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WASTE COLLECTION VEHICLE ROUTING PROBLEM BENCHMARK DATASETS AND CASE STUDIES: A REVIEW

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ABSTRACT

Waste collection vehicle routing problem (WCVRP) is one of the most studied areas and has received high interest from the modern society today. This corresponds to the cost efficiency, population growth, and environmental concerns. The growth of the WCVRP awareness is the result of continuous supports from government and private organizations. This paper reviews several established benchmark datasets and successful real-life case studies. Respectively billions of dollars have been saved from the operational costs. The current trend for benchmark datasets presented and case studies are accordingly grouped by countries and continents, thus revealing the need for WCVRP. Investigation on objectives, constraints and algorithms are also discussed. Results showed the increased interest of researchers in using benchmark datasets as well as the case studies and some of the constraints that should be considered in WCVRP. It also suggested that environmental or quality of service issues can be integrated into the common objectives of minimizing cost and distance travelled. Methods used in WCVRP are exact methods and approximate methods. Results showed that approximate methods have the capability in providing good results for large-scale data. Conclusively, this study analyzes the gap and provides recommendations for researches.

Keywords: *Waste Management, Approximate & Exact Algorithms, Benchmark Datasets, Vehicle Routing Problem*

1. INTRODUCTION

Waste collection vehicle routing problem (WCVRP) is an important and emerging research topic as it is vital from economic and environmental perspective due to the increase amount of generated waste and the complexity of the products.

Waste is defined as by-products or end products of the production and consumption process and can be classified as residential, commercial, and industrial or roll-on-roll-off [1]. Residential waste generally involves waste collection from residential communities and private homes, in which vehicles move along the streets to collect garbage from small bins. The frequency of the waste collection service depends on the climate, geography, and service charge. Commercial waste is waste collected from malls, restaurants, and small office buildings, which usually have bigger size of bins. It is fairly static and has a consistent frequency of service. Industrial waste, on the other hand, involves garbage collection from construction sites, downtown area, and large shopping malls. Industrial and commercial waste collections do not only differ by the size of containers, but also by their route. Industrial waste vehicles deliver an additional empty container at the customer's location, pick up the full container, travel to a disposal facility, and empty the container [2].

Waste management is a key process in protecting the environment and resources. The process includes collecting, transfer and transportation, disposal, source separation, storage, recycling, and monitoring waste materials [3]. Increasing interest in waste management has become a wide public concern in modern societies. This is due to the increase of waste amount as well as the complexity of products and components [4]. Moreover, the growth of industrial activities has also resulted in huge amounts of industrial waste. Waste collection plays an important role in waste management as it deals with optimizing cost, time, vehicles, and human resources. The main activities in waste management are collecting and transporting the

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waste to the intermediate facilities (disposal facilities or transfer station). The collection of waste is a highly visible and important municipal service. Typically, waste collection also involves a very high operation cost [4],[5]. Decisions in assigning trucks, providing intermediate facilities, and determining the best possible routes are important. Logically, collection is the most crucial and costly feature in the cycle because of the high use of labors and trucks in the collection process [6].

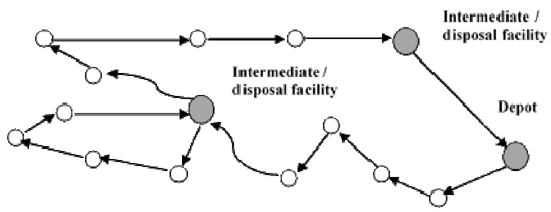

Figure 1: Illustration of A Waste Collection Vehicle Routing Problem

Solid waste is a type of waste that comes from households, streets, constructions, and hygiene debris including recyclable waste such as glass, paper, plastic, and aluminum. Solid waste collection is one of the complex logistic problems endured by municipalities. The operational costs, environmental and health concerns as well as the growing regulation burden have caused municipal and private waste collection companies to improve the collection routes [7] . In developing countries, waste collection is one of the most challenging operational problems [8]. In solid waste collection, as illustrated in Figure 1, wastes are collected from different segmented areas and are transferred to intermediate facilities [3]. A collection vehicle leaves the depot (garage), starts collecting waste from the collection points (customers), and when the vehicle is full, it reaches an intermediate facility for the unloading operation; then it starts with another collection tour and returns to the depot when all collection points are visited or when the constraints of the routing is met. All vehicles must unload waste at intermediate facilities before returning back to the depot without any waste by the end of the day [2]. But there are cases where the unloading process can be done on the next day if the unloading constraint and procedure are applied. In such cases, a vehicle travels from the depot to collect waste from a collection point and continues to the next collection point. It returns to the depot by the end of the day with waste and empties the vehicle at the disposal facility on the next day.

One of the common methods to manage waste collection is by using the vehicle routing problem (VRP). According to [8], the goal of VRP is to optimize routes without violating any specific constraints such as capacity, time window, number of vehicles, and depots. The routing problem is essential as it deals with cost and time constraints, scheduling as well as satisfying customer demands. Vehicle routing has been an important area of research and was introduced by Dantzig and Ramser in 1959 [9]. Transportation costs denote an average of one to two-thirds of the company's logistic cost and 15% of the sale price of goods. Thus, solving the vehicle routing problem efficiently is able to save logistic costs [10].

In the case of waste collection, VRP helps to reduce the number of trips and travel distances as well as the reduction of fuel consumption and vehicle emissions [11]. Despite the facts, for the last 40 years, the academic paper researchers about the WCVRP are quite limited [4]. However, today, due to the fast development of new and more efficient optimization and computing methods, they have slowly attracted the attention and interest of academics and practitioners.

Part of their focuses are on two crucial elements in seeking optimum routes. The first is realistic data and constraints such as time, distance, capacity, route, depot, and vehicle fleets [8], as well as the number of trucks, workers, and collection facilities. They are selected from a range of continuous research and analysis.

The second crucial element for route optimization is the formulation of an algorithm. Optimization methods are classified into approximate algorithms and exact algorithms. Optimal or near-optimal solution is generally achieved by using either approximate or exact algorithms. One of the challenges in optimization is VRP is considered as a nondeterministic polynomial time (NP) and hard combinatorial optimization problem.

Since WCVRP is an essential and developing research topic, there are plenty of room for improvement. However, before any advancement can be made, a review is required on problem description and direction of previous researchers in this area.

Thus, the main aim of this paper is to identify the objectives, constraints and methods used for benchmark datasets and case studies including trends specifically in WCVRP of previous research.

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The scope of this review is on solid waste, which are organic and recyclables waste. The waste is classified as residential, commercial and industrial waste. Other types of waste such as hazardous and liquid are not included. This study limits the coverage to the past 11 years of published papers.

The sources for this paper are selected from: (1) academic databases and journals such as Elsevier, Springer, Science Direct, Scopus, and Scientific Research. Keywords used are vehicle routing problem, waste collection, trash collection, rubbish collection, refuse collection, junk collection, garbage collection, methods, algorithms, techniques, heuristic, and metaheuristic.; (2) bibliographies of survey papers and book chapters; (3) books focused on algorithm, waste, and vehicle routing problem. The searching process is confined to articles published from 2005 to 2016 to expose the latest results and trends.

Taking these introductory remarks into account, this paper is organized as follows. Section 2 is devoted to benchmark datasets in waste collection problems. Section 3 deals with waste collection case studies in real-life applications. Classification of constraints on the waste collection problem are discussed in Section 4. Finally, WCVRP methods and algorithms for benchmark datasets and case studies are introduced in Section 5. Section 6 discusses the comparison of research objectives and comparisons of algorithms. As a final point, a conclusion is drawn in Section 7.

2. BENCHMARK DATASETS

In reaching the optimum route for the waste collection problem, there are parameters and constraints that need to be identified. However, they are differed with environments such as regions, situations, and climate. Thus, the parameters and constraints collected become the benchmark and are limited for such environment. In particular, this paper discusses the five benchmark datasets used in waste collection. They are the waste collection benchmarks by [12], [13],[14], [15], and [16]

Table 1: Benchmark Datasets

BENCHMARK: [12] , Commercial waste	
DETAILS: 22 instances, 48 and 96 customers, and 5 or 7 depot	
Ref.	**Objectives**
[2]	Maximize route compactness and reduce costs
[17]	To improve to multi-depot vehicle routing problem and minimize costs
BENCHMARK: [13], Commercial waste	
DETAILS :10 instances, 2092 customers, 19 intermediate disposal facilities, 1 depot	
Ref.	**Objectives**
[13]	Minimize the number of vehicles and travel time, maximize route compactness and vehicle workload balance
[14]	Minimize the vehicle travel cost, distance, and time
[18]	Minimize the number of vehicles and distance, maximize route compactness, and balance the workload among the vehicles
[19]	Minimize the total distance
[20]	Minimize the travel cost within the time window
[21]	Minimize the number of vehicles and total distance
[22]	To improve the previous [19] solution
BENCHMARK: [14] , Commercial waste	
DETAILS : **Original data: :** [23] 22 instances, 48 to 288 customers, 5 to 7 depots **Modified data :** 22 instances, 48 to 216 customers, 3 to 6 intermediate facilities, 1 depot	
Ref.	**Objectives**
[14]	Minimize the vehicle travel cost, distance, and time
BENCHMARK: [15] , Commercial waste	
DETAILS : **Hybrid data:** [12] + [23] 22 instances, 48 to 288 customers, 5 to 7 depots	
Ref.	**Objectives**
[15]	Minimize the total travel cost and time
BENCHMARK : [16] , Industrial waste	
DETAILS: **34 instances: (Type A) + (Type B)** Type A: 14 instances from US real data Type B: 20 instances artificially generated	
Ref.	**Objectives**
[16]	Minimize the number of vehicles and total travel time

As reported in Table 1, there are five established benchmark datasets used in WCVRP. The table provides entrancing information on their waste type, details, and objectives. The benchmark instances introduced by [12] contain 48 and 96 customers and 5 or 7 depots and can be downloaded at http://chairelogistique.hec.ca/en/scientific-data/. [2] and [17] used the instances as the benchmark in their researches.

On the other hand, the benchmark instances introduced by [13] used real-life case studies of North America with nearly 26,000 collections in 10 different datasets. The benchmark dataset consists of 10 instances with a single depot, 19 intermediate disposal facilities, and 2092 containers. A new constraint is introduced, which is not vital in other benchmark datasets. The constraint is a lunch break, which is considered as one of the time window constraints. [13] introduced and addressed this benchmark as a waste collection vehicle routing problem with time window problem. The research objectives were to minimize the number of vehicles and travel time, maximize route compactness, and allocate equal assignment among the vehicles. Researches that refer to [13]'s instances generally have the same objectives, which were to minimize the number of vehicles and travel time, maximize route compactness, and allocate equal assignment among the vehicles. Route compactness is defined as setting all stops into the routes; routes without overlapping is considered more compact as compared to crossover routes.

[18] conducted a research using [13]'s benchmark datasets with the objectives to minimize the total number of vehicles and distance, maximize route compactness, and balance the workload among the vehicles. On the other hand, [14] initially intended to minimize costs such as fixed cost for vehicles, travelling and wage, distance, and time. [19],[20] used the same waste collection problem as in [14]. [21] aimed to reduce the number of vehicles and total distance. [22]'s objective is to improve the previous [19] solution. This benchmark dataset can be retrieved from: https://sites.google.com/site/logisticslaboratory/research/research-areas/waste_collection_vrptw_benchmark.

[23] generated 22 instances, 48 to 288 customers, and 5 to 7 depots from those proposed by [12]. Subsequently, [14] modified the set of [23] to suit with the waste collection problem with a single vehicle depot. The new instances comprise 4 to 6 available vehicles, 22 instances of 48 to 216 customers, 3 to 6 intermediate facilities, and a single vehicle depot.

A new benchmark dataset was proposed by [15], which combines instances by [12] and [23]. This is possible because both datasets have the same set of customers. The number of customers and intermediate facilities, the maximum duration, and maximum capacity are taken from [23]'s instances. The number of days of the planning period and service frequencies are taken from [12]'s instances. The main objectives were to minimize the total travel cost and total travel time.

[16] introduced an industrial benchmark dataset with 34 instances; 14 were derived from a real waste collection company in the US and the other 20 were artificially generated. The objectives were mainly to reduce cost and distance travel as well as to complete tasks within the time window. The benchmark dataset is available at http://logistics.postech.ac.kr/RR-VRPTW_benchmark.htm.

Figure 2 shows the trend of studies for benchmark datasets over the years starting from 2006 to 2016.

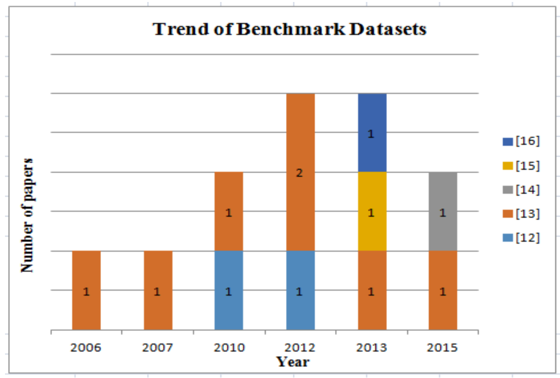

Figure 2: Trend of Benchmark Datasets

[12] publications are in 2010, and 2012, showing the relevance and interest of researchers that still exist although it was first published 15 years ago. 50% of publications used [13]'s benchmark dataset. The interest of using [13]'s benchmark dataset is increasing as two papers were published in 2012 as compared to one paper in the previous years. Contrary to [12]'s benchmark dataset, the trend showed a horizontal pattern, indicating few interests in using the benchmark dataset. Interestingly, [13]'s benchmark dataset includes the lunch break time window constraint, allowing the data to be complex and reliable to researches. Other benchmark datasets show consistency where [14], [15], and [16] were included in only one publication each.

3. CASE STUDIES

A case study is used to test a solution method and demonstrate the understanding of real-life applications. This paper discusses the municipalities and private companies' case studies from various countries from four continents. Waste type, details, and results that indicate the performance by each benchmark dataset are tabulated as in Table 2.

To further summarize Table 2, Figure 3 presents the trend of published case studies by continent and countries since 2005. Concluding from this rising trend, the number of studies for WCVRP is

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expected to increase in the near future. Most of the case studies are mainly from developed countries, but the number of case studies in developing countries is increasing. It is believed to increase due to the environmental awareness, the need for a clean environment and healthy lifestyle, and the availability of modern facilities.

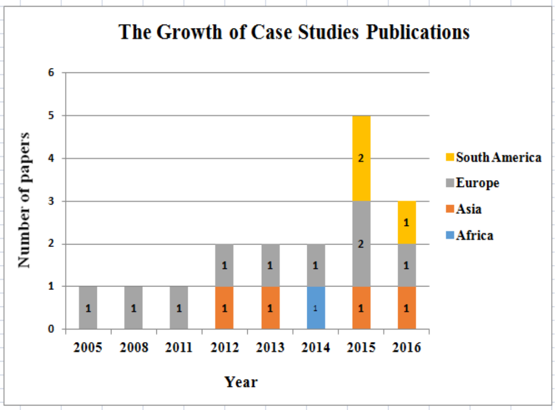

Figure 3: The Growth of Case Study Publications

4. CONSTRAINTS CLASSIFICATION

In the previous sections, reviews on the WCVRP benchmark and case studies have been discussed. This section continues with identifying the constraints used in the researches. In general, constraints influence the solution results. The problem becomes more complex and realistic by adding more constraints to the problem. Constraints in waste collection include service, capacity, time, route, vehicle type, number of vehicles, and depot. In most cases, vehicles are not allowed to violate the constraints given.

Service refers to waste collection in which a collection point can only be visited once. Capacity can be categorized as vehicle capacity that holds the maximum volume and weight for each vehicle at any given time [12]. Vehicle volume and weight capacity cannot be violated at any point in the tour [7]. Fuel weights during the consumption distance are also taken into account [36]. When a vehicle is full or has reached the maximum volume, it needs to go to the intermediate facility or landfill to be emptied. Then, it can continue the trip to collect more waste. Vehicle capacity states the maximum number of volume and weight that can be handled per vehicle per day. In route capacity, the maximum number of stops is identified. Vehicles are also allowed to make multiple disposal trips per day [1]. This is to achieve route compactness, where stops are grouped into a route to avoid or minimize overlapping. Driver capacity is the maximum capacity of working hours for each driver per any given day. This is due to the eight-hour work day limit, permitted by the national legislation [34]. Most vehicles will return to the depot without loading where the last stop is the intermediate facilities. In cases where vehicles return to the depot with loading either fully or partially, they will be emptied the next day. The purpose is to reduce the cost and time constraints. [14] believed that it is seldom optimal for a vehicle to return to its origin depot especially in rural areas.

Time window restricts the time of the vehicles leaving the depot, in which the vehicles should only leave the depot after the start time and they must return to the depot within the finish time. It is also considered that all vehicles leave the depot at the same time without a queuing problem. Lunch break is considered as the time window where drivers are given a specific time to have lunch at the nearby area. Traffic congestion is considered as one of the dynamic constraints since it affects vehicle travel time. The area of collection in urban areas usually takes more travel time compared to rural areas. Time windows are divided into two types, which are hard time and soft time windows. Normally, in hard time window, vehicles must wait until the start of the time window before service can commence [37]. In contrast, soft time window allows vehicles to violate the time window constraint, but at the price of some penalty [38].

A route is a number of streets or some nearby streets that are grouped together as one unit and represents the customer's location. During the routing, every stop appears on exactly one simple route and every stop must be visited only once [2]. Vehicles may start and end at the same depot or other depots for the multi-depot vehicle routing problem. An arc can also be a two-way route, meaning that a vehicle can travel from a starting point to an ending point of the arc and vice versa. In other words, it can be directed or undirected possibly because of the presence of one-way streets or the different costs for each direction. Residential waste is usually considered as an arc routing problem. Vehicles move along the arc without identifying the exact location of every customer. Industrial waste is a node routing problem with a specific customer location and vehicles move directly to the known location. A route can be classified as symmetric or asymmetric. Vehicles using symmetric use the same route to and fro, while asymmetric use different routes. In real world

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applications, asymmetric routes need to be considered because of the one-way streets.

Subject to the different waste characteristics and complexity of the problem, different types of vehicles are used for waste collection [3]. The vehicle type can be categorized as homogeneous and heterogeneous. The number of vehicles can be categorized as unlimited and limited. The constraints with unlimited vehicles allow waste collection without limiting the number of vehicles. However, limited constraints require the waste to be collected using a specific number of vehicles provided. Initially, vehicles are stationed at the depot, and for a single depot, a vehicle starts from a depot and must return to the same depot at the end of the day [14]. On the other hand, a multi-depot allows vehicles to start and end at different locations. In a multi-depot situation, it is usually a mix of urban and rural regions, and therefore, it is not always optimal for a vehicle to return to the same depot [7].

Table 3 summarizes the main constraints used in the benchmark and case study datasets reviewed in the previous sections. As shown in the table, most constraints are used extensively, but several of the constraints need to be considered such as driver capacity, return to depot with loading, lunch break, travel time, and asymmetric route. Several situations allow vehicles to return to the depot with loading and can be emptied on the next day. Subsequently, it reduces travel distance and cost, especially for urban WCVRP.

5. METHODS AND ALGORITHMS

This section analyzes different methods and algorithms used to solve the previous waste collection benchmark datasets and case studies. Methods and WCVRP are associate with each other in order to find the minimum distance and reducing cost. Main objective of WCVRP is to optimize the routes and decrease the total cost of the routes by reducing travel period with minimum distance along with capacity constraints and vehicle used. The shortest distance travelled by all the vehicles without violating any rules is considered as feasible solution [39].

5.1 Benchmark Datasets Methods and Results

Table 4 outlines the benchmark datasets, methods, and results used by researchers with engaging results. Researchers used benchmark datasets to achieve their objectives and most of the researchers produced interesting results by using different methods and algorithms. The previous studies are grouped according to the benchmark datasets, and comparisons on the algorithms used and results against each study are presented. Interestingly, most of the results show improvement and some of them outperformed the best known solutions.

5.2 Case Studies Methods and Results

Pertinent to the previous section above, this section reveals the results of solutions from real-life waste collection problems using various methods and algorithms. Table 5 below presents the results from classification of case studies by continents along with the methods and algorithms used.

Table 5 summarizes the methods and algorithms used in case studies according to continent and countries. The results reveal the success of each case study. Importantly, billions of dollars have been saved and total operational costs have been reduced. A few researchers measured the reduction of carbon dioxide emissions, and thus indicated the successfulness in taking a step forward in integrating environmental awareness as one of the research objectives.

6. DISCUSSION

In this section, the research objectives and methods used in previous researches are discussed.

6.1 Comparison of Research Objectives

The objectives in vehicle routing problems are categorized as economical, climate and environmental (ecosystem and health). The most common objective in waste collection is economical with the purpose of minimizing the cost, time, travel distance, routes or number of vehicles.

Whereas in the environmental aspect, it refers to the capability of the route to maximize the quantity of waste, the capability of the route to reduce fuel emissions, and the capability to reduce noise from the trucks. These objectives include minimizing the number of vehicles or resources to use, minimizing distance, minimizing the risk of material transportation, minimizing the time of the routes, maximizing the waste collection, maximizing social and environmental profits, and maximizing the compactness of the route.

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The results in Table 6 shows that more than two third of the researchers concentrated on how to minimize costs, minimize distance or travel time, and minimize vehicle numbers, but less than one third have taken into consideration to maximize route compactness, workload balance, environmental emissions, and service quality. Route compactness is how stops are grouped together to form a route. Routes without crossovers are more compact as compared to routes with crossovers. Routes that have many crossovers are considered less compact compared to those without overlapping. Some researchers mentioned route compactness implicitly and it has not become the vital or important element in their research; whereas a few researchers expressed explicitly its details in their studies and it has become a part of their contribution

Table 6: Statistics on Research Objectives

Research objectives	No. of papers Benchmark data	Case study	Total	% Percentage
Minimize cost	7	12	19	38.0
Minimize distance/travel time	7	10	17	34.0
Minimize vehicles	5	3	8	16.0
Route compactness	2	0	2	4.0
Workload balance	2	0	2	4.0
Environmental emissions	0	1	1	2.0
Maximize service quality	0	1	1	2.0
Total	23	27	50	100

The environmental issues, quality of service, and maximizing the collection of waste were mentioned by a few researchers, but were barely stressed explicitly by some of the researchers. Respectively, the combination of optimal solutions from the quantity of waste collected, number of vehicles, and vehicle travel distance ultimately reduce the environmental emissions. The quality of service is indicated by frequency and balanced period of each visit at each collection point. To correspond, the environmental issue, quality of service and workload balance among the vehicles are rare, but are considered to be significant issues.

Relevant to Table 6, some researchers focused on mono-objective, whereas modern waste collection today sets its purpose to be multi-objective. In multi-objective optimization problems, two or more goals or parameters have the ability to affect the overall result. But frequently, each of these objectives might affect each other in a complicated nonlinear way.

Hence, this is the gap and challenge for researchers to find a set of values that is able to produce optimized results. Multi-objective serves as a significant contribution to waste management not only for economical purpose, but the effects to environmental issues such as emissions and noise. For that reason, there is a need for researchers to incorporate these objectives together.

6.2 Comparison of Methods

The previous sub-topics have analyzed two main relationships, which are the benchmark datasets and the solution methods. The relationships are concluded by analyzing the relationships from different point of views, which are the data and their relation to algorithms.

Algorithms are categorized into approximate and exact algorithms. Approximate algorithm is preferable and commonly used in practice as it is able to find very near-optimal solutions for large-scale problems within a very satisfactory computational time. Since 1980s, there are a variety of approximate algorithms, which include heuristics and metaheuristics that efficiently solve different variants of VRP. Heuristic is a classic VRP. Some of the common types of metaheuristics are Simulated Annealing, Tabu Search, Variable Neighborhood Search, Large Neighborhood Search, Evolutionary Algorithms, and Ant Colonies [40], [41]. Heuristics and metaheuristics have less computational time for solving problems as compared to exact methods. Heuristics are specific algorithms for a problem; to find good solutions, not necessarily the optimal one. A heuristic method is capable to handle a very large and complex problem with effective computational time. Whereas metaheuristics have the capacity of avoiding local optimums as they have better exploration in solution space. Exact algorithms can only tackle problems usually of a small scale [38] and some of the commonly used algorithms in VRP are branch-and-bound, branch-and-cut, and branch-and-price algorithms [40].

Table 7 compares between approximate and exact algorithms used based on the above benchmark datasets and case studies. The number of customers to be served is relative to the selection of algorithms and results. It also presents the

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Table 7: Methods Comparison

	ALGORITHM	RESULTS
Approximate Algorithm	**Heuristics** • Two-Phase Algorithm • Three Phase • CROSS-exchange neighborhood	Maximum number of bins: 1) **Benchmark datasets** ▪2092 bins ▪Improved result compared to BKS, but slows computational time 2) **Case study** ▪2773 bins ▪Improved result
Approximate Algorithm	**Metaheuristics** **Local Search** • Simulated Annealing (SA) • Variable Neighborhood Search (VNS) • Large Neighborhood Search (LNS) • Tabu Search (TS) • Variable Neighborhood Tabu Search (VNTS) **Population Search** • Ant Colony Optimization (ACO) • Improved Multiple Ant Colony System (IMACS) • Clustering-based multiple ant colony system (CMACS) • Genetic Algorithm (GA)	Maximum number of bins: 1) **Benchmark datasets** ▪2092 bins ▪9% improvement from best known solution and same computational results 2) **Case study** ▪15,000 inhabitants ▪Improved distance
Exact Algorithm	• Dynamic programming (DP) • Integer Linear programming • Linear programming • Binary Integer Linear Programming (BILP) • Mixed Integer Linear Programming (MILP) • Mixed Integer Programming (MIP) • Branch and Bound (B & B)	Maximum number of bins: 1) **Benchmark datasets** ▪2092 bins ▪Slow computational times compared to approximate algorithms 2) **Case study** ▪1453 bins ▪No optimal solution in suitable computational time

comparisons of algorithms used in previous benchmark datasets and case studies. Significantly, it shows the relation between the algorithms and the total numbers of bins.

In order to compare the relevance of instance size and the algorithms, this research selects the maximum number of collections or bins. The benchmark dataset introduced by [13] consists of 2092 bins and has been tested by researchers using approximate and exact methods. From the analyses, basically, it was proven that heuristics and metaheuristics are capable to produce better results as compared to exact methods for big-scale instances with respect to the constraints used. The results also show that by using approximate algorithms in the benchmark dataset, the computational time is faster than when using exact algorithms. In contrast, there is no optimal solution in a suitable computational time for exact algorithms. When it comes to large-scale instances, approximate algorithms have the capability to cater the data and produce a quality result as compared to exact algorithms. Therefore, the strength of the metaheuristic algorithms is the capability in optimizing large-scale data with better computational time.

7. CONCLUSION

With respect to this research aim, this study has identified several contributions. Firstly, some of the constraints that should be considered are highlighted. Secondly, this investigation concluded that most papers have mono objectives mainly on minimizing cost or distance travelled. The environmental issue and quality of service are rare but are considered as significant issues. Additional objective of reducing environmental emissions or maximizing service quality can be incorporate and becomes multi objectives research in WCVRP field. Multi objectives studies can serve as a significant contribution for both the economic and environmental issues.

Thirdly, results showed the relationship of methods with the size of instance. The size of benchmark data or case study is one of the factors that affect the performance by using exact methods or approximate methods. Exact methods are suitable for small dataset size whereas heuristic and metaheuristic methods cater for bigger size of data. The strength of the approximate methods is the capability in providing good result for large-scale data.

Subsequently, there is an increasing pattern of trends using benchmark data and case studies in WCVRP. Most of publications used benchmark data that include the real environment constraints of time window and lunch break. More case studies came from developing countries indicating the interest for a healthy lifestyle and environmental awareness.

The result of this study potentially represents a step forward and guidance for researchers in WCVRP.

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Table 2: Case Studies Grouped by Continents

COUNTRY	DETAILS	REF.	OBJECTIVES
AFRICA			
Ghana	• Residential waste, 590,240 liters waste bins, 4.2 tons of solid waste per day, 18,000 citizens	[24]	Minimize the total cost and distance
ASIA			
China	• Commercial waste, Vehicle load capacity (2t, 5t, 8t),584 vertices • 371 edges, 473 arcs, 95 required links (19855 m), 80,000 citizens	[25]	Minimize the travel distance
China	• Industrial waste , Number of vehicles: 349, Total costs (travelling, handling, time penalty) are 861,370.6	[26]	Minimize the costs for vehicles, travel, handling, and penalty
India	• Residential waste, 65 collection centers, 50 transfer stations, 100 points, Total distance: 126.15 km, Vehicle capacity: 4-5 tons	[3]	Minimize collection and transportation costs
Vietnam	• Residential waste, Tricycle capacity: 6601 bins (170kg) or 2401 bins (140kg/bin), Forklift and hook-lift capacity: 9 tons	[27]	Maximize the quantity of waste collected and minimize the environmental emissions (reduce the number of vehicles and travel distance)
EUROPE			
Austria	• Residential waste, 3 instances, First instance (387 customers, 2 vehicles, 3 IF), Second instance (184 customers, 1 vehicle, 1 IF), Third instance (78 customers, 1 vehicle, 2 IF)	[15]	Minimize the total travel cost and time
Denmark	• Commercial waste, 8 vehicles, 3 disposals, 228 customers, Drivers working hours less than 9 hours	[20]	Minimize the travel cost within the time window
French	• Residential waste, 15 instances, 150 containers	[7]	Minimize the costs, distance, and time
Greece	• Commercial waste, 100 loading spots, 0.5 $km^{2,}$ 8500 citizens, 3800 tons solid waste per year	[28]	Minimize the cost and number of vehicles
Italy	• Residential waste, 2773 bins, 1491 pick-up positions, Vehicle capacity: 102 bins, Working time: 6 hours, Each node less than 200 minutes	[29]	Minimize the distance
Portugal	• Residential waste, 5 vehicles, 994 containers, 6 working days per week	[30]	Minimize the operation cost and distance travel
Spain	• Residential waste, 5 trucks, Capacity: 25 cubic meters per vehicle, Road length is 55,993m with 220 edges and 459 arcs	[31]	Minimize the travel distance and total cost
Spain	• Residential waste, 4 real instances, 48 villages	[32]	Minimize the transportation costs and maximize service quality
Switzerland	• Commercial waste, 15 instances, 35 tours, 7 to 38 containers, 4 dumps per tour	[14]	Minimize the vehicle cost and travel distance
SOUTH AMERICA			
Colombia	• Residential waste, 13 blocks, 51 corners, 1453 houses, 3860 users, 2 trucks (23 km/h, 2800 kg), 1 wheelbarrow (4.4 km/h, 120 kg).	[33]	Maximize the amount of waste collected by taking into consideration the city's real situation
Brazil	• Residential waste, 2 vehicles, 90,000 citizens, Vehicle capacity: 17 tons, 6 tons, Collection area: 71,420m	[34]	Minimize the travel distance and total cost
Chile	• Residential waste, 20 islands, 33 sites, 300 to 1200 inhabitants per island	[35]	Minimize the total transportation costs

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Table 3: Constraints in Waste Collection Vehicle Routing Problem

CONSTRAINTS	TYPE		DETAILS	REFERENCE	
				BENCH MARK	CASE STUDY
Service	**Waste Collection**		Each customer can only be visited once	[12][13] [14] [15]	[3] [7] [14] [15] [20] [24] [25] [26] [27] [28] [29] [30] [31] [32] [33] [34] [35]
Capacity	**Vehicle capacity**		Maximum volume or weight for each vehicle at given time or per day. When a vehicle reaches the maximum weight, it must go to a disposal facility.	[12][13] [14] [15]	[3] [7] [14] [15] [20] [24] [25] [26] [27] [28] [29] [30] [31] [32] [33] [34] [35]
	Route capacity		Maximum number of stops, lifts, and weight per day	[12][13] [14] [15]	[3] [7] [14] [15] [20] [24] [25 [26] [27] [28] [29] [30] [31] [32] [34] [35]
	Driver capacity		Maximum capacity of working hours for each driver daily	[13][23]	[7] [14] [20] [26] [27] [29] [30] [32] [33]
	Return to depot	**Empty**	Vehicle returns to the depot without any waste	[12] [13] [14][15]	[3] [14] [20] [24] [25] [26] [27] [28] [29] [30] [31] [32] [33] [34] [35]
		With loading	Vehicle returns to the depot with waste and is allowed to unload at the depot on the next day (at intermediate facilities)	[15]	[15]
Time	**Time window**	**Break**	Time restriction for lunch break or entitled breaks after maximum working limit	[13] [14]	[7] [14] [20]
		Node	Time restriction at intermediate facilities (disposal facility, transfer station) or limitation time of daily tour	[13][14] [15]	[3] [7] [14] [15] [20] [24] [25] [26] [27] [28] [30] [31] [32] [33] [34] [35]
		Travel time	Average time during traveling and during collecting bins. The number of traffic lights and area of the collection affect the travel time	[14]	[14][15][25][26] [27] [29] [30] [31] [32] [35]
Route	**Symmetric**		Vehicle travels back and forth using the same route. Starts and ends at the same route.	[12][13]	[15] [20] [24] [26 [28] [29] [30] [32] [33] [35]
	Asymmetric		Vehicle travels back and forth using different routes. Includes turn constraint (streets with forbidden turn) or one-way streets	[13][14]	[3] [7] [14] [25] [27 [31] [34]
Vehicle type	**Homogenous**		Use the same vehicle type for all routes	[12][13] [15]	[20] [24] [26] [28] [29] [30] [31] [32] [33]
	Heterogeneous		Use different vehicle types for all routes	[14] [15]	[3] [7] [14] [15] [25] [27] [34] [35]
Number of Vehicle	**Unlimited**		Use unlimited number of vehicles	[12][13] [14]	[3] [14] [24] [25] [26] [32] [27] 29] [35]
	Limited		Only limited number of vehicles are available	[15]	[7] [15] [20] [28] [30] [31] [33] [34]
Depot	**Single Depot**		Same starting and ending points	[12][13] [15]	[3] [15] [20] [24] [25] [26] [27] [28] [29] [30] [31] [32][33] [35]
	Multi-Depot		Different starting and ending points	[12][14] [15]	[7] [14] [15] [34]

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Table 4: Benchmark Datasets, Methods and Results

BENCHMARK	REF	METHODS/ALGORITHMS	RESULTS
[12]	[2]	▪ Ant Colony System (ACS) ▪ 2 Opt local search	▪ Improvement 2.13% from BKS for instance b2 ▪ Improvement 0% from BKS for instance a2 ▪ Produces solutions with better route compactness, smaller number of crossover among the routes
	[12]	▪ Tabu Search	▪ Produces better solution in a short computational time
	[17]	▪ Improved Multiple ACS	▪ Comparison with the best known result, IMACS produces good solutions 0.28% above the a2 instances
[13]	[13]	▪ Simulated Annealing (SA) ▪ CROSS exchange local search	▪ Less overlapping, outperformed results for route compactness, route overlap, and workload balance ▪ Travel distance improved 10.2% ▪ Saves 1 route and increases productivity by 6.36 yards/hour ▪ Possibility to reduce 984 routes per year and saves $18 million
	[14]	▪ Greedy Insertion heuristic ▪ Neighborhoods (swap, 2-opt, reinsert) ▪ Mixed integer programming	▪ Obtains significant improvements results over best known solutions, but the computational times are slower due to the incompatible sizes and constraints
	[18]	▪ Multi-objective Genetic Algorithm (GA) ▪ Best-Cost Route Crossover ▪ Pareto ranking	▪ GA competes well with [13] ▪ Not considering route compactness or workload balance
	[19]	▪ Variable Neighborhood search (VNS) ▪ Tabu Search (TS) ▪ Variable Neighborhood Tabu Search (VNTS)	▪ Metaheuristic solutions (TS, VNS, and VNTS) use less distance than [13] approximately 5.4%. ▪ Variable Neighborhood Search (VNS) was the most effective of these metaheuristics
	[20]	▪ Adaptive Large Neighborhood Search (ALNS) metaheuristic ▪ Greedy algorithm ▪ Simulated annealing acceptance criteria	• Average improvement of 9% from best known solution • Provides better results within the same time as [19]
	[21]	▪ Ant Colony Optimization ▪ Nearest Neighborhood search	• Compare BKS results [13] and [19] • Improved distance except dataset 102 • Less or same number of vehicles than the other algorithms • Total computational time is 1776.6 seconds
	[22]	▪ Variable Neighborhood search (VNS) ▪ Tabu Search ▪ Variable Neighborhood Tabu search (VNTS) ▪ Disposal Facility Positioning (DFP)	▪ Improvement of less two vehicles from [19] and travel approximately 14% & 5% less distance than [13] and [19]. ▪ Large reduction in distance travel, but requires more computational time ▪ Improved heuristic algorithm using Disposal Facility Positioning (DFP) for the new route evaluation procedure ▪ VNS has a lower average time than either TS or VNTS ▪ VNTS (with or without vehicle reduction) produces better quality solutions than TS and VNS
[14]	[14]	▪ Greedy Insertion heuristic ▪ Neighborhoods (swap, 2-opt, reinsert) ▪ Mixed integer programming	▪ Result with average gap of 0.53% compared to best known result ▪ Average solution for 10 runs with the gap of 1.81% compared to best known result
[15]	[15]	▪ Variable Neighborhood Search (VNS) ▪ Dynamic Programming (DP) ▪ 2-opt & 3-opt	▪ The result shows improvement on average and best known results for 49 out of the 76 instances. The remaining 27 instances have the same result
[16]	[16]	▪ Large Neighborhood search (LNS)	▪ Type A: reduces total route time on average 5.92% and maximum computational time 10 minutes ▪ Generates a better solution in terms of the vehicles required and total route time

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Table 5: Case Studies, Methods and Results

CASE STUDY	REF.	METHODS/ALGORITHMS	RESULT
AFRICA			
Ghana Africa	[24]	▪ Ant Colony Optimization ▪ Nearest Neighborhood	▪ Reduces vehicles from 8 to 6 ▪ Reduces 40% of vehicle distance travelled per week ▪ Reduces operational time and costs
ASIA			
China	[25]	▪ Clustering-based multiple ant colony system (CMACS)	▪ Saves routes length at 89984.96m (with turn constraint) and 92330.04m (without turn constraint), which are 31.1% and 31.9%, respectively ▪ Only requires 3 vehicles with 6t capacity ▪ Produces better route compactness
China	[26]	▪ Ant Colony Algorithm	▪ Reduces 24% of the number of vehicles from 349 to 265 and total cost reduces 22.6%
India	[3]	▪ Integer programming	▪ Optimal road length is 58.33 km ▪ Reduces more than 30% of the total waste collection path length
Vietnam	[27]	▪ ArcGIS Network Analyst	▪ Reduces travel distance by 16.4% ▪ Reduces 14.3% of operational time
EUROPE			
Austria	[15]	▪ Variable neighborhood search (VNS) ▪ Dynamic programming ▪ Clarke and wright	▪ Saves 25% of the average costs
Denmark	[20]	▪ Adaptive Large Neighborhood Search (ALNS) metaheuristic ▪ Greedy algorithm ▪ Simulated annealing acceptance criteria	▪ Improves routes by 8-13% ▪ Solution quality improves 30% to 45%
French	[7]	▪ Greedy insertion ▪ Neighborhood (swap, 2-opt, reinsert)	▪ Able to solve all instances and reach optimal solution with computational time of 1 second ▪ Heuristic results are better and with less runtime ▪ Average optimality gap of less than 2%
Greece	[28]	▪ Ant Colony System (ACS)	▪ Improves routes by 24% ▪ Average route result is 8725m compared to the empirical route of 9850m
Italy	[29]	▪ Two-phase algorithm (clustering and farthest insertion heuristic)	▪ Saves 3 vehicles (15%) and 7 routes (18%)
Portugal	[30]	▪ Mixed Integer Programming (MIP) ▪ Clark and Wright heuristics	▪ Reduces distance by 26% (610 km) ▪ Reduces route by 3.8% (1 route)
Spain	[31]	▪ Ant System ▪ Nearest Neighborhood Heuristic	▪ Reduces route length by 35% using Nearest Neighborhood and 37% using Nearest Insertion

		▪ Nearest insertion heuristic	▪ Computational time for Nearest Neighborhood is much smaller than Nearest insertion ▪ Reduces route length to 17,000 km per year
Spain	[32]	▪ Tabu Search (TS) ▪ Sweep algorithm	▪ Reduces the total transport cost by 34% ▪ Maximizes the service quality by 36%
Switzerland	[14]	▪ Greedy Insertion heuristic ▪ Neighborhoods (swap, 2-opt, reinsert) ▪ Mixed integer programming (MIP)	▪ Ranges of computational times are from 0.05 to 7.58 s. and an average of 1.21 s. ▪ Per instance improvement of average from 1.73% to 34.91% and mean of 14.64% ▪ Estimation on financial savings are from 300,000 USD annually for labor and fuel costs
SOUTH AMERICA			
Colombia	[33]	▪ Mixed integer programming (MIP)	▪ Total waste collected is 604.43 kg and 6891.19 meters ▪ No optimal solution in a reasonable computational time
Brazil	[34]	▪ Mixed Integer Linear Programming (MILP) ▪ Binary Integer Linear Programming	▪ Reduces 1.5% in total distance for undifferentiated collection. Saves US $3825 per year ▪ Reduces 7.5% in total distance for selective collection. Saves US $4146 per year ▪ Reduces carbon dioxide emissions of approximately 914 kg per year
Chile	[35]	▪ Mixed Integer Programming (MIP) ▪ Branch and Bound (B&B)	▪ Reduce cost by 3.3% in one zone scenario ▪ Should employ one barge, one waste compactor, and 220 bins