



A stochastic optimization framework for planning of waste collection and value recovery operations in smart and sustainable cities



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ARTICLE INFO

Article history:

Received 8 December 2017

Revised 1 May 2018

Accepted 11 May 2018

Keywords:

IoT-enabled waste collection and recovery

Smart cities

End-of-life recovery

Chance-constrained programming

ABSTRACT

The concept of City 2.0 or smart city is offering new opportunities for handling waste management practices. The existing studies have started addressing waste management problems in smart cities mainly by focusing on the design of new sensor-based Internet of Things (IoT) technologies, and optimizing the routes for waste collection trucks with the aim of minimizing operational costs, energy consumption and transportation pollution emissions. In this study, the importance of value recovery from trash bins is highlighted. A stochastic optimization model based on chance-constrained programming is developed to optimize the planning of waste collection operations. The objective of the proposed optimization model is to minimize the total transportation cost while maximizing the recovery of value still embedded in waste bins. The value of collected waste is modeled as an uncertain parameter to reflect the uncertain value that can be recovered from each trash bin due to the uncertain condition and quality of waste. The application of the proposed model is shown by using a numerical example. The study opens new venues for incorporating the value recovery aspect into waste collection planning and development of new data acquisition technologies that enable municipalities to monitor the mix of recyclables embedded in individual trash bins.

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1. Introduction

The smart city can be defined as a smart combination of infrastructure, activities and aware citizens with well performance in fundamental components such as smart economy, environment, mobility, quality of living and smart government (Giffinger et al., 2007). As urban population is growing very fast (Fazio et al., 2012), there is an urgent need for efficient utilization of resources in urban areas and mega cities. In order to manage advanced, newly emerging and fundamental needs, the use of smart infrastructure and capabilities offered by Industry 4.0 is considered as one solution (Balakrishna, 2012). The use of the wireless sensors and actuators will enable technologies such as Internet of Things (IoT) to reconstruct urban activities in smart cities in almost all aspects of daily life (Jara et al., 2014).

One fundamental challenge in improving the quality of life in urban area is the proper management of growing waste generated

as a result of industrial development and consumers' consumption behaviors. Waste generation rate is growing rapidly due to the rise in the standards of living, rapid urbanization and developed economies (Minghua et al., 2009). In order to increase the quality of life for citizens and minimize negative environmental effects, the effective management of the waste becomes very critical.

Waste management practices deal with different activities ranging from waste collection, and waste separation to waste recovery and recycling. Various waste collection and recovery systems have been developed for effective management of different types of wastes during their entire lifecycles. Information and communication technologies (ICT) offer fundamental advantages for solving waste management issues when incorporated with existing systems. One example is the dynamic collection of waste due to the capabilities offered by ICT. In past years, waste collection was treated in a static manner, but nowadays dynamic solutions are enabled by the production of newly developed sensors, actuators and IoT technologies (Carli et al., 2013), where bins can be equipped with various IoT components and sensors such as capacity sensors, weight sensors, temperature sensors, humidity sensors, chemical sensors, pressure sensors and actuators (Li et al., 2013).

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Although recent research in smart cities has proposed some IoT-based strategies for waste collection, transportation, dynamic routing, and dynamic waste collection scheduling, some important issues are still remaining. The objective of value recovery from waste is one of the important issues on which very few studies, if any, has been done. The focus of previous research mainly has been on the on-time waste collection rather than the value recovery.

In this paper, we offer a stochastic optimization model for enhancing the value recovered from collected waste in smart communities. It should be noted that the proposed approach can be employed for any types of waste or mixture of waste. We have developed a waste value recovery function and an allocation model for simultaneous maximization of waste value recovery and minimization of transportation costs. The value embedded in each trash bin is modeled as a random variable with normal distribution. The model has been solved using chance constrained programming method to deal with the uncertainty in the objective function. An example of plastics waste recovery has been provided to show the application of the model, since plastics have a high daily use, high waste rate and high levels of recycling.

The rest of this paper is organized as follows. Section 2 presents the related research and prior studies. Section 3 represents the proposed system architecture for waste management in smart cities. Section 4 describes our allocation models. Section 5 represents the application of the proposed models and several sensitivity analyses on the model parameters. Finally, Section 6 concludes the paper and discusses the future scope.

2. Literature review

Waste management practices can be divided into different categories, ranging from waste collection, and separation to waste recovery and recycling. While an extensive literature exists regarding the optimization of general waste collection and recovery operations, the literature on waste management in smart cities is limited. In this section, first we will provide an overview of research on the scheduling of waste collection and recovery operations, and then we will discuss the most recent studies on waste management practices in smart cities.

In order to identify research gaps in waste collection problems in smart cities, first we will review the literature on vehicle routing problems. Various heuristic and non-heuristic models have been offered in transportation literature for solving routing problems, to name a few studies Reed et al. (2014) have proposed a dynamic model for capacitated vehicle routing problems using Ant Colony System algorithm (Reed et al., 2014). Hemmelmayr et al. (2013) have proposed a heuristic solution for solid waste collection as a periodic truck routing problem (Hemmelmayr et al., 2013), where the collected waste can be delivered into some intermediate facilities and not every collection points need to be covered every day. Banditvilai and Niraso (2017) have proposed a simulation framework for modeling the night shift solid waste collection in Phuket Municipality, Thailand and developed a heuristic approach for assigning waste collection zones and routings (Banditvilai and Niraso, 2017). In order to solve periodic routing problem in the municipal waste collection, Triki (2017) developed a model for defining the routing of collection vehicle with considering the extended planning horizon for some zones, where not all the zones should be served in one planning horizon and the planning horizon can be flexible depending on the needs of different regions (Triki, 2017). To serve multiple disposal facilities with huge amount of waste, Wy et al. (2013) have developed a routing model by integrating several heuristics algorithms to minimize the number of collection vehicles and the total route time considering several

factors and constraints such as multiple disposal facilities, different types of client demands (e.g. residential, commercial, industrial), different time periods for demands, and different sizes of containers (Wy et al., 2013).

Moreover, various dynamic models and algorithms have been proposed in the literature to facilitate both waste collection and recovery practices. Gruler et al. (2017) have combined metaheuristics with simulation and proposed a hybrid algorithm for waste management in clustered urban areas (Gruler et al., 2017) considering the impact of cooperation among vehicles departed from different depots and the corresponding savings this cooperation could create. Braier et al. (2017) have proposed an integer programming model to optimize the dynamic routs of collection vehicles for the case of waste collection in Morón, Argentina (Braier et al., 2017). To perform routing enforced with the conflicts context and time windows, Minh et al. (2013a, 2013b) introduced a memetic algorithm to achieve multi-objective optimization for determining the number of vehicles and the trip times considering several constraints such as the time window of waste collection for each regions, the conflicts between waste characteristics, and the availability of multiple landfills (Minh et al., 2013a, 2013b).

Most recently, the concept of waste management in smart communities has been the point of attention in the literature. Overall, the studies that have addressed information technology-based waste collection objectives can be categorized into four main groups: (1) studies that have focused on the development of data acquisition technologies such as sensor-based technology, geographic information systems (GIS), and image processing technologies, (2) studies that have discussed data transformation platforms for transferring data collected through data acquisition technologies to central control platforms used by municipalities, (3) studies that have developed analytical models to demonstrate the application of capabilities of IoT enabled technologies for proper waste collection activities, and finally (4) studies that have shown the capabilities of information technology in real case studies. The main focus of the current study is on the third group of studies, waste collection operations in a smart environment, however, we will briefly review several studies from other categories.

To name a few studies from each category, Vicentini et al. (2009) designed a testing prototype of intelligent containers to measure the actual weight and volume of waste present in each container in Pudong, New Area, Shanghai and transfer the information to a central control system for municipalities. Faccio et al. (2011) defined a framework for integrating real-time data collected from traceability devices into waste collection routing models to determine the number of vehicles, travel time, and areas covered by each vehicle. Chang et al. (1997) also applied a multi-objective optimization model within a GIS environment to optimize the routing and scheduling of waste collection vehicles in Taiwan. Zamorano et al. (2009) also conducted a GIS-based data collection in Churriana de la Vega, Spain to show that the number of location of trash containers can be optimized to reduce the costs resulting from an excessive number of containers. In addition to minimizing operational costs, some studies have adopted multiple objectives. For example, Anghinolfi et al. (2016) have formulated a multi-objective mixed integer linear programming model that aims to not only minimize costs but also environmental impacts. Rada et al. (2013) discussed the application of Web-GIS with RFID in multiple Municipalities in the north of Italy and showed the waste separation efficiency and cost reduction in several aspects.

Most of the IoT-enabled waste management studies have been focused on optimizing routing and scheduling of waste collection vehicles within smart communities. Two types of methods have been developed to facilitate waste collection in smart cities, namely static and dynamic planning models (Anagnostopoulos et al., 2015b). The static models ignore the real-time status of trash

bins, while the purpose of *dynamic* models is to include the most up-to-date information received by sensors on the trash bin status into consideration when defining the waste collection plans. Since static approaches do not consider the dynamic capabilities offered by IoT, a number of studies have developed dynamic models with the aim of reducing the total cost, time and distance (Anagnostopoulos et al., 2015b; Minh et al., 2013a, 2013b). Christodoulou et al. (2016) have worked on a project named Dynacargo (Dynamic Cargo Routing on-the-Go), where they have proposed various routing algorithms to solve dynamic routing problems using IoT components and real-time monitoring of waste bins trash levels (Christodoulou et al., 2016).

Sharmin and Al-Amin (2016) developed an Ant Colony algorithm and solved a dynamic routing system to find the shortest path while minimizing transportation costs with the overall purpose of waste management in smart cities (Sharmin and Al-Amin, 2016). Shinde et al. (2017) have designed a dynamic smart solid waste management system by integrating RFID, GSM, GIS system to manage the solid waste in an automatic waste monitoring system (Shinde et al., 2017). Anagnostopoulos and his colleagues developed several studies that handle dynamic routine models for waste collection in smart cities (Anagnostopoulos et al., 2015b,c; Anagnostopoulos and Zaslavsky, 2014). For more information about the waste collection and routing problems in smart cities, we refer readers to the following review paper by Anagnostopoulos et al. (2017).

Al Mamun et al. (2016) have proposed a design for automatically monitoring of trash bin status by developing an integrated sensing system (Al Mamun et al., 2016). In addition to the capabilities offered by IoT infrastructure, Elia et al. (2016) have discussed the importance of evaluating the performance of new business models coming to the waste management market as a result of IoT-based solutions. They compared the cost efficiency of dynamics scheduling models of waste pick up (based on household needs) with the traditional waste collection models such as fixed routing and call-based service (Elia et al., 2016).

As discussed above, the previous literature on waste management in smart cities has mainly focused on enhancing waste collection activities by solving dynamic vehicle routing and scheduling problems. While the collection of waste is an important issue, the waste separation and recovery are other key aspects that should be included in smart waste management planning practices.

Waste separation has a very high impact on the effectiveness of waste management systems (Sukholthaman and Sharp, 2016). Waste separation from origin in household is an essential element to achieve high rates of recycling and reuse (Stoeva and Alriksson, 2017). A considerable number of survey studies have been conducted to identify the psychological and demographic factors that influence people's recycling behavior. To name a few, Xu et al. (2017) have constructed several questionnaires and survey analyses to identify the impact of individual moral obligation and past experience on household waste separation intention and behavior (Xu et al., 2017). Ofstad et al. (2017) designed a questionnaire to better understand the mechanisms behind changing people's recycling behavior (Ofstad et al., 2017).

Improving the waste separation and recovery operations by relaying mainly on the household behavior seems challenging and impractical. The most recent capabilities offered by IoT-enabled solutions may solve some of the challenges by providing some intermediate solutions, where the reported weight and types of the waste could help city officials in planning waste collection activities and giving priorities to regions with higher potential of value recovery. While the concept of value recovery from waste is well-addressed in the sustainability literature, the value

recovery has not received sufficient attention in prior smart cities studies.

So far, most of the previous studies have been focused on the design of new sensor-based IoT technologies, dynamic routing, and scheduling problems to reduce operational, fixed and transportation costs and time. To the best of our knowledge, no study has been focused on the importance of value recovery from trash bins in smart cities. The main contribution of this paper is on pointing out the importance of value recovery efforts and proposing a framework for incorporating the uncertain value of recovered waste from individual bins in decision making during waste collection operations. The existing studies optimize the allocation of waste collection vehicles based on minimizing the operational costs without considering the potential value recovered from collection activities. To address this research gap, in this study we have developed a stochastic optimization model with the aim of maximizing the uncertain value recovery from trash bins while minimizing transportation costs. The study also reveals the need for designing new sensor technologies such as infrared spectroscopy sensors that facilitate the detection of the mix and conditions of waste in trash bins. The current data acquisition technologies only focus on collecting the weight, volume and location of waste containers with little attention to the mix of waste. This is particularly important in societies where not all types of waste (e.g. plastic, glass, food, metal) are separated from origins and technological advancements are needed to facilitate waste detection, separation, collection and recovery.

Once products reach their end-of-use phase, there are several options available for their value recovery ranging from repair and reuse to remanufacturing and recycling. It should be noted that the value recovery is not limited to only economic outcomes and can refer to any economic, environmental and social outcomes (e.g. recovering specific goods for reuse, social outcomes, less pollution). In this paper, we focus on the economic value rather than environmental or social value of recovery operations. However, the objective function of the proposed model can be tuned to reflect other environmental and social aspects as well.

3. Overview of waste collection and recovery infrastructure

The proposed model in this paper assumes similar configuration for smart cities as (Anagnostopoulos et al., 2015a). In the proposed model the smart city is divided into discrete multiple sectors where a heterogeneous fleet of trucks handle the waste collection operations. Each sector within the city has an intermediate depot or a set of intermediate depots which serves as a waste separation unit and a temporary waste storage and a certain number of Low Capacity Trucks (LCTs) that serve the sector. In addition, the city has a certain number of High Capacity Trucks (HCTs) that transfer collected wastes in depots in large quantity to a recovery site outside of the city (Fig. 1). Similar to Anagnostopoulos et al. (2015a), the current study aims to assign trash bins to LCTs, but the proposed method and objective are different than the previous study. While Anagnostopoulos et al. (2015a,b,c), developed a heuristic assignment algorithm with the aim of minimizing operational costs, the current study develops an optimization model and aims to maximize the value recovery. Therefore, although both studies try to solve assignment problems, their proposed methods and objectives are different.

Each house has several smart bins for collecting different types of waste. For example, plastic waste bin, paper waste bin, food waste bin and a bin for other waste. Specifically, LCTs move within the city and transfer waste bins from households to the intermediate depots. An intermediate depot serves as a temporary waste

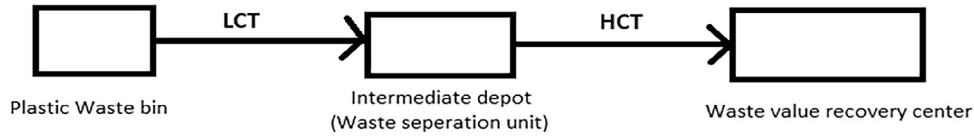


Fig. 1. An overview of the infrastructure available for waste collection and recovery.

storage unit and also as a waste separation unit. Depots separate the waste according to their types and determine the value recovery variable according to the quantity and the type of waste collected. HCTs collect a specific type of waste (e.g. plastics) from the intermediate depots and transfer it to the recovery plants outside the city where collected waste is recycled. The number of LCTs and HCTs depends on the total quantity of waste and trucks capacity. An additional truck can be used if the transportation cost saving by adding an extra truck is greater than the cost of an additional truck. The recycling of plastics has been used as an example since recycling is a very common end-of-use recovery options, and also plastics have a long history of recycling. The history of plastic recycling gets back to 1970s (Hopewell et al., 2009).

To be aware of bin's status, bins are equipped with IoT components such as RFID tag, capacity sensor, actuator and a static GPS. RFID tag is used for identification of certain beans. Capacity sensor is used to measure volume of the waste in bin. Actuators is used to lock the lid of bin when in bin gets full with waste. Static GPS is used to identify locations of the bins. Truck drivers are embedded with a smart phone which has a GPS tracker and a Google map android app. When the bin gets full or reaches to a predefined threshold, the system is informed through a wireless sensor network (Anagnostopoulos et al., 2015a).

4. Proposed chance-constrained optimization model

Fig. 2 shows the general schematic diagram of the smart city with waste bins, waste collection depots, LCTs and HCTs.

The system illustrated in Fig. 2 is mathematically represented as follows:

Sectors : $S = 1, 2, 3, \dots, s$

Depots : $D = 1, 2, 3, \dots, d$

Bins : $B = 1, 2, 3, \dots, b$

LCT : $L = 1, 2, 3, \dots, l$

HCT : $H = 1, 2, 3, \dots, h$

B_s = The number of bins in sector s

L_s = The number of LCTs in sector s

$w_{s,b}$ = Weight of Bin b in sector s

W_d = Weight of Depot d

λ_d = Waste value recovery variable
= percentage of value recovered = recycling yield

C_b = Capacity of Bin b

C_d = Capacity of depot d

C_l = Capacity of LCT l

C_h = Capacity of HCT h

$s, d, b, l, h \in N$

The optimization model for collection and recovery of waste includes two sub models. (1) First the waste generated in each sector is transferred to its corresponding depot through LCTs, (2) Second, the waste collected in each depot is transferred into recovery center through HCTs. The purpose of the model is to allocate LCTs and HCTs to bins and depots and determine the quantity of waste collected by each LCT and HCT. It should be noted that depots can be assigned to sectors in different ways. For example, one depot can be assigned to more than one sectors, or the opposite, more than one depot per sector, or one per recycling unit of the smart city. In configuration shown in Fig. 2, at least one depot is assigned to each sector.

Sub-Model 1: Collection of waste from all sectors by LCTs and transport to depots

$X_{b,l}$ = Transportation cost of collecting a unit waste from Bin b by LCT l

$Q_{b,l}$ = Quantity of waste to be collected from Bin b by LCT l

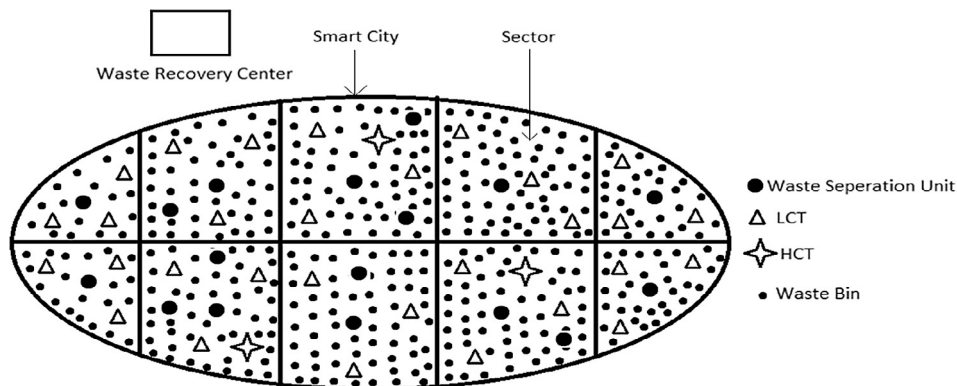


Fig. 2. Different elements of waste collection and recovery system.

The use of capacity sensors makes it possible for municipalities to know the waste volume of every bin in all sectors.

It is assumed that the main decision-makers in Sub-model 1 are municipalities whose main objective often is not necessarily the economic viability of waste collection, but the collection of all waste generated in a region while minimizing the total collection cost.

Each LCT has different transportation cost to collect waste from particular bin as the distance between each LCT and that bin are different. The transportation or shipment cost is calculated for one unit waste. More accurately, the transportation cost $X_{b,l}$ can be calculated considering both the fixed cost of collection and the variable cost based on the travel distance as follow:

$$X_{b,l} = v + c_{b,l}$$

where v is the fixed cost and $c_{b,l}$ is the variable cost calculated based on the distance.

We have assumed that the average transportation cost can be calculated based on the historical data available from the average distance traveled by LCTs and the unit cost of transportation. All transportation costs between LCTs and bins are assumed as different fixed numbers. Municipalities calculate $X_{b,l}$ by considering different cost items such as the fixed cost of opening a collection site, fixed cost of a new truck, and the operational cost based on the distance traveled. By increasing the investment cost, for example for increasing the fleet size, the fixed cost per unit waste increases. Since Sub-model 1 is developed to help municipalities with planning the short-term waste collection activities (e.g. daily or weekly waste collection), it does not determine the long-term decision variables such as the optimal number of trucks, the optimal number of depots, and the optimal collection calendar.

The optimal fleet size can be calculated by considering different factors such as the amount of waste that should be collected, the maximum delay of waste collection, and the cost of adding trucks. In Sub-model 1, the number of LCTs in each sector is given L_s , and is not considered as a decision variable. However, the fixed cost of adding LCT can still be considered when calculating $X_{b,l}$.

Currently, the problem is formulated as a resource-allocation model as shown in Table 1. The proposed model can be integrated with the traveling salesman problem to determine the accurate value of $X_{b,l}$ based on the shortest path method and Dijkstra's algorithm (Bast et al., 2016) since the cost depends on the route planned. This requires adding several constraints related to path planning and the use of graph modeling techniques in determining the shortest path based on the locations of bins that should be visited by LCT l and the location of Bin b .

It should be noted that the model does not limit the assignment of each bin to just one truck, so each bin can be covered by a set of trucks. The model aims to allocate the quantity of waste from bins into LCTs to minimize the transportation cost for the whole system. The model can be solved for each sector separately. In this model, known input parameters are bin's weights ($w_{s,b}$), LCT's capacity (C_l), and unit transportation costs ($X_{b,l}$). The allocation problem can be solved using excel solver by the linear programming

method. The output of this model are the quantity ($Q_{b,l}$) of waste transformed from bins to the depot in sector s .

$$\text{Objective function : Min } \sum_{b \in B} \sum_{l \in L} Q_{b,l} (X_{b,l}) \quad (1)$$

$$\text{S.t. : } \sum_{b \in B} Q_{b,l} \leq C_l, \forall l \in L \quad (2)$$

$$\sum_{l \in L} Q_{b,l} = w_{s,b}, \forall b \in B \quad (3)$$

The objective function of Sub-model 1 can be improved by considering the trade-off between the cost of collection and the efficiency of collection such as prioritizing neighborhoods or bins based on the waste value and urgency. Chemical sensors are being developed that can identify waste nature and decay parameters to prioritize bins for collection which may become an annoyance to neighborhoods due to possible stench coming out of those bins. In future research, this could be an additional source of data for routing and prioritized collection scheduling.

As the number of IoT-enabled waste management project increases, more data will be available for optimization of the collection efforts. For example, as part of the European Union H2020 project biotope (Biotopo, 2017), two use cases relevant to waste collection are developed including Smart Waste Management use case by ITMO University (Lamichhane, 2017), and Bottle Bank Management from the city of Lyon, France (Gastaud, 2017) where capacity sensors, temperature sensors, accelerometer, and GPS are used to optimize routing and waste pick-up schedules.

Sub-Model 2: Collection of waste from depots by HCTs and transport to the recycling site

$Y_{d,h}$ = Transportation cost to collect a unit waste from depot d by HCT h

$q_{d,h}$ = Quantity of waste to be collected from depot d by HCT h

As discussed before, the aim of this model is to maximize the value that can be recovered from the waste collected in each region. The value that can be recovered from each unit of waste is an uncertain parameter and depends on the condition and mix of waste. It can also refer to the recycling yield. To formulate the profit obtained from recovery, let's define a new function Z which depends on both transportations cost and the value recovered by recycling the waste. Basically, the total revenue is the product of the quantity of waste, the value recovery percentage, and the amount of money recovered per unit of weight. For example, if the purpose is to calculate the total profit obtained from recovering plastic in the region, Function Z can be defined as the difference of the total money recovered through recycling of plastic and the total transportation cost. The recovered value of recycled plastic is varying between \$0.1 and \$ 4.0 per Kg according to the type of plastic waste and its condition with the average value around

Table 1
Sub-Model 1: Allocation of LCTs to Bins in Section s .

		Bin's Weight in Sector s (Kg)					
LCT's Capacity (Kg)		$w_{s,1}$	$w_{s,2}$	$w_{s,3}$	.	.	$w_{s,b}$
		$Q_{1,1} (X_{1,1})$	$Q_{2,1} (X_{2,1})$	$Q_{3,1} (X_{3,1})$	.	.	$Q_{b,1} (X_{b,1})$
	C_1	$Q_{1,1} (X_{1,1})$	$Q_{2,1} (X_{2,1})$	$Q_{3,1} (X_{3,1})$	.	.	$Q_{b,1} (X_{b,1})$
	C_2	$Q_{1,2} (X_{1,2})$	$Q_{2,2} (X_{2,2})$	$Q_{3,2} (X_{3,2})$	.	.	$Q_{b,2} (X_{b,2})$
	C_3	$Q_{1,3} (X_{1,3})$	$Q_{2,3} (X_{2,3})$	$Q_{3,3} (X_{3,3})$	.	.	$Q_{b,3} (X_{b,3})$
	.	.	.	.	.	.	.
	.	.	.	.	.	.	.
	C_l	$Q_{1,l} (X_{1,l})$	$Q_{2,l} (X_{2,l})$	$Q_{3,l} (X_{3,l})$	.	.	$Q_{b,l} (X_{b,l})$

\$0.6 per Kg (Plastics News, 2017). For more information about plastics recovery operation, we refer the readers to (Al-Salem et al., 2009).

$$Z = \text{Value recovery by recycling}() - \text{Transportation cost}()$$

$$Z = \text{Value recovery parameter}$$

$$\begin{aligned} & * \text{revenue obtained from recycling(per unit)} \\ & - \text{unit transportation cost} \end{aligned}$$

$$Z_{d,h} = \lambda_d * p - Y_{d,h} \quad (4)$$

By using Sub-model 1, at this point waste from all bins are collected and transferred by LCTs to the respective depots. Using Sub-model 2, we will determine the quantity of waste that should be transferred from depots to the recycling site (Table 2). At depots, wastes are separated according to the type and condition of plastics. Also, the value recovery parameter λ_d is an uncertain parameter and depends on the type and condition of the waste. We can find a distribution for this parameter using historical data. In this study, we assume that parameter λ_d follows normal distribution with mean (μ_i) and standard deviation (σ_i).

Considering the normal distribution for the amount of waste generated is not an invalid assumption and appears to be an adequate representation of the waste generated in the system over time, due to the application of Central Limit Theorem and the analyses provided in prior studies (Johansson, 2006). In addition, Chang and Davila (2008) conducted several sampling campaigns in solid waste landfills in the Lower Rio Grande Valley in Texas to identify the statistical distributions of key recyclable items such as paper, plastic and food and concluded that population distributions are normally distributed after a log transformation.

The value recovery from each individual trash bin depends on both weight and parameter λ_d which could vary from one neighborhood to other depending on the level of affluence and socio demographic characteristics of residents. In this study, it is assumed that with the current sensor-based technologies municipalities have access to the weight and trash level of individual bins at the time of planning and running the optimization model, so they use the information of individual bins as inputs to the optimization model. In the current study, λ_d is defined as an uncertain variable with its own normal distribution and is an input to the optimization model. However, in the future, new infrared spectroscopy and image processing technologies would make it possible to monitor the content of each trash bin and determine the actual value of each trash bin and better estimate parameter λ_d for each trash bin. The waste generation behavior of residents can be simulated based on historical data as well. For example, Johansson (2006) conducted a discrete event simulation to analyze the waste generation and collection events in Malmoe, Sweden. The purpose of the study was to first simulate waste generation and then calculate the total operational costs of different collection strategies. For example, what would be the total costs if each full container should be emptied out within 24 or 48 h. The compar-

ison of different scenarios showed that depending on the number of containers and the distance between them, different static and dynamic collection strategies are preferred. In the current study, however, we have used an optimization approach rather than simulation models. While we have considered a distribution for the value embedded in each container, we have incorporated the distribution to the objective function of the model and have solved the model to find the optimal collection strategy. The benefits of the optimization model are to allow municipalities to run the model based on their semi-predefined calendar rather than assuming a free calendar and timing for collection operations. In this study, we do not assume a free calendar for waste collection in which each full container is emptied out as soon as possible or within a certain timeline. The previous studies showed that free calendar is often costly and may not be preferred to residents. Therefore, we assume that municipalities monitor the status of the city at certain times and they will collect targeted full or semi-full containers that need to be emptied out. This is different than traditionally fixed calendar schedules in which municipalities visit every container at certain times no matter if the container is full or not. In Section 5, we further discuss the impact of different types of collection calendar to both municipalities and residents.

The objective function of Sub-model 2 based on the recycling profit can be written as:

Objective function:

$$\text{Max} \sum_{d \in D} \sum_{h \in H} q_{d,h} (Z_{d,h}) = \text{Max} \sum_{d \in D} \sum_{h \in H} q_{d,h} (\lambda_d * p - Y_{d,h})$$

$$\text{Or Min} - \sum_{d \in D} \sum_{h \in H} q_{d,h} (\lambda_d * p - Y_{d,h}) \quad (5)$$

$$\text{S.t. : } \sum_{d \in D} q_{d,h} \leq C_h \quad \forall h \in H \quad (6)$$

$$\sum_{h \in H} q_{d,h} = W_d \quad \forall d \in D \quad (7)$$

Constraint (6) assures that the collection weight assigned to each HCT is less than its maximum capacity and Constraint (7) guarantees that all the waste in depot d is assigned to HCT. Since the objective function is uncertain, the problem cannot be solved using simple linear program. We have applied chance constrained method to solve the problem. According to chance constrained method, we can restate the objective function by a decision variable ($\bar{m}$) and then add a probabilistic constraint into the optimization model.

Min $\bar{m}$

$$\Pr \left(- \sum_{d \in D} \sum_{h \in H} q_{d,h} (\lambda_d * p - Y_{d,h}) - \bar{m} \right) \geq \alpha \quad d \in D, h \in H$$

The objective function defines the target value with confidence level α , where

Table 2
Sub-Model 2: Allocation of HCTs to Depots.

		Depot's Weight (Kg)					
HCT's Capacity (Kg)		W_1	W_2	W_3	.	.	W_d
C_1		$q_{1,1} (Z_{1,1})$	$q_{2,1} (Z_{2,1})$	$q_{3,1} (Z_{3,1})$	.	.	$q_{d,1} (Z_{1,h})$
C_2		$q_{1,2} (Z_{1,2})$	$q_{2,2} (Z_{2,2})$	$q_{3,2} (Z_{3,2})$	.	.	$q_{d,2} (Z_{2,h})$
C_3		$q_{1,3} (Z_{1,3})$	$q_{2,3} (Z_{2,3})$	$q_{3,3} (Z_{3,3})$	.	.	$q_{d,3} (Z_{3,h})$
.		.	.	.	.	.	.
.		.	.	.	.	.	.
C_4		$q_{1,h} (Z_{1,h})$	$q_{2,h} (Z_{2,h})$	$q_{3,h} (Z_{d,3})$	.	.	$q_{d,h} (Z_{d,h})$

$$\bar{m} = \min \left\{ m \mid \Pr \left(- \sum_{d \in D} \sum_{h \in H} q_{d,h} (\lambda_d * p - Y_{d,h}) < \bar{m} \right) \geq \alpha \right\}$$

We can convert the above-mentioned constraint to its crisp equivalent. Let us define G as follow:

$$G = - \sum_{d \in D} \sum_{h \in H} q_{d,h} (\lambda_d * p - Y_{d,h}) - \bar{m}$$

λ_d is the only random variable in the above expression. Since λ_d follows normal distribution, G also follows normal distribution with the following expected value and variance:

$$E(G) = - \sum_{d \in D} \sum_{h \in H} q_{d,h} (\lambda_d * p - Y_{d,h}) - \bar{m}$$

$$\text{Var}(G) = \text{Var}(\lambda_d) \left[\sum_{d \in D} \sum_{h \in H} q_{d,h}(p) \right]^2$$

Since G follows normal distribution, $\frac{G - E(G)}{\sqrt{\text{Var}(G)}}$ follows standard normal distribution.

$$\Pr \left(\frac{G - E(G)}{\sqrt{\text{Var}(G)}} < - \frac{E(G)}{\sqrt{\text{Var}(G)}} \right) > \alpha$$

Let us define:

$$\omega = \frac{G - E(G)}{\sqrt{\text{Var}(G)}}$$

$$\Pr \left(\omega \leq - \frac{E(G)}{\sqrt{\text{Var}(G)}} \right) > \alpha$$

$$\Psi^{-1}(\alpha) \leq - \frac{E(G)}{\sqrt{\text{Var}(G)}}$$

Therefore, the probability constraint can be written as follow:

$$\Psi^{-1}(\alpha) \sqrt{\text{Var}(G)} \leq -E(G)$$

$$\Psi^{-1}(\alpha) \sqrt{\text{Var}(\lambda_d)} \left[\sum_{d \in D} \sum_{h \in H} q_{d,h}(p) \right] \leq \sum_{d \in D} \sum_{h \in H} q_{d,h} (\mu_d * p - Y_{d,h}) + \bar{m}$$

The stochastic optimization model is now converted to a linear programming. The linear optimization model can be solved with existing solution algorithms such as simplex algorithm offered in the available software packages such as Matlab or Excel solver in order to obtain the global optimum solution.

5. Numerical example

This section provides an example of the model application. Due to the unavailability of data regarding the amount of waste generated in each neighborhood and the mix and configuration of the city and the number of waste collection vehicles, we have used a simple numerical example. According to an estimation by Navigant Research (2016), the global market for smart waste collection technology is growing from \$57.6 million in 2016 to over 223.6 million in 2025, therefore it is expected that new sets of real-world data will be available in the future to test the feasibility of the proposed model.

Fig. 3 shows an overview of different elements of the system for this particular example, and a specific configuration of Fig. 2 in which the number of waste depots in each neighborhood is 1. Tables 3–5 summarize the values of input parameters to the

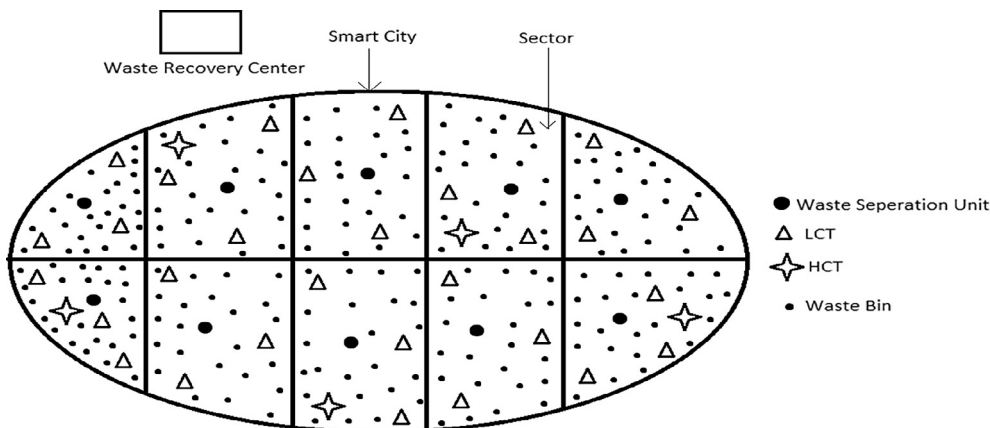


Fig. 3. Different elements of the waste collection and recovery system.

Table 3

The input data assumed for infrastructure parameters.

Sectors = $S = 10$	HCTs = $H = 5$	Capacity of Depots = $C_D = 1500$ Kg
Depots = $D = 10$	Bins in each sectors = $B = 23$	Capacity of LCTs = $C_L = 300$ Kg
LCTs = $L = 3$	Capacity of bins = $C_B = 50$ Kg	Capacity of HCTs = $C_H = 2000$ Kg

Table 4

The values assumed for the weights of 23 bins in Sector i at the time of running the model.

$w_{1,1} = 50$ Kg	$w_{1,6} = 41$ Kg	$w_{1,11} = 32$ Kg	$w_{1,16} = 49$ Kg	$w_{1,21} = 45$ Kg
$w_{1,2} = 45$ Kg	$w_{1,7} = 11$ Kg	$w_{1,12} = 46$ Kg	$w_{1,17} = 47$ Kg	$w_{1,22} = 50$ Kg
$w_{1,3} = 40$ Kg	$w_{1,8} = 5$ Kg	$w_{1,13} = 26$ Kg	$w_{1,18} = 15$ Kg	$w_{1,23} = 27$ Kg
$w_{1,4} = 25$ Kg	$w_{1,9} = 50$ Kg	$w_{1,14} = 16$ Kg	$w_{1,19} = 6$ Kg	
$w_{1,5} = 38$ Kg	$w_{1,10} = 44$ Kg	$w_{1,15} = 48$ Kg	$w_{1,20} = 35$ Kg	

Table 5The input values for unit transportation costs ($X_{b,i}$), weights of Sector i 's bins ($w_{i,b}$) and LCT's capacity (C_i) for allocation model 1.

		Bins Weight (Kg)																						
		50	45	40	25	38	41	11	5	50	44	32	46	26	16	48	49	47	15	6	35	45	50	27
LCT capacity (Kg)	300	0.09	0.15	0.19	0.10	0.08	0.02	0.14	0.14	0.20	0.40	0.24	0.15	0.14	0.14	0.10	0.20	0.02	0.14	0.12	0.20	0.14	0.14	0.05
	300	0.04	0.06	0.05	0.14	0.09	0.02	0.25	0.16	0.05	0.15	0.25	0.15	0.08	0.08	0.15	0.25	0.20	0.13	0.13	0.15	0.14	0.11	0.07
	300	0.15	0.25	0.01	0.15	0.14	0.03	0.03	0.20	0.25	0.16	0.25	0.15	0.09	0.18	0.20	0.30	0.14	0.12	0.14	0.20	0.20	0.09	0.09

model. In this particular example, one waste separation unit or depot is assigned to each sector.

Sub-Model 1:

The linear programming model has been solved for the above-mentioned example using the Excel solver. Table 6 shows the quantities of waste that should be collected by LCTs from 23 bins in each sector in order to minimize the total transportation cost as the outputs of the allocation model 1. While we have not included any constraint that limits the assignment of each bin to just one truck, the results in Table 6 shows that each bin is mainly assigned to one LCT.

The output of Sub-model 1 illustrates the quantity of waste that should be collected by each LCT from each bin to reduce the transportation cost.

Sub-Model 2:

Tables 7 and 8 summarize the input values used in Sub-model 2 to determine the quantity of waste that are collected from depots by HCTs and transferred to the recycling site.

Sub-model 2 has been formulated in Excel solver and the quantities of waste that should be collect by HCTs from depots in order to minimize transportation cost and maximize waste value recovery function are listed in Table 9.

The output of Sub-model 2 illustrates the quantity of waste that should be transferred by each HCT from each depot to increase the

Table 6

Outputs of allocation model 1.

		The quantity of waste collected from Bin i (Kg)																						
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
		50	45	40	25	38	41	11	5	50	44	32	46	26	16	48	49	47	15	6	35	45	50	27
LCT's Capacity (Kg)	LCT 1	300	0	0	0	25	38	8	0	5	0	44	32	0	0	0	48	0	47	0	6	0	0	27
	LCT 2	300	50	45	0	0	0	13	0	0	50	0	0	0	26	16	0	0	0	0	35	45	0	0
	LCT 3	300	0	0	40	0	0	0	11	0	0	0	0	46	0	0	0	49	0	15	0	0	50	0

Table 7The weights of waste collected in Depot i (obtained from model 1) and the input parameters for Sub-model 2.

$W_1 = 791$ Kg	$W_4 = 1240$ Kg	$W_7 = 451$ Kg	$W_{10} = 450$ Kg	$\alpha = 0.005$
$W_2 = 1118$ Kg	$W_5 = 1489$ Kg	$W_8 = 1477$ Kg	$\text{Var}(\lambda_d) = 0.05$	$\mu_{jd} = 0.5$
$W_3 = 699$ Kg	$W_6 = 552$ Kg	$W_9 = 987$ Kg	$p = 0.6$	

Table 8Inputs of Sub-model 2 ($Z_{d,h}$).

		Depot's Weight (Kg)									
		1	2	3	4	5	6	7	8	9	10
		791	1118	699	1240	1489	552	451	1477	987	450
HCT's Capacity (Kg)	2000	0.244	0.125	0.219	0.780	0.256	0.470	0.490	0.189	0.147	0.147
	2000	0.154	0.158	0.890	0.580	0.178	0.312	0.143	0.123	0.189	0.174
	2000	0.256	0.178	0.860	0.145	0.240	0.214	0.289	0.147	0.165	0.201
	2000	0.880	0.145	0.147	0.217	0.560	0.104	0.410	0.289	0.147	0.207
	2000	0.125	0.174	0.360	0.140	0.184	0.212	0.140	0.240	0.125	0.109

Table 9

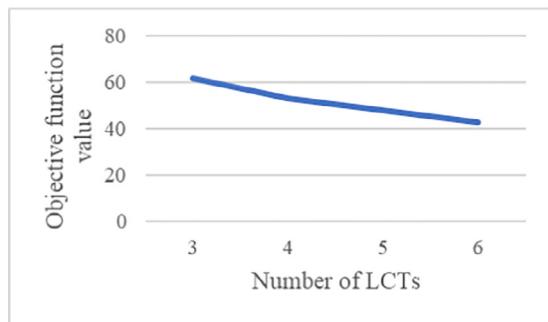
Outputs of Sub-model 2: the quantities of waste collected by HCTs and transferred to the recovery center.

		Depot's Weight (Kg)									
		791	1118	699	1240	1489	552	451	1477	987	450
		791	1118	699	1240	1489	552	451	1477	987	450
HCT's Capacity (Kg)	2000	226	0	0	0	1489	0	0	0	0	0
	2000	0	0	0	0	0	552	0	0	987	0
	2000	565	0	0	534	0	0	451	0	0	450
	2000	0	0	0	523	0	0	0	1477	0	0
	2000	0	1118	699	183	0	0	0	0	0	0

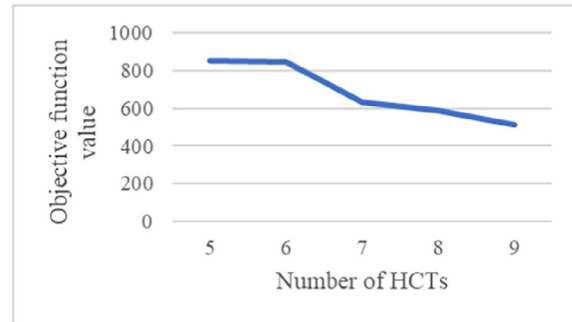
value recovery profit.

It should be noted that the optimization model can be run based on calendars defined by municipalities on daily, alternate daily or weekly basis. Often, historical data on the amount of waste generated during predefined periods would be helpful in guiding municipalities about the best timeline and calendar for scheduling of collection activities. In the proposed approach in this study, we assume that municipalities have access to real-time waste levels in each trash bins and can include full or even partially full trash bins as inputs to the model. In practice, we can consider three types of waste collection calendar: (1) Fixed calendar, (2) Free contender, and (3) Variable calendar (Anghinolfi et al., 2016). In Fixed calendar, the day and time of collection are known to households and municipalities make decisions on the allocation of LCT to trash bins. In the case of the free calendar, the days and timing of collection are not known in advance, so municipalities can monitor the waste levels

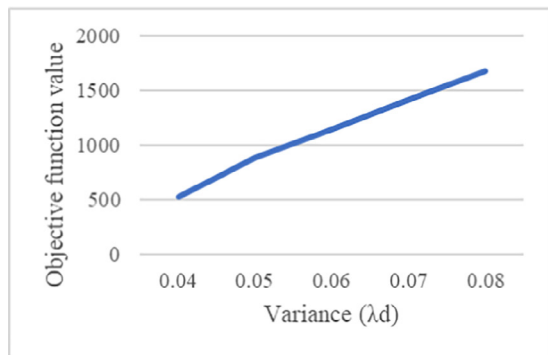
in each individual bin and decides on the timing of collection and which trash bins to cover. Finally, the variable calendar is an intermediate scenario in which municipalities decide about the collection day, but all eligible trash bins (e.g. full or partially full based on a defined threshold) will be covered by different LCTs. Overall, while the free calendar and the flexibility of running the model at any time is cost efficient, the free calendar option may not be considered fully satisfactory to citizens since they perhaps would like to know if their neighborhood is covered and what would be the collection days. Therefore in this study, we assume that municipalities have a predefined calendar for running the model, while they cover all full trash bins or trash bins that reach to a predefined threshold value during the collection day, this can be regarded as a version of variable calendar. Also, since the focus of the proposed model is on value recovery, determining the optimal time of collection will be a future extension of the current study.



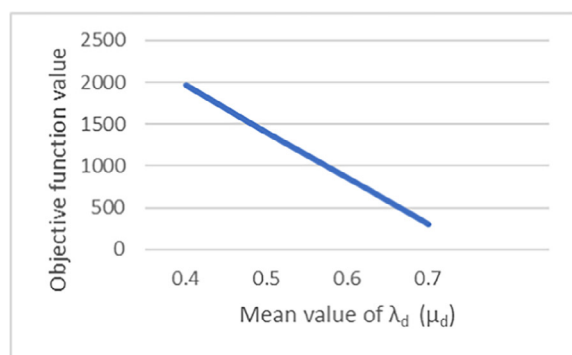
(a) Sensitivity analysis on the number of LCTs,



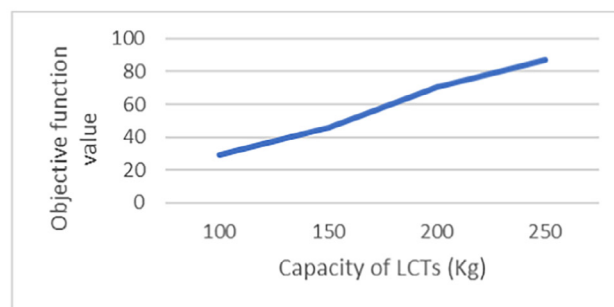
(b) Sensitivity analysis on the number of HCTs



(c) Sensitivity analysis on the variance of λ_d ,



(d) Sensitivity analysis on the mean of λ_d (μ_d)



(e) Sensitivity on the capacity of LCTs

Fig. 4. (a) Sensitivity analysis on the number of LCTs, (b) Sensitivity analysis on the number of HCTs. (c) Sensitivity analysis on the variance of λ_d , (d) Sensitivity analysis on the mean of λ_d (μ_d). (e) Sensitivity on the capacity of LCTs.

We have run some sensitivity analyses on several parameters of the model. Fig. 4(a)–(c) respectively show the sensitivity analysis on the number of LCTs, the number of HCTs, and the variance of (λ_d).

Fig. 4(a) shows that as the number of LCTs increases, the value of the objective function or the transportation cost decreases. This is due to the point that the fixed cost of adding new LCTs is not considered in this example. Also, we should note that based on the total amount of waste that needs to be collected and the capacity of each truck, the minimum number of truck required in this example is 3, so the sensitivity analysis is run for values more than 3. Fig. 4(b) shows that as the number of HCTs increases, the value of the Sub-model 2's objective function ($\min \bar{m}$) decreases, meaning the waste value recovery increases and the transportation cost decreases. This is an expected result since by adding more number of vehicles, the lower-price service could be offered. We should note that in the current model, the fixed cost of adding new vehicles to the waste collection fleet has not been considered, so the sensitivity results are intuitive. In reality, adding more vehicles would decrease transportation costs up to a certain level, after than increasing the number of vehicles would increase the total cost of the system since each additional vehicle means additional costs. Therefore, there is a point in which that cost of adding more vehicles is no longer off set by the profit of waste collection efforts. The optimal number of vehicles also depends on the demand for waste collection which varies among different regions depending on the population, and the waste generation rate in each region.

Fig. 4(c) shows that as the variance of λ_d increases, the value of the objective function ($\bar{m}$) increases meaning that the waste value recovery decreases and the transportation cost increases. Fig. 4(d) shows that as the mean value of λ_d (μ_d) increases, the objective function ($\bar{m}$) and transportation cost decreases since the waste value recovery increases as λ_d increases. Finally, Fig. 4(e) illustrates the sensitivity analysis on the capacity of LCTs. Increasing the capacity of LCTs allows for the collection of more waste and higher transportation cost. It should be noted that in the current model, the fixed cost of adding capacity, and the penalty cost of not collecting all waste is not included in the current model, otherwise, there will be a tradeoff between the penalty cost and the profit of value recovery.

6. Conclusion

The immediate collection of the waste is a very challenging problem in the modern societies. The concept of smart trash bins and waste collection in smart cities opens the opportunity for municipalities to monitor the amount of waste collected in each region and facilitate the timely collection and recovery of the waste generated. This paper has introduced a stochastic optimization model to enhance the value recovery of waste collection operations considering the point that the value embedded in waste collected is uncertain due to different mix and conditions of waste. The model consists of two Sub-models: (1) a resource allocation model that determines the quantity of waste that should be collected and transferred to waste separation units by several low-capacity trucks assigned to each sector or neighborhood in a city, and (2) a model that determines the amount of waste collected from depots and transferred to a recovery center by high-capacity trucks. The chance constrained method has been used to convert the stochastic model into a linear programming model. The main contribution of the paper resides on the use of information of the uncertain value embedded in individual containers in planning the collection operations. The objective is to maximize the profit obtained from the recovery operations. The application

of the model has been shown using an example of plastics recovery.

The directions for future work of this paper include the use of real data to formulate and solve the allocation models in smart cities, the use of more accurate estimation models to quantify the value that can be recovered from collected waste, quantify environmental and social impacts of value recovery operations in addition to economic outcomes, and considering the role of other factors such as citizens contribution in waste generation and recovery to develop innovative structure for waste management practices in smart cities. In addition, the model could be extended to include other decision variables such as the optimal number of vehicles that should be added to the fleet, the route planning of each vehicle, and the timing of collection operations. Furthermore, the use of simulation techniques such as agent-based modeling would help decision makers better formulate the status of a smart city and model the interactions among different stakeholders involved in the entire waste generation, collection and recovery chain.

Acknowledgement

This material is based upon work supported by the National Science Foundation – USA under grant # CBET-1705621. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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