Smart and Green Urban Solid Waste Collection Systems: Advances, Challenges, and Perspectives

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Smart and Green Urban Solid Waste Collection Systems: Advances, Challenges, and Perspectives

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***Abstract*—This paper provides a thorough literature review of current state-of-the-art systems analysis techniques for urban solid waste collection and identifies four intrinsic deficiencies of the existing studies over different types of cities. As a demonstration, a multiconstrained and multicompartment routing problem is modeled with roll-on roll-off scheduling strategies in a two-stage decision-making process to exhibit the highest complexity of its kind in practical implementation. The constraints of time windows, intermediate facilities, multishifts, and split deliveries make an ideal combination of all essential complexities in modeling practices. To overcome the relevant challenges, a unified heuristic algorithm is proposed for addressing node routing and roll-on roll-off routing problems. The proposed heuristic algorithm that concatenates initialization and improvement phases solves the models with numerical efficiency to search for the most cost-effective and environmentally benign solutions. Results indicate that differentiated collection increases opportunities to pursue the best routing strategies with sustainable implications through sensitivity analysis at the expense of higher collection costs. The analysis concludes with the perspectives of a smart and green waste collection system designed to create a more sustainable waste management systems in the future.**

***Index Terms*—Multicompartment, multiconstrained, roll-on roll-off scheduling, systems analysis, waste collection, waste separation.**

I. Introduction

URBAN solid waste generation increases with rapid urbanization and population growth. To improve resilience, municipalities need to promote waste prevention and recycling at the local scale rather than relying heavily on regional waste treatment and disposal facilities. However, using a combination of waste separation and differentiated collection complicates the current schemes of waste collection because more types of bins and containers are needed at collection nodes, and vehicles must deal with various types of waste streams. To improve collection efficiency, cost-effectiveness, and sustainability, the systems analysis of waste collection strategies has grown in importance yet has become more complicated.

Increasing attention has been paid to optimization of waste collection schemes since the early 1970s [7], including fine-tuning waste allocation with the aid of vehicle routing strategies. Several reviews provided comprehensive coverage of various waste collection vehicle routing problems (VRPs) [10] and optimization models for better waste management [12]. These previous studies involved various decision-making factors covering economy, technology, society, environment, and even ecology. However, they neither addressed regional differences nor involved the local complexity of waste collection with an ideal combination of different modeling practices over different scales. Few studies addressed the coordination of holistic waste collection processes with regard to waste separation and recycling for promoting sustainability. Additionally, the current integration of system analysis methods and informatics is mostly at a basic level. Hence, the existing methods often cannot be immediately applied to manage waste collection VRPs with different types of constraints for sustainability concerns facing both developing and developed countries. The global trend indicates that increasing efforts will be needed to integrate system analysis methods with various informatics, such as global positioning system (GPS), geographic information system (GIS), and radio-frequency identification (RFID), leading to utilization of Internet-of-things for smart and green waste management strategies in the future [26].

This paper provides a thorough literature review of the optimization schemes for waste collection and vehicle routing, followed by a demonstration of a representative two-stage waste collection system to show the highest complexity of its kind over all current urban solid waste collection schemes. This system shows that all contemporary advancements of existing optimization strategies can be well coordinated to provide smart and green solutions. The novelty of this paper is the inclusion of multiple constraints in node routing and multicompartment vehicle routing with roll-on roll-off routing schemes. The routing efficiency is compared in great depth between co-collection and separate collection. This type of routing scheme allows split deliveries for not only collection nodes but also for each of the waste streams to improve routing efficiency. This paper finally elucidates the modern views of smart and green urban solid waste collection systems with respect to future perspectives.

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TABLE I
SUMMARY OF EXISTING STUDIES ON THE OPTIMAL LOCATION FOR SITING THE COLLECTION NODES

Scope	Methodology	Reference
Screen candidate sites by GIS	GIS analysis and IP	[2]
Allocate recycling drop-off stations with appropriate size	Genetic algorithm-based multi-objective IP	[5]
Develop a location model with shortest service	Binary programming	[8]
Evaluate the impact of road slope on node selecting	P-median model	[11]
Locate multi-compartmented containers for waste separation	GIS spatial analysis and multi-objective IP	[13]
Consider the accessing convenience when making collection plan	IP and ant colony algorithm	[25]

Notes: IP = Integer programming.

II. LITERATURE REVIEW

Waste collection systems analyses have been the focus of almost 80 core articles, whose spectrum can be classified into five categories including: 1) optimal location for siting the collection nodes; 2) simultaneous node and arc routing problems; 3) roll-on roll-off routing problems; 4) planning with the aid of informatics technologies; and 5) planning with multiple criteria.

A. Optimal Location for Siting the Collection Nodes

Determining optimal locations for the collection nodes, such as bins, containers, and transfer stations, is often tied to cost-effectiveness and access convenience. Selecting too many collection nodes would increase the collection cost, whereas selecting too few would reduce service quality [8]. A smart waste collection system should address the optimal number of collection nodes and their locations. Integer programming models are usually used for optimizing the selection of collection nodes (see Table I). These models aim to minimize the collection costs and maximize the access convenience and can be also enhanced by GIS if the existing and candidate nodes are positioned by GIS maps [2], [11], [13].

B. Simultaneous Node and Arc Routing Problems

The routing and scheduling of waste collection are generally modeled as VRPs (see Table II), which aim to minimize the total travel distance without violating any constraints. As noted in the literature [35], [44], the waste collection VRPs in the U.S. include node routing problems for commercial waste, arc routing problems for household waste, and roll-on roll-off problems for the transport of large containers. Among them, the node routing problem is the focus of most VRP studies. When the collection demand of each node is much less than the vehicle capacity, a vehicle can visit many nodes along the arcs of the road network. This scenario leads to an arc routing problem, in which the vehicle must visit all nodes along an arc once this arc is visited. The node and arc routing problems have a modeling framework in common; the subtle difference is that the demand for waste collection belongs to nodes in node routing but to arcs in arc routing. However, the arc routing problem can be transformed into a node routing problem *per se* [47].

TABLE II
SUMMARY OF EXISTING STUDIES ON THE SIMULTANEOUS NODE AND ARC ROUTING PROBLEMS

Scope	Methodology	Reference
Using mathematical programming methods		
A composite approach for the capacitated ARP with vehicle/site dependencies	Mathematical programming	[30]
Two exact algorithms for the cluster VRP derived from waste collection	Branch and cut, branch and cut and price	[32]
Using heuristic methods		
The VRP with time windows and intermediate facilities inspired by waste collection	Constructive heuristic, local search, ACS	[34, 35]
The periodic VRP with multiple disposal sites inspired by waste collection	TS, VNS, dynamic programming	[36, 37]
A real-life VRP with multiple constraints inspired by waste collection	Simulated annealing, Chaotic particle swarm	[38, 39]
The VRP with multiple constraints inspired by waste collection	Various meta-heuristics	[40, 41]
The VRP with stochastic demands inspired by waste collection	GA, Adaptive GA, TS	[42, 43],
The capacitated ARP with side constraints inspired by waste collection	Lower-bounding and heuristic	[46]
Solving an extended capacitated ARP for household waste collection	Trips aggregation	[49]
Proposing lower and upper bounds for the split-delivery capacitated ARP	Cutting plane, evolutionary local search	[51]
Optimizing an e-waste collection system	Modified ACS	[54]
Optimizing routing and bin allocation	VNS	[57]

Notes: ACS = Ant colonies system; GA = Genetic algorithm; TS = Tabu search; VNS = Variable neighborhood search.

Earlier studies often modeled residential and commercial waste collection systems as capacitated VRPs without considering many real-life constraints. They allowed a customer (i.e., a collection point) to be visited periodically and allowed the vehicle no more than one trip per day. Angelelli and Speranza [37] did not even consider waste collection as a VRP in case a vehicle has more than one collection route per day. This kind of simplification is no longer reasonable given the advancement of operation research theories, computational capacity, and current complexity associated with modern urban solid waste collection systems. To approximate a more accurate and representative reality, recent studies [35], [39], [41], [43] in this century largely involved multiple realistic constraints such as time windows, lunch breaks, intermediate facilities, multiple shifts, and stochastic demands.

In principle, the optimal or near-optimal solutions for the waste collection VRPs can be obtained by mathematical programming techniques or heuristic algorithms, and solutions can be integrated into a GIS environment for visual decision support [53]. Although mathematical programming techniques can lead to exact solutions or credible bounds, heuristic algorithms are preferred because they can obtain appropriate solutions reasonably quickly. These heuristic algorithms include classical heuristics and metaheuristics. Classical heuristics are often applied to help initialize a near-optimal solution and aid in a local search, and metaheuristics are used for global improvement. Classical heuristics for the capacitated VRP can be modified to manage constraints such as time windows [56] and lunch breaks [39]. For intermediate facilities or multicompartments,

TABLE III
SUMMARY OF EXISTING STUDIES ON THE ROLL-ON ROLL-OFF ROUTING PROBLEM

Scope	Methodology	Reference
Decompose the skip collection to several elementary routes	Clarke-Wright saving, and enumerative algorithm	[1]
Determine solution approaches for the RRVRP	Mathematical programming, hybrid meta-heuristic	[3] [4]
Analyze an RRVRP with multiple constraints	Smart-coll heuristic algorithm	[6]
Analyze an RRVRP with time windows	Large neighborhood search based iterative heuristic	[9]
Transform an RRVRP to a time-dependent VRP in multi-graph	Bounding techniques	[14]

elementary routes are first obtained and then assembled. Classical heuristics improve an initial solution by performing the local search with iterative move operations, which alter the current solution by replacing or relocating nodes and edges. To avoid trapping in a local optimum, metaheuristics are combined with the local search for solution improvement. Various metaheuristics, such as simulated annealing [39], guided local search [60], tabu search (TS) [37], variable neighborhood search [36], [40], ant colonies [34], and genetic algorithm [42], [43], were reported to perform well for solving the issues of waste collection VRPs.

C. Roll-on Roll-Off Routing Problem

The roll-on roll-off routing problem is defined by the inclusion of large containers required to collect waste in rotation. This type of problem is a special variant of the regular waste collection VRPs because each truck (or tractor) is limited to carrying a single large container at a time. This problem is also called the 1-skip collection problem in the literature [6]. If the demand of each customer is an integral multiple of the vehicle capacity, it also can be considered as a roll-on roll-off VRP (RRVRP), which is less complicated than the node and arc routing problem but more complicated than the transport problem. This kind of waste collection VRP was solved by combining multiple bounding methods with heuristic methods (see Table III).

D. Planning With the Aid of Informatics Technologies

Informatics methods including information technologies and dedicated information systems may assist the planning of waste collection (see Table IV). End-to-end solutions can be addressed by positioning vehicles with GPS, tracing containers with RFID, and promoting data utilization within dedicated information systems. For instance, image recognition and sonar technologies can be used to estimate remotely whether a container is full to reduce unnecessary trips. Some commercial products such as Sotkon and Enevo are available for this purpose. Software packages [21], [23] and heuristic algorithms [28] can be employed to help system planning, design and operation, and support decision making. GIS can provide visual feeling to decision makers, and GIS network analysis can calculate real traveling distances that include terrain effects [19], [20]. However, some current basic-level studies limit GIS use to simply generating the alleged best routes without fully considering practical conditions [21].

TABLE IV
SUMMARY OF EXISTING STUDIES ON PLANNING WITH THE AID OF INFORMATICS

Scope	Methodology	Reference
Use a GIS network analysis to optimize waste collection	GIS network analysis	[15-18]
Use a 3D route modeling to optimize waste collection	3D-based GIS network analysis	[19, 20]
Use software packages to optimize waste collection	Software packages such as MapInfo and Roadnet	[21, 22]
Develop a system for the operational decision making of waste collection	Simulation Software, linear programming, Web-GIS	[23, 24]
Improve efficiency and accuracy	Incident recording	[27]
Integrate information technologies into waste collection optimization	GIS, GPS, and traceability technology	[28, 29]
Incorporate RFID and mobile app technology for waste management	RFID, data mining, and Web-based system	[31]
Integrate dynamic time warping and multi-layer perceptron for estimating the amount of waste inside the bin	Image recognition and statistical inference	[33]

TABLE V
SUMMARY OF EXISTING STUDIES ON PLANNING WITH MULTIPLE CRITERIA

Scope	Methodology	Reference
Allocate trucks to disposal sites with consideration of variable waiting times	Marginal analysis	[45]
Create a flexible scheme in which the frequency to unload is determined dynamically	Markov decision process	[48]
Determine multi-criteria optimization for planning an infectious medical waste collection system	Compromise programming	[50]
Develop a multi-objective route selection for nuclear waste transport	GIS-based binary programming	[52]
Coordinate regional waste routing and treatment plant construction under uncertainty	Grey mini-max regret IP	[55]
Assess environmental impact of routing solutions generated by vehicle routing methods	Heuristic, scenario analysis, LCA	[58]
Assess impact of source segregation intensity on fuel consumption and collection costs	Scenario analysis	[59]
Reduce operation costs and pollutant emissions by waste collection optimization	GIS	[61]
Redesign routes for collecting plastic waste by integrating VRP and eco-efficiency	Tabu search, scenario analysis	[62]
Assess environmental and economic impacts for curbside solid waste collection	Mixed IP, scenario analysis, LCA	[63]

Notes: IP = Integer programming; LCA = Life cycle assessment.

E. Planning With Multiple Criteria

Planning with multiple criteria involves more aspects of the optimization strategies than the waste collection VRPs (see Table V). This category of studies considers uncertain waiting times, dynamic demands, fuel consumptions, transportation risks, pollutant emissions, and ecological impacts. Statistical approaches usually deal with the uncertainty [48]. Homogeneous criteria, such as the traveling time and the fuel consumption, can be composited into one objective function, whereas inhomogeneous criteria, such as economic, social, and environmental, are often coordinated by means of multiobjective programming models.

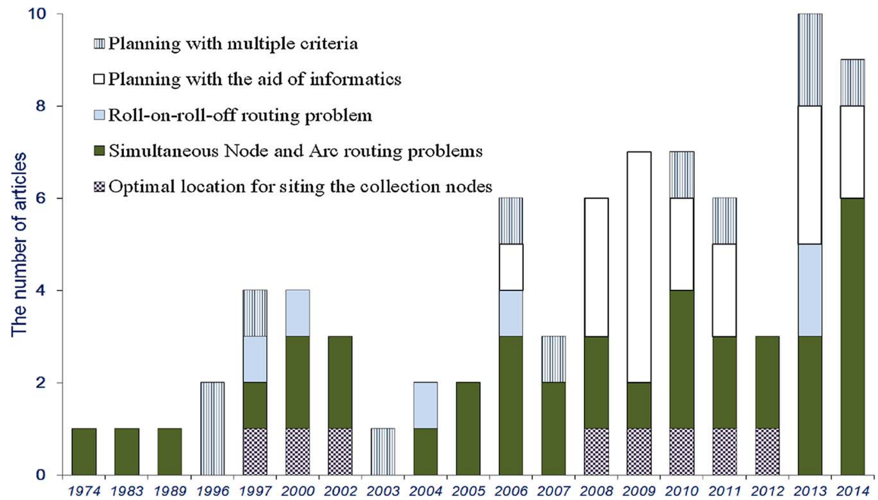

Fig. 1. Trends in the number of publications concerning on the optimization of waste collection.

F. Comparative Analysis

Various kinds of investigations and applications of the optimization analyses and heuristic algorithms have systematically improved both the planning capacity and the reliability of decision making for waste collection, and the number of studies has been growing rapidly in this field (see Fig. 1). However, these existing studies have four intrinsic deficiencies:

1) These studies focused largely on waste collection in the U.S. and Europe but little in Asia, where waste collection issues in many developing countries are changing with rapid urbanization. Because the planning scheme of waste collection varies with population densities, generation rate, operation sequences, cultural habits, waste composition, and management structures, there are remarkable differences among different areas, even within the same countries or regions. For example, periodic collection is often adopted in developed countries, where container monitoring is used to avoid unnecessary trips. By contrast, daily collection is needed in densely populated areas such as many cities in China, India, Thailand, due to the intensive waste generation. Therefore, different collection systems require customized approaches in model implementations.
2) Most existing studies neglect the influences of the waste load of container equipment and the vehicle configuration associated with collection strategies. In densely populated areas such as many Chinese cities, a vehicle often has two working shifts, and a container in the transfer station is often transported many times per day to reduce fixed investments. Time windows will be created because a transfer station sometimes has no container to render service. A daily collection system must manage all waste streams every day rather than allocate different waste streams on different days, such as periodical collection systems in some developed countries [64]. Hence, waste collection in densely populated areas is much more complicated.
3) Previous studies rarely focused on waste separation and differentiated collection. Related studies used multiobjective programming models to deploy multicompartment containers [13], developed an integer programming model to deploy collection points for a two-stream collection system [25], planned daily collection routes for three waste streams [64], and compared operational costs between differentiated and undifferentiated collection schemes [37]. Because differentiated collection is more expensive, some modeling analyses converted a three-stream collection system into a single stream [65]. In addition, using a multicompartmented vehicle to co-collect various types of waste streams brings in an emerging VRP variant named the multicompartment VRP (MC-VRP) [66]. Several comparative studies showed that co-collection outperforms separate collection under ordinary circumstances [60], [67]; however, studies on the MC-VRP cannot be immediately applied to waste collection system analysis because of the lack of realistic constraints.
4) Previous studies rarely addressed the coordination of multiple collection stages. If the shipping distance is too long, a waste collection system involves transfer stations that divide a collection system into two or even three stages. The first stage can be modeled as the node or arc routing problem, whereas the second and third stage can be modeled as the roll-on and roll-off routing problem. There is likely an interaction effect among these stages, particularly when the constraints are complicated. A better optimization model should consider the coordination across different stages, although none is currently available.

III. Modeling for the Two-Stage Waste Collection System With Highest Complexity

The two-stage waste collection system has been widely applied in many Chinese cities such as Beijing, Guangzhou, and Shenzhen, and while more representative than the single-stage

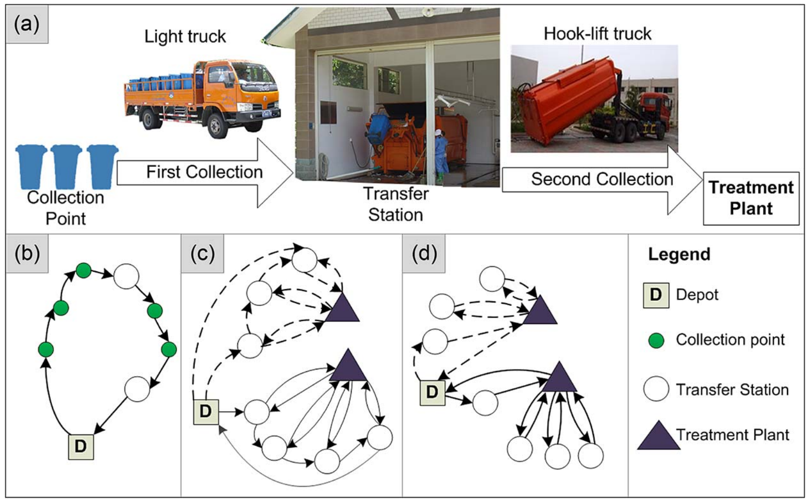

Fig. 2. Two-stage waste collection system. (a) Whole working process. (b) First collection (FC1). (c) Round-trip (SC1). (d) Exchange-trip (SC2).

collection system, it complicates the modeling practices. These waste collection systems do not currently differentiate waste streams but will be reformed soon in view of waste separation initiatives proposed over the past several years. The following modeling practice demonstrates the complexity of a multiconstrained and multicompartment roll-on roll-off waste collection system. The modeling analysis assumes that the amounts of each waste stream at each collection point are the same every day.

A. *Undifferentiated Waste Collection*

1) Daily Waste Collection: The two-stage waste collection system (see Fig. 2) employs two types of vehicle, each of which initiates and terminates its work at the same depot. The start time of the second collection is later than that of the first collection, and the vehicles are required to have two working shifts per day. In the first stage, a light truck collects filled bins from collection point to collection point and when fully loaded will visit the nearest open transfer station to transfers the waste into large containers. Each transfer station has one to several large containers. The empty light truck then starts another collection trip and finally ends its working shift at the depot. During the second stage, hook-lift trucks transport filled containers from the transfer station to a treatment plant or disposal site. Every hook-lift truck is restricted to delivering one container at a time. A trip that delivers the empty container back to its original location of the transfer station is referred to as a round-trip mode, and a trip that delivers the empty container to another transfer station is referred to as exchange-trip mode. The exchange-trip mode is more efficient than the round-trip mode but needs unified management and deployment. For modeling convenience, the undifferentiated collection of a light truck is denoted by FC1 (i.e., first collection mode 1), whereas round-trip and exchange-trip are denoted by SC1 (i.e., second collection mode 1) and SC2 (i.e., second collection mode 2), respectively.

2) Modeling Analysis: The two collection stages can be modeled as node routing and roll-on roll-off routing problems, respectively. Node routing is more appropriate than arc routing for waste collection in densely populated areas, first because the vehicle can load waste at fixed locations with convenience, and second because each node has a high collection demand.

The two different routing problems are coordinated by a supply–demand balance and temporal correlation. Because such a waste collection system has a high collection load, a container is often transported many times at a frequency predetermined during the design stage. If a container has more than one disposal trip per day, it is out of service when full or shipped off, creating a time window complication for the first collection stage. It is important that the time windows of a container are determined by the routing and scheduling of hook-lift trucks. To simplify the problem, the roll-on roll-off routing problem is solved before the time windows of each container are obtained. Subsequently, a transfer station with multiple disposal trips is decomposed into multiple intermediate facilities for the node routing problem, each with a fixed time window. For example, if a transfer station has two containers, each of which has three disposal trips, this transfer station would be decomposed into six intermediate facilities. In other words, if a container has three disposal trips, it has three mapped intermediate facilities, whose time windows must have enough intervals for the container's disposal trips (see Fig. 3).

Based on this two-stage coordination, the node routing model can be formulated as a VRP with multiple constraints, including intermediate facilities, time windows, two shifts, and split deliveries. The vehicle capacity of node routing is integer because waste streams on board are segregated by bins. Two kinds of time windows (TW1 and TW2) correspond to round-trip and exchange-trip (SC1 and SC2), respectively. The time interval of TW1 is narrower than TW2. If each intermediate facility remains open for the duration of the first collection, the constraints of the time windows disappear, creating a hypothetical time window denoted by TW0. Two shifts mean that the vehicle must return to the depot when the time for changing shifts ends. Split deliveries increase efficiency because customer demand is relatively high, and a light truck can only visit a few collection points per trip. Split deliveries here are implemented not only

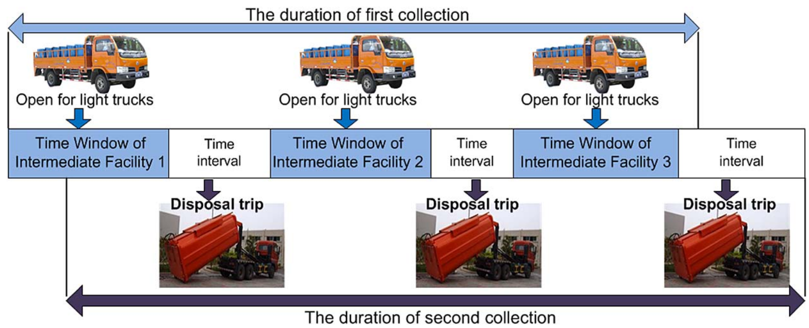

Fig. 3. Coordination of two collection stages by the time windows of intermediate facilities mapped from the same container.

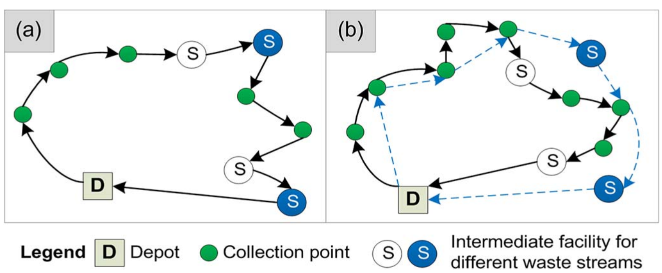

Fig. 4. Two differentiated collection alternatives of light truck. (a) Co-collection (FC2). (b) Separation collection (FC3).

for customer, but also for each waste stream to increase the model flexibility.

Similarly, the roll-on roll-off routing problems can be formulated as a VRP with intermediate facilities, time windows, and multiple shifts. The vehicle capacity of roll-on roll-off routing is ruled as one because a hook-lift truck is restricted to delivering one container at a time. The time windows of roll-on roll-off routing are different from node routing, as noted previously.

B. Differentiated Collection

1) Daily Waste Collection: The current waste separation plan in China often classifies solid waste as four waste streams, including organic, recyclable, toxic, and residual. However, collection firms only address two waste streams during the daily operation because the amount of toxic waste is small, and because the scavengers and scrap dealers sort the recyclable materials before collection. When the two-stage waste collection system is tied to differentiated collection operations, bins and containers are allocated to collect two waste streams at fixed locations. The working processes of second collection are not changed because what the hook-lift truck needs to do is to transport a filled container to a suitable treatment plant or disposal site. The light truck has two alternatives: separately collecting a single stream as an unpartitioned vehicle, or co-collecting various streams as a multicompartmented vehicle. The light truck can be used as a multicompartmented vehicle because waste streams on board are segregated by bins. Note that the total capacity of a vehicle is fixed, but the capacity of a certain compartment is variable (see Fig. 4). Co-collection and separate collection schemes are denoted by FC2 (i.e., first collection mode 2) and FC3 (i.e., first collection mode 3) in the modeling practice, respectively.

2) Modeling Analysis: When the two-stage collection system is reorganized to include the differentiated options for two waste streams in the daily operation, a few minor changes must be implemented in the modeling analysis. For the second collection, a suitable treatment plant for handling a particular waste type is added to the roll-on roll-off routing problems; however, models of SC1 and SC2 need not be changed if the treatment plants can manage different types of waste streams. For the first collection, however, separate collection (FC3) requires using two models to optimize the two types of waste stream, each of which is similar to undifferentiated collection (FC1). Whereas co-collection (FC2) uses one model to optimize both types of waste stream, the FC2 model is different from FC1 in terms of vehicle capacity limitation and supply–demand balance constraints.

C. Models for the Waste Collection VRPs

Waste collection VRPs can be formulated as integer programming models designed to minimize vehicle number and the routing costs (i.e., total travel distances). An implicit objective is added for balancing the workload among vehicles. The main constraints that must fit our modeling analyses are:

- — degree constraints, which impose the number of arc entering and leaving each vertex, ensure vehicle flow continuity, represent the number of shifts, and indicate split deliveries;
- — route capacity, which imposes the maximum workload for a vehicle, is important for balancing the workload among vehicles. In our VRPs with intermediate facilities, route capacity is limited to the maximum number of unloading trips allowed for each vehicle (i.e., the maximum number of elementary routes for each vehicle route), denoted by N^*;
- — vehicle capacity;
- — working durations, which limit travel time for each vehicle;
- — time windows;
- — supply–demand balance; and
- — subtour elimination.

TABLE VI
SUMMARY OF THE VEHICLE ROUTING MODELS

Model features	Node routing			Roll-on roll-off routing	
	FC1	FC2	FC3	SC1	SC2
The number of model	1	1	2	1	1
Multicompartment	×	○	×	×	×
Main constraints					
Intermediate facilities	○	○	○	Treatment Plants	
Multishifts	○	○	○	○	○
Split deliveries	○	○	○	×	×
Time windows	Determined by the roll-on roll-off scheduling.			The time intervals in Fig. 3.	
Route capacity	○	○	○	○	○
Vehicle capacity	○	○	○	○	○
Supply-demand balance	○	○	○	○	○

Notes: ○ indicates the feature is included; × indicates the feature is absent.

This paper demonstrates the ability to employ VRP models for the node routing and roll-on roll-off problems. To facilitate understanding, the two types of waste collection VRP model for a two-stage decision analysis are summarized (see Table VI).

IV. Solution Procedure With the Heuristic Algorithm

Heuristic algorithms have been proposed to obtain vehicle routing and scheduling for the waste collection VRP models with highest complexity. The proposed algorithms have a unified framework to obtain solutions for both collection stages. The unified framework concatenates two steps to approximate the optimal solution of this multiconstrained and multicompartment roll-on and roll-off waste collection issue (MCMC-RORO algorithm). The initialization step constructs an initial feasible solution, and the improvement step then combines local search and TS to achieve the alleged best solution. A solution is composed of multiple vehicle routes, each of which may be partitioned into multiple elementary routes by intermediate facilities. In the unified framework, each waste collection VRP involves three kinds of vertices: the depot, customers, and intermediate facilities. The difference in the solution between two collection stages in sequence is the number of customer on an elementary route.

A. Initial Solution

The proposed method for the initial feasible solution (Algorithm 1 in Table VII) is inspired by the tentative insertion methods used in [40] and [41]. Each vehicle located at the current vertex r keeps searching for the nearest customer u in the unrouted customer set U. Customer u will be visited if and only if its nearest feasible intermediate facility $F(u)$ exists. The feasibility of $F(u)$ means that time and capacity constraints are not violated in the travel, including visiting u, unloading at $F(u)$, and returning to the depot. Note that $F(u)$ consists of two unloading facilities for handling two waste streams in a co-collection system. If the vehicle has ample time and capacity after visiting u, the procedure will decide whether it needs to visit another unrouted customer; otherwise, the vehicle goes to

TABLE VII
ALGORITHM 1—THE GENERAL STRUCTURE OF SOLUTION INITIALIZATION

```
start a route;
repeat
    obtain the nearest customer u and associated F(u);
    if F(u) exists then
        visit u , then update the customer demand;
        if the customer demand is zero then
            U←U \ u;
        end if
        if it's time to change shift then
            unload at F(u) and return to the depot;
        else if the vehicle is full then
            unload at F(u);
        end if
    else
        start a new route;
    end if
until U = Ø
```

$F(u)$ for unloading. If it is time to change shifts, the vehicle should return to the depot.

Algorithm 1 uses two methods to obtain the nearest customer u and associated $F(u)$. For a roll-on roll-off routing problem with a small number of vertices, the solution procedure scans over U to find an appropriate u. Because each iteration requires multiple subcycles to check all the intermediate facilities for each unrouted customer, this method could become hugely time consuming if the number of vertices is large. For a node routing problem with many vertices, the solution procedure generates the visiting sequence of customers by efficient algorithms for the traveling salesman problem (TSP), such as GENI [68], and then inserts appropriate intermediate facilities into the TSP tour. This substitute method can save computational time because it omits much of the meaningless scanning and subcycles; however, the substitute method could decrease the quality of the solution.

B. Local Search

The local search process uses a move operation to improve the initial solution. A move operation removes arcs from two different vehicle routes, decomposes each vehicle route into two or three strings, and recombines strings into two new vehicle routes. After a move operation, the positions representing the shift change of a vehicle route must be relocated. Five move operations (see Fig. 5) are designed for the MCMC-RORO algorithm. Their performances are compared in the preliminary test to select the best one for each specific case.

1) Two Kinds of 2-opt Operations:* The 2-opt* operation decomposes each vehicle route into two strings by removing one arc. This method was shown to be effective in reducing the vehicle number [35]. This study uses two kinds of 2-opt* schemes. The 2-opt*_1 deletes arcs $(j, F(j))$ and $(w, F(w))$ before the intermediate facility or facilities, and the 2-opt*_2 deletes arcs $(F(j), l)$ and $(F(w), x)$ after the intermediate facility or facilities. After deletion, inter-route arcs are built to generate new vehicle routes.

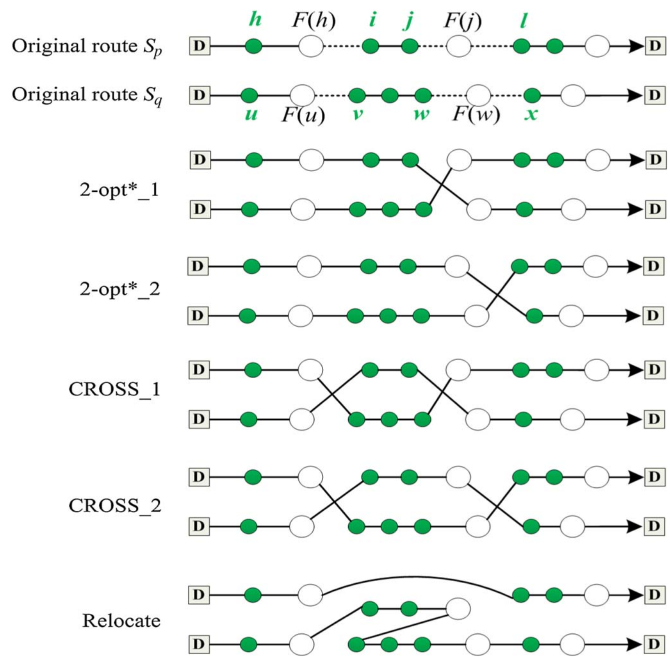

Fig. 5. Five move operations used in this study.

2) Two Kinds of CROSS Operations: The CROSS operation is a more computationally expensive generalization of the 2-opt* moves and decomposes each vehicle route into three strings by removing two arcs. This study uses two kinds of CROSS schemes: CROSS_1 exchanges two groups of consecutive customers between two vehicle routes, and CROSS_2 exchanges two elementary routes.

3) Relocate Operation: The relocate operation removes an elementary route from a vehicle route and inserts it to another vehicle route.

C. TS

The TS method is inspired by the TABUROUTE [69]. Infeasible solutions are allowed by imposing penalties on the objective function $f(s) = c(s) + \sum_{i=1}^{4} \mu_i p_i(s)$, where $c(s)$ is the routing cost, $p_1(s)$ penalizes the case of violating the route capacity, $p_2(s)$ penalizes the case of exceeding the allowable working duration, $p_3(s)$ penalizes the case of violating the time windows, $p_4(s)$ penalizes the case of violating the supply–demand balance, and μ_i is the coefficient for each penalty. These four penalties are used to orient the search process, and the penalty coefficients can be adjusted to stress the importance of a certain constraint. If the penalties add up to zero (i.e., $f(s) = c(s)$), then s is feasible; otherwise, s is infeasible.

The TS procedure gradually seeks a better solution until the number of iterations λ is equal to the maximum number $\lambda_{\max}$. During the procedure, a solution that has been examined is immediately set to be tabu. In this paper, a move operation is identified by those vertices with disconnected original vehicle routes (see Fig. 5), and the tabu list then uses those vertices to characterize the tabu solution to save memory. The tabu state of a vertex decreases to zero stepwise unless it is involved again.

TABLE VIII
ALGORITHM 2 THE GENERAL STRUCTURE OF SOLUTION IMPROVEMENT

initialization;
repeat
  generate $N(s)$ with a certain move;
  for $s' \in N(s)$
    if $f(s') < f(s^*)$ **and** $f(s') = c(s')$ **then**
      update s^*, s, and the tabu list;
    else if the move of s' is not tabu **then**
      if $f(s') \geq f(s)$ **then**
        diversificate s';
      end if
      update $s'_{\min}$ which minimize $f(s')$;
    end if
  end for
  if s^* was not updated **and** $f(s'_{\min}) = c(s'_{\min})$ **then**
    $s \leftarrow s'_{\min}$, update the tabu list ;
  end if
  update the algorithm parameters;
until $\lambda = \lambda_{\max}$

Algorithm 2 in Table VIII presents the general structure of the TS improvement procedure. After initialization, the procedure uses a certain move operation (see Fig. 5) to generate the neighborhood $N(s)$ for the current solution s. Its size $|N(s)|$ is set as five times larger than the vehicle number. At every iteration, each neighbor $s' \in N(s)$ is compared with s and the best solution s^* so far. If s' is better than s^* and is feasible simultaneously, s^* is replaced by s' according to the aspiration criteria; otherwise, another nontabu neighbor worse than s should be selected and penalized for joining the campaign according to the diversification strategy, which diverts the search process from the most frequent moves. The intensity of diversification can be adjusted by using a scaling factor.

In this MCMC-RORO algorithm, two complementary strategies are used for making the procedure more flexible and robust. One is to fine tune the penalty coefficients μ_i after every iteration by dividing μ_i by a factor if the associated $p_i(s)$ is equal to zero, and multiplying μ_i by the same factor if not. The other is to adjust the tabu tenure θ iteratively. If s^* is improved at one iteration, then shorten θ; but if s^* is not improved after a certain number of iterations, then lengthen θ. Note that the tabu tenure θ can only have a value in the range $[\theta_{\min}, \theta_{\max}]$.

V. RESULTS AND DISCUSSION

The MCMC-RORO algorithm is coded and complied in a MATLAB 7.8 environment. The program is run on a computer with 3.2-GHz processor (Intel Core 2 Duo E5800) and 2-GB memory. The Luohu district of Shenzhen in China was selected for the purpose of demonstration.

A. Real-life Example

The study area in the Luohu district of Shenzhen, China (see Fig. 6) is an ideal case to elucidate the complexity of an urban solid waste collection system. Its two-stage waste collection scheme involves 3 treatment plants, 43 transfer stations, and numerous collection points. The system uses two kinds of collection vehicles to collect 1130 tons of waste per day. The

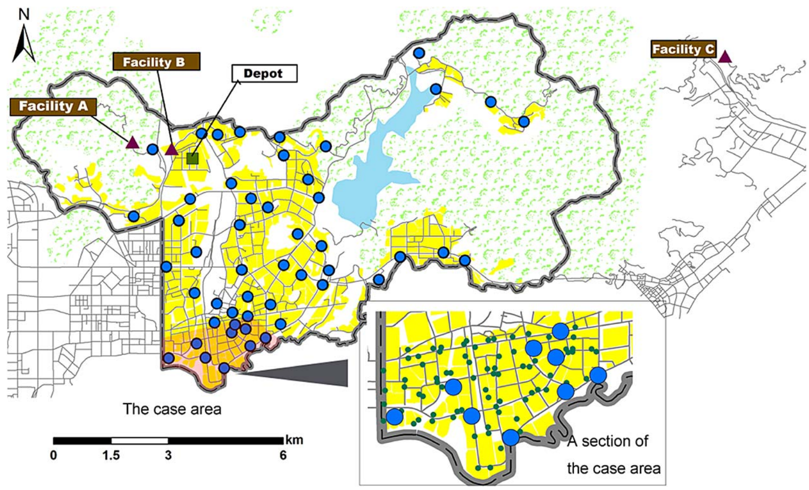

Fig. 6. Study area in Shenzhen, China.

light truck can carry 18 bins (about 2 tons) at most, whereas the hook-lift truck can carry about 10 tons of waste in one container per trip. The waste collection business is divided into various sections. The northwestern section covering about 3 km^2 was chosen for modeling analysis to solve the node routing problem. This section involves 9 transfer stations and 80 collection points, aiming to collect 118.6 tons of waste per day. All the containers associated with 9 transfer stations would have 18 disposal trips in total per day; therefore, there are 80 customers and 18 intermediate facilities in the node routing problem *per se*. In more detail, the total customer demand is 1244 bins, the average demand per customer is 15.6 bins, and the demands for two waste streams are 753 and 491 bins when using differentiated collection.

The light trucks work during the period between 4:00 and 20:00 and change shifts at the period from 12:00 to 13:00. The working duration of hook-lift trucks is 2 h later than the light trucks. The time windows in the node routing problem are obtained by solving the roll-on roll-off routing problem with regard to the prescribed coordination systematically. TW1 generated in SC1 is about 116 min narrower than TW2 generated in SC2. TW0 assumes that the intermediate facilities remain open. The travel times and distances among locations can be acquired from a GIS database.

According to the financial analysis, the first collection cost is evaluated by $550.20|K| + 1.22c(s)$, whereas the second collection cost is evaluated by $658.99|K| + 2.43c(s)$, where K denotes the vehicle number, and $c(s)$ denotes the total traveling distance in kilometers. The unit cost is the collection cost per ton, denoted by ¥/tonne (¥ represents RMB, the monetary unit in China; the 2014 currency ratio was 6.3¥ to 1 US).

B. Results of the Roll-on Roll-Off Routing Problems

The roll-on roll-off routing should be calculated first to determine the time windows for the node routing. The values of model parameters are determined by preliminary tests and analyses, and the computational results for SC1 and SC2 are then compared with empirical scheduling outputs (see Table IX). The optimization analysis has proved effective for roll-on roll-off routing; the vehicle number and total traveling distance are substantially reduced, and SC2 has a better performance than SC1.

TABLE IX
COMPUTATIONAL RESULTS OF THE SECOND COLLECTION STAGE

Working mode	Vehicle number	Total traveling distance (km)	Unit cost (¥/tonne)
Before optimization	12	2825.0	12.66
SC1 after optimization	11	2105.6	10.94
SC2 after optimization	10	1749.7	9.59

C. Results of the Node Routing Problems

The values of model parameters are determined by preliminary tests based on the literature [40], [69]. The maximum number of iteration is set equal to 800, which guarantees both the calculation accuracy and relatively low computational time. The CROSS move operation was found superior to other move operations.

After the preliminary tests, the heuristic algorithm is run to obtain the results (see Table X). The improvement rates of TS over the initial solutions prove the effectiveness of TS. The zero improvement of TS in the case of TW1 reveals that the narrow time windows handicap optimization. The results show that the optimization process approximated by the MCMC-RORO algorithm has an immense advantage over other empirical scheduling counterparts. Most important, the results provide invaluable insight into implementation of differentiated waste collection. Table X reveals that differentiated collection increases the collection costs, and routing costs show that FC3 may outperform FC2. Although it seems that FC3 uses one more vehicle, the extra vehicle only serves a few customers and can be laid off by adjusting the route capacity or the length of work duration. In addition, the weakness of the narrow time windows (TW1) is particularly conspicuous in FC2, as evidenced by the difference in unit cost.

TABLE X
COMPUTATIONAL RESULTS ON THE REAL-LIFE INSTANCE

Working mode	Time windows	Initial Solution			Improved Solution			Improvement rate over initial solution	
		Vehicle number	Routing cost (m)	Unit cost (¥/tonne)	Vehicle number	Routing cost (m)	Unit cost (¥/tonne)	In routing cost	In unit cost
Before optimization									
FC1	TW1	6	408000	32.16	-	-	-	-	-
After optimization									
FC1	TW0	4	182612	20.52	4	175052	20.44	4.14	0.38
	TW1	4	208942	20.79	4	208942	20.79	0.00	0.00
	TW2	4	191535	20.61	4	178681	20.48	6.71	0.64
FC2	TW0	4	292742	21.65	4	257498	21.29	12.04	1.68
	TW1	5	340120	26.80	5	340120	26.80	0.00	0.00
	TW2	4	329246	22.03	4	290568	21.63	11.75	1.81
FC3	TW0	5	214577	25.50	5	212027	25.48	1.19	0.10
	TW1	5	220335	25.56	5	220335	25.56	0.00	0.00
	TW2	5	216060	25.52	5	214106	25.50	0.90	0.08

Note: The currency ratio of ¥(Chinese Yuan Renminbi) and US$ is 6.3 in 2014.

TABLE XI
ELAPSED TIME IN SECONDS ON THE REAL-LIFE INSTANCE

Working mode	Solution initialization	Solution improvement				
		2-opt*_1	2-opt*_2	CROSS_1	CROSS_2	Relocate
FC1	34.71	27.68	27.28	29.36	29.92	29.28
FC2	65.20	96.88	95.12	93.6	97.6	91.6
FC3	69.42	55.36	54.56	58.72	59.84	58.56

Furthermore, the computational time is a key factor in the feasibility of the proposed algorithm, and the computational time is modest with respect to the complexity of our problem (see Table XI). Solution initialization is time-consuming because the GENI algorithm is run multiple times to generate a TSP tour with the lowest cost. FC3 costs twice as much computational time as FC1 because the algorithm is run twice for two waste streams. FC2 also costs more in computation than FC1 because its solution structure is more complicated.

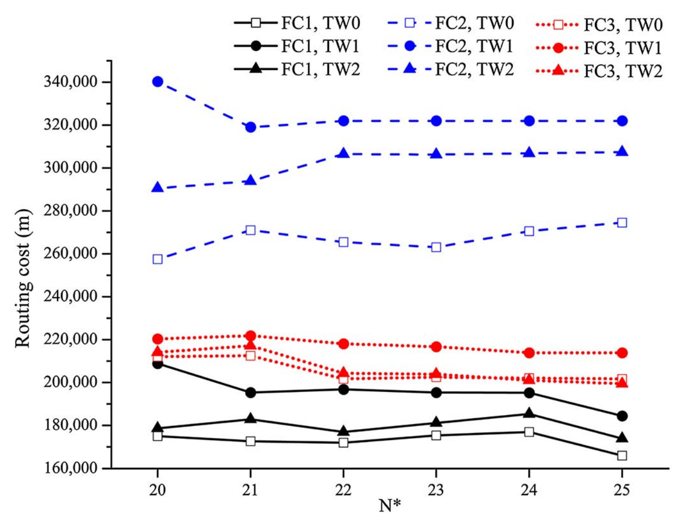

Fig. 7. Impact of route capacity N^* on the routing costs.

D. Sensitivity Analysis

The most problematic point for differentiated collection is whether the separation collection maintains an advantage over co-collection when the main constraints and parameters vary. The sensitivity analysis is thus employed for this purpose.

1) Extent of Time Windows: Table X shows that the initial solutions are more difficult to improve under the time window of TW1. When we artificially widen TW1 for a certain intermediate facility from 109 to 700 min, the routing cost of the initial solution is reduced by 3.3 km and the initial solution is improved by 3.79% with the aid of CROSS_1 move operation. We speculate that the temporal distribution of time windows acutely affects further improvement of the routing cost as well as the average width of time windows.

2) Route Capacity N^*: The results in Table X are computed when the route capacity N^* is set equal to 20. Although the collection efficiency is raised by 66.7% in comparison with the empirical scheduling counterpart when $N^* = 20$, each vehicle has more than 100 min of free time after completing 20 elementary routes. Hence, the impact of N^* on routing costs is assessed. Increasing the value of N^* is seemingly beneficial (see Fig. 7), but the effect is irregular and not always useful; therefore, the value of N^* remains the same.

3) Vehicle Capacity: The results in Table X are computed when the vehicle capacity $m_k = 18$ (i.e., the capacity of light truck), indicating that the routing cost of separate collection is lower than that of co-collection with respect to any designated time windows. This phenomenon is different from [60] and [67], in which the co-collection outperforms the separate collection but is in line with speculation about when the advantage of co-collection disappears because the customer demands are large. In our real-life case, the demand per customer per commodity is more than one third of m_k. Hence, the impact of m_k on routing costs is assessed to determine whether increasing m_k may make co-collection better than separate collection

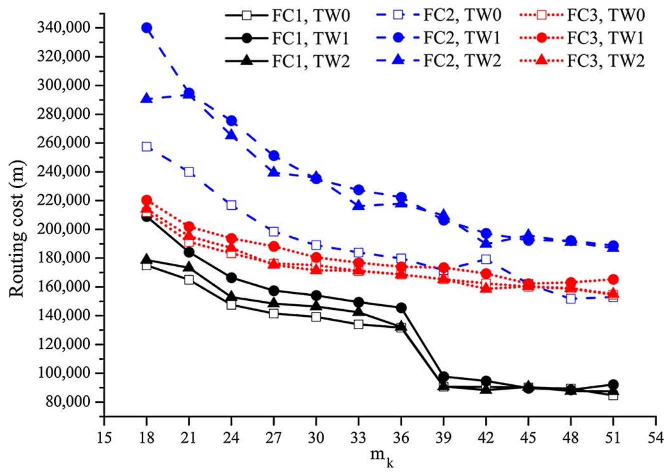

Fig. 8. Impact of vehicle capacity m_k on the routing costs.

TABLE XII
IMPACT OF VEHICLE CAPACITY ON THE VEHICLE NUMBER

Vehicle capacity	FC1			FC2			FC3		
	TW0	TW1	TW2	TW0	TW1	TW2	TW0	TW1	TW2
18	4	4	4	4	5	4	5	5	5
21	4	4	4	4	5	5	4	4	4
24	3	4	3	3	5	4	4	4	4
27	3	3	3	3	4	4	4	4	4
30	3	3	3	3	5	4	4	4	4
33	3	3	3	3	5	4	4	4	4
36	3	3	3	3	5	4	4	4	4
39	2	2	2	3	5	4	4	4	4
42	2	2	2	3	4	4	4	4	4
45	2	2	2	3	5	5	4	4	4
48	2	2	2	3	4	4	4	4	4
51	2	2	2	3	4	4	4	4	4

when involving multiple constraints such as time windows and intermediate facilities. When m_k increases, the routing costs and the number of unloading trips are reduced, and the influence of time windows on the routing cost subside (see Fig. 8). If the time window is TW0, co-collection prevails when $m_k \geq 45$; however, the constraint of time windows exists and prevents co-collection from out-performing separate collection. Separate collection maintains a significant advantage over the co-collection when m_k almost triples (see Fig. 8).

Table XII also presents the impact of m_k on the vehicle number. The vehicle number decreases with the growing m_k under TW0 but fluctuates under the real-time windows TW1 and TW2; however, the vehicle number of differentiated collection is never smaller than that of the undifferentiated collection under the same time window. Enlarging m_k may change the vehicle type and increase the fixed costs, and the collection firm requires deploying at least four vehicles for the differentiated collection if not increasing the vehicle capacity. In practice, the crews usually tilt the hydraulic lifting tail-board and carry three more bins for the sake of fewer trips, which in practice makes m_k equal to 21; therefore, FC3 has an advantage over FC2 in terms of the vehicle number when $m_k = 21$ (see Table XII).

E. Recommended Routing Strategies

The preferred routing strategies of differentiated waste collection can be summarized through the sensitivity analysis. First, hook-lift trucks should perform the exchange-trip service to make the light trucks work in association with the time window TW2. Second, light trucks need some small technical retrofits to increase the capacity to 21 bins. Lastly, light trucks can be divided in to two fleets, each of which is in charge of one waste stream. This way, the unit cost of differentiated collection is 20.65 ¥/tonne, slightly more than the unit cost of undifferentiated collection (20.48 ¥/tonne) under the same time windows.

VI. SMART AND GREEN URBAN SOLID WASTE COLLECTION SYSTEMS: FUTURE PERSPECTIVES

The VRP models and heuristic algorithms contribute to the green solution with shorter traveling distances, fewer vehicle numbers, and reduced environmental impacts. These models and algorithms can aid in the waste collection performance if integrated with information techniques such as RFID, GPS, and GIS, techniques known to promote the planning of waste collection and contribute to a smart waste collection systems. Such green goals are not difficult to achieve because information systems for waste collection have already been developed in big cities such as Shenzhen [70]; however, these systems have only basic-level integration, such as tracking vehicles by GPS. If a few technical barriers can be improved, these methods can enhance the efficiency and cost-effectiveness of the whole waste collection process with less environmental impact.

1) Identification and Tracking: Different waste streams stored in different bins can be identified and traced by RFID, and different waste types can be distinguished by image sensing. The RFID tag communicates with RFID readers, image sensor nodes, and even smartphones. The attributes of a bin attached with a RFID tag are pulled from the remote database through querying the unique identification code of the tag. Moreover, RFID, GPS, Wi-Fi, and other sensor nodes can be combined as a trilateration-based real-time location system, which can provide positioning for not only collection vehicles but also indoor and outdoor collection points. With the aid of RFID and real-time location, the waste flow can be finely and more efficiently controlled from spatial and temporal perspectives.

2) Weighing at the Source: Weighing at the source is a precondition of many fine management strategies such as weight-based motivation and punishment. Waste streams can be weighed *in situ* through the vehicle-mounted scales and self-weighing containers or *ex situ* through the platform scales at transfer stations [26], and the weight is immediately associated with the identification code of RFID tag. The weight could be also estimated by the volume observed from image sensors that can be applied to avoid unnecessary waste collection trips in suburban or rural areas.

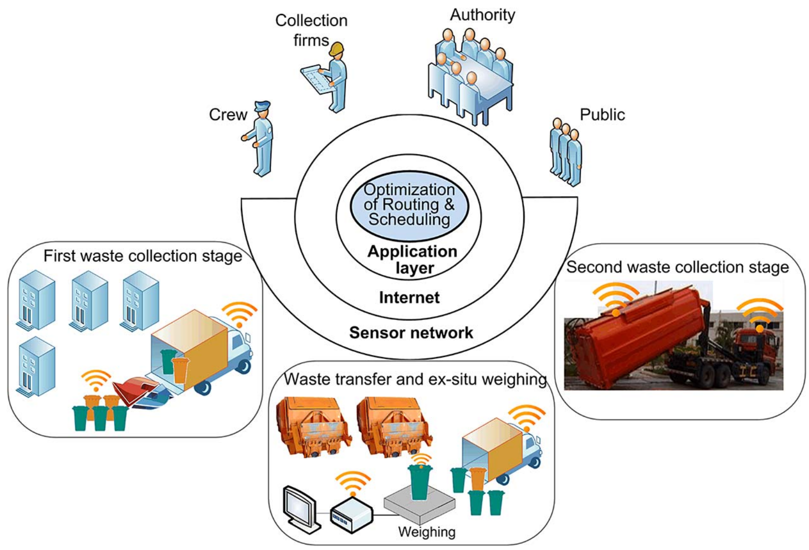

Fig. 9. Smart and green urban solid waste collection system.

3) Sensor Networks: Sensor networks come from the communication and cooperation of various sensor nodes such as sensors, GPS terminals, RFID tags, and RFID readers those perceive and measure real-world features and convert them into digital signals. The spectrum of sensor nodes used for waste management ranges from photoelectric to resistive, capacitive, magneto-electric, strain gauged, semi-conductive, and biological [26]. Sensor networks extend the ubiquitous sensor nodes for various applications. They are mostly bidirectional, enabling the transmission of data and the reception of instruction, and mostly wireless, enabling the spatial distribution of autonomous sensor nodes. Sensor networks can be integrated with other kinds of wireless mesh networks, such as a Wi-Fi-based medium-range network, to reduce the complexity and cost for a large-scale and self-adaptive smart application.

Sensor networks can be divided into centralized and decentralized. A centralized sensor network processes and utilizes data by central nodes. It has a high level of accuracy but requires strict communication and computing resources. In contrast, a decentralized sensor network allows each node to manage data *in situ* and uses some sink nodes to fuse the processed data. It is more scalable and robust than the centralized network because the failure of a few nodes does not affect the overall availability and stability.

4) Smart and Green Waste Collection Strategies: Future information systems may help perform smart and green waste collection across the whole process (see Fig. 9). In such a system, RFID tags are attached to bins and containers, RFID readers and GPS are equipped to vehicles, and weighing scales are distributed at transfer stations. All the elements can communicate with each other through sensor networks with the aid of centralized and/or decentralized servers to gather information in real time and dynamically run the proposed MCMC-RORO or similar algorithms. The optimized routing and scheduling strategies can be sent to vehicles with instructions via the smartphone and other terminals. The performance of vehicles and other equipment linked to these communication networks can be monitored and analyzed at all times, and the improvement strategies can be continually generated and reported back to the crew members and mission-control staff. The decision makers, public agencies, collection firms, crew members, and other stakeholders may interactively participate in such sustainable solid waste management plans through these smart and green waste collection systems. For more details about how to perform the integration of system analysis models and information technologies, please refer to the literature [26].

VII. Conclusion

We conducted a thorough literature review on the optimization of urban solid waste collection systems and summarized four intrinsic deficiencies of the existing studies regarding sustainable waste management. Because the existing studies neglected regional differences in waste collection and associated optimization schemes between developing and developed countries, we analyzed the differences between the cities of developing and developed countries. The two-stage collection scheme deemed as a standard urban solid waste collection scheme in China falls under not only the node routing problem but also the roll-on roll-off routing problem in systems analysis. As a demonstration, such a system in Shenzhen, China, was selected for modeling analysis. Considering multiconstrained, multicompartment, and RRVPs, the models help implement waste separation and differentiated collection, which is recognized as the most complicate urban solid waste collection scheme to date. The MCMC-RORO algorithm was inspired by some existing studies and combines novel designs to carry out modeling and problem solving. The MCMC-RORO algorithm performed well in the real-life case of Shenzhen, China. Results indicate that the optimization has an immense advantage over empirical scheduling outputs and reveal that differentiated collection increases the routing cost. Sensitivity analysis was conducted to recommend better strategies for differentiated collection. This paper shows that separate collection outperforms co-collection in the real-life instance with multiconstraints. Supplementary measures were suggested for reducing the collection cost, including deploying hook-lift trucks to perform the exchange-trip service and enabling light trucks to carry 21 bins by implementing small technical retrofits. We integrated various information technologies to aid in designing a smart and green urban waste collection system. Such futuristic delineation may benefit various simulation and optimization schemes with varying realistic constraints for sustainable solid waste management across heterogeneous, fast growing urban environments.

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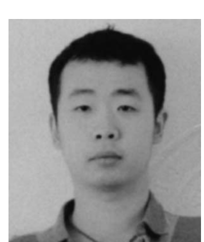

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