regards to the time constraints mentioned by Babaee Tirkolaee *et al.* (2018) and Armington and Chen (2018), they confirmed that the total travel time should not exceed the time window based on (Equation 15).

V. EVALUATION OF PERFORMANCE METHODS

It has been observed in related research that the optimisation methods depend on several objective functions, which we outline in the next steps: 1) minimising the error rate, 2) maximising the solution's precision, and 3) improving the time efficiency of optimisation techniques to produce high-performance results. It is worth noting that some criteria influence the solution quality, including the number of iterations, population size, criteria for stopping algorithms, and algorithm parameter tuning.

Hence, several methods exist for evaluating algorithms' performance in adaptation, modification, and hybridisation cases. In this review, we concentrate on two methods: 1) Evaluate the performance of the proposed method relative to the fundamental method. 2) Evaluate the performance of the proposed method relative to other optimisation techniques. Both methods depend on a specific benchmark dataset and may have dataset classes. In Table 3, we evaluate the performance of improvement methods, including a maximum number of iterations with populations set in each solution method, comparing current methods with proposed methods, objectives, evaluation method, criteria for stopping the algorithms, and eventually, the columns of advantages and disadvantages.

Some authors evaluated the proposed methods based on real data and compared them to other studies, such as a study conducted by Buhrkal *et al.* (2012). The proposed method used two datasets and compared the results of the Adaptive Large Neighborhood Search algorithm (ALNS) algorithm with Variable Neighbourhood Search (VNS) and Tabu Search (TS) algorithms. The experiment results show larger improvements starting from 30% to 45% if the time windows vary in 2, 4, and 8. Instead, Kuo *et al.* (2012) proposed a method that used nine different dataset classes. In addition, the authors utilised a Particle Swarm Optimization with a Genetic Algorithm (HPSOGA). The purpose behind this modification is to generate a possible solution. Although HPSOGA obtained better solutions in different iterations and faster convergence, it still suffers from a feasible solution. Above employing 100 nodes, the proposed method compared with Discrete Particle Swarm Optimization-Simulated Annealing (DPSO-SA) and Genetic Algorithm (GA). The study did not consider the travel time and the time window variants.

Among several simulation studies published, a study carried out by Akhtar *et al.* (2017) was on a modified Backtracking Search Algorithm (BSA) that evaluated the performance of the basic BSA with local search algorithms on six datasets. All the simulation datasets used to test the algorithm can be found at (http://www.coin-or.org/SYMPHONY/branchandcut/VRP/data). There is no best solution value with an increase in the number of nodes, and the gap between the fundamental BSA value and the best-known value increases. For more credibility, the proposed algorithm has been compared with other published optimisation algorithms, such as the Hybrid Discrete Particle Swarm Optimization (HDPSO) algorithm and the standard Particle Swarm Optimisation (PSO) algorithm in different dataset classes.

A similar simulation study by Hannan *et al.* (2018) followed the same approach but did not compare the proposed algorithms (PSO) with the fundamental PSO. Instead, it compared only Hybrid Particle Swarm Optimization (HPSO) and HPSOGA, as referred to by Kuo *et al.* (2012) and Akhtar *et al.* (2017). In contrast, some researchers evaluated the proposed methods based on real data but did not compare them to other studies. In a study conducted by Wy *et al.* (2013), they used a Large Neighborhood Search (LNS) algorithm approach that comprises the construction algorithm and several improvement algorithms with 32 benchmarks of real data cited from (http://logistics.postech.ac.kr/RRVRPTWbenchmark.html). Still, the computation time of the proposed method was not addressed to evaluate the efficiency of the proposed algorithm. Assaf & Saleh (2017) used GA and Nearest Neighborhood Algorithm (NNA) to get a good starting point for the GA, thereby saving computational time and reducing the number of iterations required to find a solution, using data collected from ArcGIS software (https://www.arcgis.com). In this article, there is only one drawback: the lack of validation of the proposed algorithm's efficiency. Anagnostopoulou *et al.* (2017) considered the Local Search Heuristic (LSH) and TS. The solution approach proposed two stages: the construction stage using the insertion algorithm for the initial feasible solution and the improvement stages using relocated edge-exchange neighbourhood structures. Note that experiments demonstrated the competitiveness of the proposed solution approach based on the current municipality case city of Piraeus.

Subsequently, a study by Mat *et al.* (2017) utilised a constructive heuristic algorithm and a comparison to the existing vehicle routes in northern Malaysia to configure the initial solutions for the VRP referred to as a Nearest Greedy (NG) that provided a significant reduction in travel time. Other than that, Marković *et al.* (2019) proposed the Saving Heuristic Algorithm (SHA) for constructing the initial solution, along with two algorithms for improving solutions: the Improved Harmony Search Algorithm (IHSA) and the 2-opt local search heuristic. Although the results of the study succeeded in reducing 10% vehicle fuel costs, this study needs to consider the computation time of the proposed algorithm to evaluate its efficiency since the fuel costs directly depend on reducing the distance travelled to collect containers (Ferrer & Alba, 2019; Vu *et al.* 2020).

A. *Criteria of Algorithm Efficiency*

The stopping criteria or termination criteria of the proposed algorithms are divided into Maximum Iteration Number (MIN), Maximum Run Time (MRT), and Maximum Iteration After Global Solution (MIAGS). Note that the Maximum iteration without improvement (MIWI) and Maximum Operating Time (α) is a number greater than 1, with N being the population size (MOT). Buhrkal *et al.* (2012) suggested limiting the number of iterations (e.g., number of generations) to 200 for repetition-run ALNS that should work after finding a global solution MIAGS. Another study by Anagnostopoulou *et al.* (2017) proposed a method that defined the MIN as between 20 and 40 if there is no improvement (MIWI). The stopping case impacts the computational effort of the proposed solution, and values less than 100 give good compromise for large-size problems.

On the other hand, Assaf and Saleh (2017) advised that the algorithm has been subjected to a limited computation time (10 minutes), which would stop if it converged to a solution before a limited time. All studies considered the criteria MIN (Kuo *et al.*, 2012; Akhtar *et al.*, 2017; Hannan *et al.*, 2018; Adedokun *et al.*, 2018; Wy *et al.*, 2013; Marković *et al.*, 2019). Meanwhile, other studies such as (Anagnostopoulou *et al.*, 2017; Babaee Tirkolaee *et al.*, 2018; Fermani *et al.*, 2021; Rossit *et al.*, 2021; Jorge *et al.*, 2022; Delgado-Antequera *et al.*, 2020) used MIWI. Regarding MOT, only one study by Marković *et al.* (2019) depends mainly on the population size and operating time. Therefore, choosing the appropriate criteria for stopping the algorithm will impact the efficiency of global solution methods.

VI. ANALYSIS OF LITERATURE AND THE KNOWLEDGE GAPS

This section analyses previous literature related to the field of study. As a result, research gaps are identified, highlighting the importance and applicability of waste collection and transportation issues. According to our findings, the first study was conducted in 2012 and witnessed the largest increase in 2017, and again increased by five studies in 2021, as illustrated in Figure 1. Most studies have focused largely on single objective methods, and its ratio was 75%. Only a few studies focused on solving multi-objective problems with a ratio of 25%.

Figure 4(a) shows the distribution of the objective function. This research gap can be filled through efficient problem-solving techniques and streamlined methodologies for multi-objective approaches. The pie scheme in Figure 4(b) demonstrates the research results on both single and multiple objectives methods and techniques utilised by the majority of researchers have been reviewed. Take note that exact algorithms (mathematical programming) were utilised in 14% of the reviewed articles, and these methods are utilised specifically to solve small problems (Özceylan *et al.*, 2020; Jia *et al.*, 2022).

In addition, the rate of heuristic methods was 11%, the lowest value among the studies. Hybrid methods contributed to 14% of the studies, sharing a similar percentage as the exact methods. Meta-heuristic methods (61%) represent more than half of the other studies. Our conclusion leads to the priority of intensifying the number of studies that hybridise the heuristic methods with meta-heuristic methods, improving the algorithms proposed in terms of exploration and exploitation stages, which will increase the efficiency of the waste collection system.

Table 3. Evaluation of the performance of the optimisation methods

Ref.	Max Iteration=MI No. of Population =PN	Compared with fundamental and other methods	Proposed methods	Objective	Evaluation	Stopping Criteria	Comments	
							Advantage	Disadvantages
(Buhrkal *et al.*, 2012)	MI=200 PN=NA	TS, VNS.	ALNSA	Minimise total cost and travel distance.	Two benchmark dataset	MIAG	Global optimisation.	Small improvement toward an optimal solution (low solution quality).
(Kuo *et al.*, 2012)	MI=50, 300, 2500 IP=10, 50	DPSO-SA, GA.	HPSOGA	Minimise travel time and travel costs.	9 benchmark datasets	MIN	Mutation operators prevent the algorithm from getting trapped in local minima.	HPSOGA cannot get a better solution with more than 100 nodes.
(Akhtar *et al.*, 2017)	PN=50 MI=120	HDPSO, PSO.	BSA	Minimise total travel distance.	6 datasets	MIN	Generated waste is collected before it reaches the overflowing.	There is no feasibility study to measure the cost of the dynamic system.
(Hannan *et al.*, 2018)	PN=50 MI=120	HPSO, HDPSO, BSA, HPSOGA.	PSO	Minimise total travel distance.	6 datasets	MIN	Generated waste is collected before it reaches the overflowing.	There is no feasibility study to measure the cost of the dynamic system.
(Wy *et al.*, 2013)	MI= 30,000 PN=NA	NA	LNS	Minimise the number of vehicles required and their total route time.	34 benchmark datasets	MIN MRT MIWI	Provide feasible solutions in a short time	The constraint of Error Rate does not always guarantee better solutions.
(Assaf & Saleh., 2017)	MI=500 PN=1000	NA	GA, NNA	Minimise total cost and travel distance.	Real data	MRT	GA with NNA can find a near-optimal solution in a short computation time.	Static solution is unsuitable for emergency status (damaged car or driver absence).
(Anagnostopoulou *et al.*, 2017)	MI=NA IP= NA	NA	TS, LSH	Minimise the total distance travelled and pollutant emissions.	Real data	MIWI	High-quality solutions in less computation time.	The waste collection system has a complex design.
(Mat *et al.*, 2017)	MI=NA IP=NA	NA	NG	Minimise total cost and travel distance.	Real data	NA	Simple to implement.	No time constraints are considered.
(Marković *et al.*, 2019)	MI=10^3, 10^6 IP=NA	NA	SHA, IHSA, 2-OPT	Minimise the total travel distance and working time.	Real data	MIN MOT	1-Local searchability. 2-Heuristic to get an optimal solution in an efficient time.	Not parameter tuning.

MIN: Maximum iteration number; **MRT**: Maximum run time; **MIAGS**: Maximum iteration after global solution; **MIWI**: Maximum iteration without improvement; **MOT**: Maximum Operating Time. ∝ is a number greater than 1, N is the population size; **VNS**: variable neighbourhood search algorithm; **SA:** simulated annealing algorithm; **ILS-SP**: iterated local search with set partitioning; **UHGS**: Unified Hybrid Genetic Search; **BCP**: branch and cut price; **ALNSA:** Adaptive large neighbourhood search algorithm; **DPSO-SA**: Discrete Particle swarm optimisation with simulated annealing; **HPSOGA**: Hybrid particle swarm optimisation with genetic algorithm; **BSA:** backtracking search algorithm; **PCO**: particle swarm optimisation; **FFA**: Firefly algorithm; **LNS**: Large neighbourhood search; **GA**: Genetic Algorithm; **NNA**: Nearest neighbourhood algorithm; **TS**: Tabu Search; **LSH**: Local Search Heuristic; **NG**: Nearest greedy; **SHA**: saving heuristic algorithm; **IHSA**: improved harmony search algorithm.

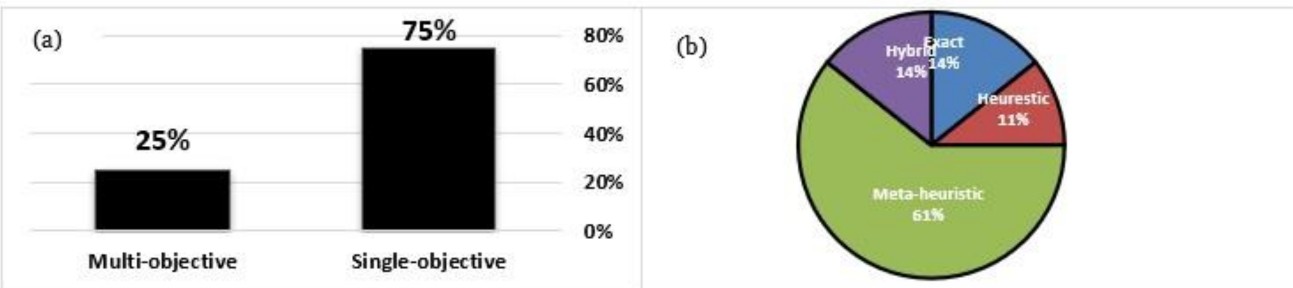

Figure 4. Distribution studies based on: (a) Objective function and (b) Solution method

Even though the number of studies that solved a single objective problem is high, some constraints still need to be studied more intensively, such as the average speed and the rate of distance allowed to be covered by vehicles. In addition to the routes service constraints such as the studies related to undirect graphs (symmetric matrices), the rate was 19% out of studies in single-objective problems according to (Hannan *et al.*, 2020a; Özceylan *et al.*, 2020; Seçkiner *et al.*, 2021; Jorge *et al.*, 2022). By referring to the undirected graph constraints in the single-objective problem and the multi-objective problem, the ratio was 19% and 29%, respectively, which still needs more attention from the researchers, as illustrated in Table 2 and Table 3.

VII. CHALLENGES AND FUTURE DIRECTION

Waste collection and transportation systems are one of the applications of service systems provided to citizens. They are regarded as crucial systems that maintain economic, environmental, and social sustainability. It is important to note in this paper, which reviews various scenarios in the literature regarding the Split Pickup and Delivery Problems (SPDP) in the waste collection context, that pickup is the process of collecting waste from collection points (CPs). Meanwhile, delivery is the unloading of waste at disposal stations that are either fixed or mobile (same depot that the vehicle started from, waste transfer stations, recycling stations, landfills or incineration locations).

For further clarification, previous waste disposal scenarios stipulate that the depot of vehicle starting is the same as a waste disposal station. Hence, the present study reviews previous studies that focused on unloading waste at disposal stations completely separated from the depot site, as well as studies that circle it, comparing the methods to solve those problems and improvement techniques and the most significant variants a waste disposal scenario may have. Note that the purpose of evaluating waste collection systems based on comparing proposed methods with fundamental and other methods is to identify significant evaluation-related steps.

Nevertheless, the classification in terms of solution methods and restrictions is one of the basic contributions considered within the scope of the study, which indicates the restrictions related to vehicles and road service restrictions. According to this matter, one of the innovative methods used in this research is the comparative way to review the evaluation of the proposed solution methods in each study in terms of its biggest advantages and disadvantages. Subsequently, compare the effect of different stopping criteria on the algorithm to determine the optimal solution. In conclusion, the recommendation forms can provide new test data by focusing on the steps as follows:

a) The contextual analysis of the benchmark datasets is a crucial factor. Using the same method with a different number of classes will result in varying degrees of precision.

b) To maintain a perfect optimising model, the following procedures should be followed:

   1. Hybrid different meta-heuristic algorithms.
   2. Compare different meta-heuristics methods.
   3. Parameter tuning reduces the dispersion of the objective functions as much as possible. It is preferable to analyse the test using one of the Taguchi design-referenced methods (e.g., standard analysis of variance or signal-to-noise ratio (s/n) (Babaee Tirkolaee *et al.*, 2019).
   4. Evaluation metrics (accuracy, time complexity, and error rate) in the visualisation graph.

To this end, several key points for future models are presented as future work accordingly. Other than that, it is necessary to use real-world data for a more realistic evaluation of SPDP and best techniques estimation of the uncertain parameter-based symmetric and bounded random variable of demand, which has become the greatest challenge in this problem (e.g. waste amount) (Akhtar *et al.*, 2017; Hannan *et al.*, 2018; Babaee Tirkolaee *et al.*, 2018; Marković *et al.*, 2019; Huang & Lin, 2015; Babaee Tirkolaee *et al.*, 2019) or based on fuzzy logic (Hashemi, 2021; Kuo *et al.*, 2012). Another challenge is operating the Solid Waste Collection (SWC) in varying environmental conditions, which must be sustainable in the real world, for instance, using the direct graph for vehicle travel on one-way roads (Liang *et al.* 2021).

VIII. CONCLUSION

This article reviews an optimisation method for municipal waste collection, concentrating on the split pickup and delivery problems. The review examined the objectives and constraints of time, vehicles, and route services, with most variants employed. Based on the review, existing studies focused on single objective methods with a ratio of 75%, whereby only 25% focused on solving multi-objective problems. The optimisation methods were also analysed to define the knowledge gap, highlight the challenges, and recommend further research. It is necessary to use real-world data for a more realistic evaluation of SPDP and provide optimal estimation techniques of the uncertain parameter, especially in symmetric and bounded random variables in demand.

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Appendix A

Table 4. Most variants used between pickup and delivery problems in solid waste collection

Ref.	Focused Variants	Mathematical description	Equations	Decision variable
(Fermani *et al.*, 2021)	Vehicle capacity (Q)	$q_i \leq u_i \leq Q, \forall i \in C$, qi: Amount of waste collected in the container. u_i: non-negative auxiliary variable for subtour elimination indexed via collection points (i∈ C) & (j∈ C) C: Set of collection points	(1)	x_{ij} =1 if a vehicle uses the path from container i to container j, ∀ (i, j) ∈ C else x_{ij} =0
	Containers service (C)	$\sum_{j \in C} x_{i,j} = 1, \forall i \in C$; where i ≠ j $\sum_{j \in C} x_{j,i} = 1, \forall i \in C$; subset $C = C \cup c_0$, where 0 is the depot	(2)	
(Huang & Lin, 2015)	1-Vehicle capacity (Q) 2-counting vehicle frequencies for containers.	$\sum_{f=1}^{x_i^*} \sum_{i \in N} q_{if}\, z_{if}^{kt} \leq Q, \quad \forall k \in K, \quad t \in Z^+$, x_i^*: optimal frequency of collection at point i to service the neighborhood	(3)	z_{if}^{kt} =1 if k collects the point i within t^{th} $trip$, $i \in N, f \in Z^+$, $k \in K, f = 1 \ldots, x_i^*$,
(Hashemi, 2021)	1-Vehicle capacity. 2-Vehicle weight 3-vehicle volumetric capacity	$\sum_s (x_{mpk}^{ts} \times w_s) \leq QW_k \quad \forall m,p,k,t$ $\sum_s (xi_{mpk}^{ts} \times vol_s) \leq QV_k \quad \forall m,p,k,t$ w_s : s^{th} product weight vol_s: s^{th} product volume QW_k: k th vehicle weight capacity QV_k : k^{th} vehicle volumetric capacity x_{mpk}^{ts}:The amount of waste s sent by the kth vehicle from the collection and recovery centre m to the recycling centre p in period	(4) (5)	$y_{lmk}^t = 1$, If the vehicle kth move from the customer l to the collection and recovery center m within period (t) else $y_{lmk}^t = 0$,
	Period of waste service	$\sum_m \sum_k y_{lmk}^t \geq 1, \quad \forall l, t$ M: Index of a collection of potential points for collection and rehabilitation centers m ∈ M K: Index of vehicles k ∈ K N: Index of potential points for a landfill and demolition centers n ∈ N T: Period index t ∈ T; waste producer: l ∈ L; S: Waste collection index s ∈ S	(6)	
(Hannan *et al.*, 2020a)	Bin capacity	$x_{ijk} \in \{0,1\}$, i, j=0, 1,.....n/$f_i \geq F$; i≠j	(7)	x_{ijk}=1, if vehicle k goes from bin i to bin j else x_{ijk}=0.
(Blazquez & Paredes-Belmar, 2020)	Characteristic of collection site	$\sum_{i \in C: d_{ij} \leq \eta} h_i . Z_{ij} \leq \sum_{k \in K} Q_k . y_{jk} \quad \forall j \in I$ i: Waste generation point, where (j, i) ∈ C C: Set of waste generation points d_{ij} : Minimum distance between a waste generator points i and a collection site j η: Maximum walking distance between a waste generator point i and a collection site j h_i: Volume of waste generation point i; k: Type of bin (small and large capacities), k ∈ K K: Set of bin types; Q_k: Bin capacity of bin type k	(8)	$Z_{ij} = 1$ if waste produce point assigned to the collection site (container)j else $Z_{ij} = 0$.

		y_{jk}: Number of waste collection bin type k required at the site j; I: Set of candidate collection sites		
(Jia *et al.*, 2022)	Capacity of the treatment plate.	$\sum_{j \in I} e_{jn} x_{jn} \leq Q_n^{plant}, \quad \forall n \in N$ N: Set of waste treatment plants, indexed by n, n = 1, 2,⋯, |N|; e_{jn}: Continuous variable, the amount of waste transported from transfer station j to treatment plant n. Q_n^{plant}: Capacity of the treatment plate. x_{jn}: distance between transfer station j and treatment plate n (km)	(9)	x_{jn}: Binary variable takes 1 if all waste from transfer station j is shipped to treatment plant n, 0 otherwise
(Blazquez & Paredes-Belmar, 2020)	Characteristic of collection site	$\sum_{i \in C: d_{ij} \leq \eta} h_i . Z_{ij} \leq \sum_{k \in K} Q_k . y_{jk} \ \forall j \in I$ i: Waste generation point, where (j, i) ∈ C C: Set of waste generation points d_{ij} : Minimum distance between a waste generator points i and a collection site j η: Maximum walking distance between a waste generator point i and a collection site j h_i: Volume of waste generation point i; k: Type of bin (small and large capacities), k ∈ K K: Set of bin types; Q_k: Bin capacity of bin type k y_{jk}: Number of waste collection bin type k required at the site j; I: Set of candidate collection sites	(8)	$Z_{ij} = 1$ if waste produce point assigned to the collection site (container)j else $Z_{ij} = 0$.
(Jia *et al.*, 2022)	Capacity of the treatment plate.	$\sum_{j \in I} e_{jn} x_{jn} \leq Q_n^{plant}, \quad \forall n \in N$ N: Set of waste treatment plants, indexed by n, n = 1, 2,⋯, |N|; e_{jn}: Continuous variable, the amount of waste transported from transfer station j to treatment plant n. Q_n^{plant}: Capacity of the treatment plate. x_{jn}: distance between transfer station j and treatment plate n (km)	(9)	x_{jn}: Binary variable takes 1 if all waste from transfer station j is shipped to treatment plant n, 0 otherwise
(Jia *et al.*, 2022)	Capacity of the transfer station	$\sum_{i \in I} w_i x_{ij} \leq z_{jh} Q_h y_j \ , \quad \forall j \in J$ ω_i: Average daily amount of waste collected at waste collection point i (t) Q_h: Capacity of transfer station of level h (t) h: Set of levels of waste transfer stations after planning, indexed by h, h = 1, 2,⋯, |H|;	(10)	x_{ij}: Binary variable takes 1 if all waste from collection point i is shipped to transfer station j, 0 otherwise
(Adedokun *et al.*, 2018)	Constraint of vehicle distance allowed.	$\sum_{i=0}^{N} \sum_{j=0}^{N} d_{ij}^k P_{ij}^k \leq D_k \quad k = 1,2 \ldots . K$ d_{ij}^k: vehicle travel distance from node i to node j (Km) D_k: total travel distance (Km).	(11)	$P_{ij}^k = 1$ if vehicle travels from customer i to j else $P_{ij}^k = 0$.
(Huang & Lin, 2015)	1-Maximum working time per day (W) 2-Average travel speed of trucks (v)	$y_{ijff'}^{kt} (H_{if}^{kt} + s_i + d_{ij}/v - H_{if'}^{kt}) \leq 0,$ $\forall k \in K, \ t \in Z^+, \ \forall i \in N, \ \forall j \in N, \ f = 1 \ldots . x_i^*, f' = 1 \ldots$ $H_{if}^{kt} + s_i + d_{ij}/v \leq W,$ $\forall k \in K, \ \forall i \in N \cup \{0\}, \ \forall j \in N \cup \{d\}, \ t \in Z^+, \ f = 1.$ $i \neq j, \ i,j \in N \ , \ t \in Z^+, f = 1 \ldots . x_i^*, \ f' = 1 \ldots . x_j^* \ f,$ $f' \in Z^+, \forall k \in K$; s_i: Time duration of waste collection at point i for each collection; H_{if}^{kt}: the time at which collection truck k on its t[th] trip starts serving point i for the f[th] collection, $H_{if}^{kt} \geq 0, \forall i \in N \cup \{0, d\}, \forall k \in K, t' \in Z^+, \ f = 1 \ldots . x_i^*$	(12) (13)	$y_{ijff'}^{kt} = 1$, if arc (i, j) belongs to the collection truck k, on its tth trip for the f[th] collection at point i and f'[th] collection at point j, Else $y_{ijff'}^{kt} = 0$
(Hannan *et al.*, 2020a)	Eliminate sub- tour	$\sum_{i,j \in S}^{n} x_{ijk} \leq \|S\| - 1 \ \ S \subseteq \{1 \ldots n\} \quad \|S\| \geq 2 \quad k = 1 \ldots . . m$ n: indicates the bins, *m: total number of vehilce*	(14)	x_{ijk}=1, if vehicle k goes from bin i to bin j else x_{ijk}=0.
(Babaee Tirkolaee *et al.*, 2018)	Constraints of vehicle cost.	$\sum_{(i,j) \in E} \sum_{o \in O} \frac{dis_{ij}}{vel_{ijk}} x_{ijkt}^o + \sum_{(i,j) \in E_R} \sum_{o \in O} Lw_{ijk}^o y_{ijkt}^o \leq T_{max} ,$ dis_{ij}: distance over the edge(i,j); vel_{ijk}: speed of k[th] vehicle for travelling over the edge (i,j); Lw_{ijk}^o: the loading time of waste for k[th] vehicle over the edge (i,j); T_{max}: the max available time for vehicles the period; y_{ijkt}^o: vehicle travel through the edges in with serviced; x_{ijkt}^o: vehicle travel through the edges without service.	(15)	NA