IoT-enabled Tip and Swap Waste Management Models for Smart Cities

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Abstract: Current technical advances in sensors, actuators, and wireless networks enable the Internet of Things (IoT) technology. Key features of IoT are the 'smart things', which have significant computational capabilities. In this paper we focus on waste management using dynamic allocation of collection and transfer points with subsequent transporting of waste to processing facilities. Waste management involves a variety of tasks from the collection of the waste in the field to the transport and disposal to the appropriate locations. The proposed waste management system contributes to innovative Smart City (SC) applications with impact in the dynamic allocation management of mobile depots in the SC. We propose a set of models, which advocate for replacing traditional way of tipping waste into larger containers by swapping full waste bins with empty ones. We also propose the concept of mobile depots as intermediate collection and transfer points. Quantitative and qualitative metrics to assess the efficiency of the proposed models are used. We incorporate the CT, TT, L, D and F quantitative metrics and the S qualitative metric. The S metric takes as input the values of the quantitative metrics and gives an output of high or low satisfaction. The models demonstrate their efficiency and potential adoption by SCs.

Keywords: Smart Cities, Internet of Things, Tip Models, Swap Models, Waste Management System

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1 Introduction

The majority of earth population (i.e., 70%) will move to urban areas by 2050, thus, forming vast cities, (Fazio et al., 2012). Certain infrastructure is required by such cities to manage citizens' needs and offer basic and more advanced services, (Balakrishna, 2012). Internet of Things (IoT) technology enables people and things to be connected anytime, anyplace, with anything and anyone, ideally using any network and any service, (Guillemin P & Friess P, 2009). *Smart Cities* (SCs), are defined in (Centre of Regional Science, 2007): *"A Smart City is a city well performing in a forward-looking way in the following fundamental components (i.e., Smart Economy, Smart Mobility, Smart Environment, Smart People, Smart Living, and Smart Governance), built on the 'smart' combination of endowments and activities of self-decisive, independent and aware citizens"*. We focus on the specific application domain of waste management in SCs.

Testbed of our system is the city of St. Petersburg, Russia. Specifically, St. Petersburg is a city covering a total area of 1,439 square kilometers with 5 million citizens, which denote a density of 3,391 citizens per square kilometer. Solid waste produced in the city is 1.7 million tons, on average, per year. During the day, the amount of municipal solid waste generated is 0.93 kilograms per citizen. On a daily basis, the municipality of St. Petersburg uses 476 waste collection trucks, each of them with a capacity of 5 tons. Fuel consumed per year is, on average, 1.8 million liters. On average, the costs spent on fuel in one year for waste collection is more than 1 million US dollars, (Anagnostopoulos et al., 2015). The fleet of waste collection trucks causes traffic congestion during rush hours, which is significant due to the narrow roads and small backyards. This causes indirect problems in citizens' activities. Obviously, it is critical to manage efficiently the waste disposed of in every location of an SC not only focusing on the collection activities but also on its transport and recycling.

In (Anagnostopoulos et al., 2017) we surveyed existing models for waste collection in SCs. We presented the strengths and weaknesses of the surveyed models. In this paper we extend our research focusing on waste management using dynamic allocation of collection and transfer points with subsequent transporting of waste to processing facilities. We use IoT as an enabling technology to apply dynamic tip and swap models on the waste collection process. Term dynamic denotes the ability of a system to change, in real time, the routing parameters that affect the collection of waste during the collection activity. Such features can result in an online set of dynamic route directions provided to the waste collection trucks. We propose a set of models, which advocate for replacing traditional way of tipping waste into larger containers by swapping full waste bins with empty ones. We also propose the concept of mobile depots as intermediate collection and transfer points. Examples of mobile depots include waste trucks or temporary waste bins placed at dynamically allocated points. We use a heterogeneous fleet, which consists by low capacity trucks and high capacity trucks serving as intermediate mobile depots in the waste collection task within the SC. *We prove that swapping models are more cost efficient than tipping models. Concretely, we use certain quantitative and qualitative metrics to assess the efficiency of the proposed models*.

The structure of the paper is as follows. In Section 2 we present the literature review performed in contemporary research. In Section 3, we describe the proposed waste management system. Section 4, describes the experimental environment. In Section 5, we present and discuss the results, while Section 6 concludes the paper and proposes future work.

2 Waste Management for Smart Cities: State of the Art

Research community has proposed a number of dynamic routing models for waste collection. Dynamic routing models are of significant interest since static approaches cannot exploit the dynamic nature of IoT technology. A simulation framework has been proposed in (Banditvilai et al., 2017) for modeling the night shift solid waste collection in Phuket Municipality, Thailand, which develops a heuristic approach for assigning waste collection zones and routings. An integer-programming model has been proposed in (Braier et al., 2017) to optimize the dynamic routs of collection vehicles for the case of waste collection in Morón, Argentina. In the project named Dynacargo (Dynamic Cargo Routing on-the-Go), has been 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).

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. (Gruler et al., 2017) have combined metaheuristics with simulation and proposed a hybrid algorithm for waste management in clustered urban areas considering the impact of cooperation among vehicles departed from different depots and the corresponding savings this cooperation could create. An Ant Colony algorithm has been developed in (Sharmin et al. 2016), which solved a dynamic routing system to find the shortest path while minimizing transportation costs with the overall purpose of waste management in smart cities.

A dynamic smart solid waste management system (WMS) has been designed in (Shinde et al., 2017) by integrating RFID, GSM, GIS system to manage the solid waste in an automatic waste monitoring system. 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. A stochastic optimization model based on chance-constrained programming is developed in (Shah et al., 2018) 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. A multi-agent system is incorporated in (Anagnostopoulos et al., 2018) for IoT-enabled waste management to stochastically reassign trucks to collect waste from bins through time in smart cities.

An urban-decision support system (U-DSS) is proposed in (Abbatecola et al., 2016), which is devoted to manage, in a unified framework, the logistic services of the smart cities, such as postal delivery (PD) and waste collection (WC) services. The U-DSS architecture is proposed by describing its main components. Specifically, the system focuses on the core of the U-DSS, i.e., the model component that provides the solutions of a general vehicle assignment and routing optimization problem with the aim of minimizing the length of the routes and satisfying time and capacity constraints. The problem of planning a door-to-door waste management of separated multiple materials for a municipality is analyzed in (Anghinolfi et al., 2016). It is incorporated a mixed integer linear programming model and a multi-objective optimization model to minimize the operational costs and face the inefficiencies which are possible to occur by the adopted waste recycling logistic system that may cause negative environmental impacts.

Figure 1 Dynamic routing adapts to real-time emergency situations like a road under construction with an online detour

Figure 2 Components of Waste Management System (WMS)

Finally, in (Anagnostopoulos et al., 2017) a survey in IoT-enabled waste management approaches is presented where the authors proposed a taxonomy to categorize waste collection in the context of SCs. We also discuss the strengths and weaknesses of the surveyed models. This paper extends research performed in (Anagnostopoulos et al., 2017) by proposing a waste management system (WMS), which is summarized as follows: *(1) a set of models, which advocate for replacing traditional way of tipping waste into larger containers by swapping full waste bins with empty ones, (2) the* *concept of mobile depots, which act as intermediate collection and transfer points. (3) certain quantitative and qualitative metrics to assess the efficiency of the proposed models.* ***Note:*** *Shifting research models towards swapping approaches lead to highly cost efficient models.* The rationale behind our approach is that mobile depots are placed at dynamically allocated points within the area of the SC. Mobile depots are invoked when there is an online need for real-time waste collection.

3 Waste Management System (WMS)

Incorporation of advanced services to SCs is enabled by IoT technology. IoT is defined to combine the spatiotemporal, technical and social context, part of the SC contextual profile. Specifically, new or efficient redesign of existing services in SCs can be enabled by incorporating IoT-enabled models, (Delicato et al., 2013). Let us focus on the waste management process where static waste management models can be transformed to *Waste Collection as a Service* (WCaaS) thus enabling online dynamic scheduling and routing of the trucks, (Lingling et al., 2011). Figure 1 presents an example for analyzing a dynamic IoT routing scenario for waste management.

Dynamic waste management can be described as an online decision process to define: (i) the exact timing to collect waste from bins (i.e., scheduling), and (ii) efficient routing the trucks should follow (i.e., routing). Specifically, scheduling is the process, which defines when the collection of the waste will take place. For example, assume that there are b waste bins per sector. Then when the volume capacity g of a certain number of bins is above a volume threshold then the system triggers a scheduling alarm and invokes the routing process to collect the waste from these waste bins.

When scheduling has triggered the system control is passing to the routing process. Specifically, routing process takes into consideration the spatial location of the full of waste bins as well as the conditions on the roads of the city. For example, a detour will be done if a road is under labor construction or a car accident has done in that specific area of the road network. Taking these conditions under consideration routing process gives directions to the c trucks and d mobile depots to follow certain trajectories to collect the waste from the full bins. For more details see research conducted in (Anagnostopoulos et al., 2015). In this paper, we propose a Waste Management System (WMS) enhanced with IoT-based components to enable dynamic scheduling and routing in a SC with the adoption of dynamically allocated mobile depots as sustainable proxies.

The proposed WMS is presented in Figure 2. We can observe that waste collection is treated as a cloud service, which interacts with a variety of mechanisms. Trucks collect waste from bins and transfer it to mobile depots. Subsequently, mobile depots transport waste to dumps and recycling/processing plants outside of the city. Such waste transportation performed by the mobile depots is proved to reduce the route trips, initially performed by the trucks, because waste is transported to the dumps with fewer trips, thus, reducing the operational costs of the waste management. Our WMS does not require any extra land space for temporary storage (i.e., static depots) of the waste, which results in a more flexible model. This leads to a better quality of life for the citizens, which is positively affected, as static depots are not required within the SC. In addition, the areas near the static depots are degraded leading to low quality of living for nearby residents. By incorporating mobile depots efficient scheduling and routing is enabled which has chain effects in the SC daily life. For instance, SCs traffic regulators can achieve efficient traffic management in rush hours. Android apps are used by the truck drivers' smartphones, which enable them to navigate in real time through route trips that can be altered dynamically; e.g., a road could be closed due to unexpected traffic or a truck could be overloaded/damaged. We also used IoT equipment embedded in the waste bins to support the waste collection scenarios studied in this paper.

Table 1 Experimental parameters

Description	Value
Number of sectors	10
Number of bins per sector	300
Number of trucks per sector	6
Number of mobile depots per sector	1
Number of containers per each truck	4
Number of containers per each mobile depot	12
Number of dumps in the SC	3
Volume capacity of each bin (Kg)	100
Volume capacity of each container (Kg)	1000
Volume capacity of each truck (Kg)	4000
Volume capacity of each mobile depot (Kg)	12000
Volume capacity of each dump (Kg)	∞
Average time required to tip a bin (min)	2.5
Average time required to swap a container (min)	1.5
Average time required to swap a bin (min)	1

4 Experimental Setup

To set up the experiments, we first defined certain parameters as shown in Table 1. SC of St. Petersburg is assumed to be divided into waste collection sectors with assigned bins, trucks, and mobile depots per sector. Bins, trucks, and mobile depots have a certain capacity. There are defined two Infrastructure Scenarios (IS). In the first scenario, IS-1, there is only a single dump and recycling/processing unit in the SC. In the second scenario, IS-2, there are multiple dumps and recycling/processing units. The models are assessed through three Use Cases (UC) per IS. The UC are differentiated by the method of collecting waste from bins. In UC-1 waste is collected by tipping bins to certain trucks. UC-2 uses the method of tipping bins to truck containers and then swapping containers to mobile depots, while in UC-3 waste is collected by swapping bins to trucks and then swapping bins from trucks to mobile depots.

4.1. Metrics

To assess the models, as described in Section 4.2, there are certain quantitative and qualitative metrics, which need to be optimized. Specifically, minimization of the following quantitative metrics is performed by the proposed models:

Collection Time (CT): It is the time required to collect waste from bins either by (1) tipping, (2) tipping and swapping, or (3) swapping. CT should be minimal since it is the basic metric of the system that affects all the waste management process.

Transport Time (TT): Is the time needed to transport waste after collected it in either (1) the single depot and the recycling/processing unit, or (2) multiple depots and recycling/processing units. Waste in UC-1 is transported by trucks. In UC-2, and UC-3 trucks and mobile depots transport the waste. Minimum values of TT mean that traffic is handled effectively in the SC.

Load (L): Is the capacity of waste transported when collected from (1) bins, or (2) containers. Maximum values of L mean that trucks and mobile depots are efficiently full of waste and perform less routing trips to serve the waste collection process in the SC.

Distance (D): Is the distance covered from the collection point to the disposal point (i.e., dumps or recycling/processing units. A minimum D value implies less fuel consumption from the trucks or depots, as well as a potentially lower TT value

Fuel (F): Is the quantity of fuel consumed during certain D, L, TT, and CT values. Low values of F mean a cost-efficient model, which is possible to be incorporated by the SC if the quality of waste management service is with an adequate satisfaction level.

Figure 3 The Tip algorithm

Input: b, c //Bins, Trucks
Output: CT, TT, L, D, F, S
// Navigation algorithm has introduced in (Anagnostopoulos et al., 2015). Current
// research incorporates navigation algorithm into Tip algorithm.
Begin
If $(g_b \geq t_b)$ **Then** // If bin volume capacity is greater or equal to bin capacity
$\{TT, L, D, F\} \leftarrow Navigate\ Truck\ to\ Bin$
$CT \leftarrow Tip\ Bin\ to\ Truck$
$\{TT, L, D, F\} \leftarrow \{TT, L, D, F\} + Navigate\ Truck\ to\ Dump$
End If
$S \leftarrow QoS(CT, TT, L, D, F)$
End

Except the quantitative metrics, there is also a qualitative metric, which should be maximized to assess the proposed models. Such qualitative metric should highlight the overall assessment level of the proposed models:

Satisfaction (S): It is the state, which defines the impact of the waste management service to the SC. It is a Quality of Service (QoS) metric, which takes one of the two discrete values, namely: (1) low satisfaction, and (2) high satisfaction. High satisfaction level indicates an efficient model, while a low satisfaction level indicates an inefficient model.

Figure 4 The Tip-Swap algorithm

Input: b, e, c, d //Bins, Containers, Trucks, Mobile Depots
Output: CT, TT, L, D, F, S
// Navigation algorithm has introduced in (Anagnostopoulos et al., 2015). Current
// research incorporates navigation algorithm into Tip-Swap algorithm.
Begin
If $(g_b \geq t_b)$ **Then** // If bin volume capacity is greater or equal to bin capacity
$\{TT, L, D, F\} \leftarrow Navigate\ Truck\ to\ Bin$
$CT \leftarrow Tip\ Bin\ to\ Truck\ Container$
End If
If $(i_c \geq t_c)$ **Then** // If truck volume capacity is greater or equal to truck capacity
$\{TT, L, D, F\} \leftarrow \{TT, L, D, F\} + Navigate\ Truck\ to\ Mobile\ Depot$
$CT \leftarrow Swap\ Truck\ Container\ to\ Mobile\ Depot$
End If
If $(j_d \geq t_d)$ **Then** // If mobile depot volume capacity is greater or equal to mobile depot capacity
$\{TT, L, D, F\} \leftarrow \{TT, L, D, F\} + Navigate\ Mobile\ Depot\ to\ Dump$
End If
$S \leftarrow QoS(CT, TT, L, D, F)$
End

4.2 Algorithms for Models

Tip Algorithm for UC-1 Model: In UC-1 model waste is collected from the SC sectors by tipping full bins to trucks. When the trucks are full they transport waste to dumps or recycling/processing units according to IS-1/IS-2. Algorithm for the UC-1 model is presented in Figure 3.

Tip-Swap Algorithm for UC-2 Model: In UC-2 model the trucks are tipping full bins to their empty container. When container is full, trucks swap the full container with an empty container from mobile depots. Subsequently, trucks continue to collect waste from the bins in the SC. When Mobile depots containers become full they transport waste to dumps or recycling/processing units according to IS-1/IS-2. Figure 4. describes the algorithm for the UC-2 model.

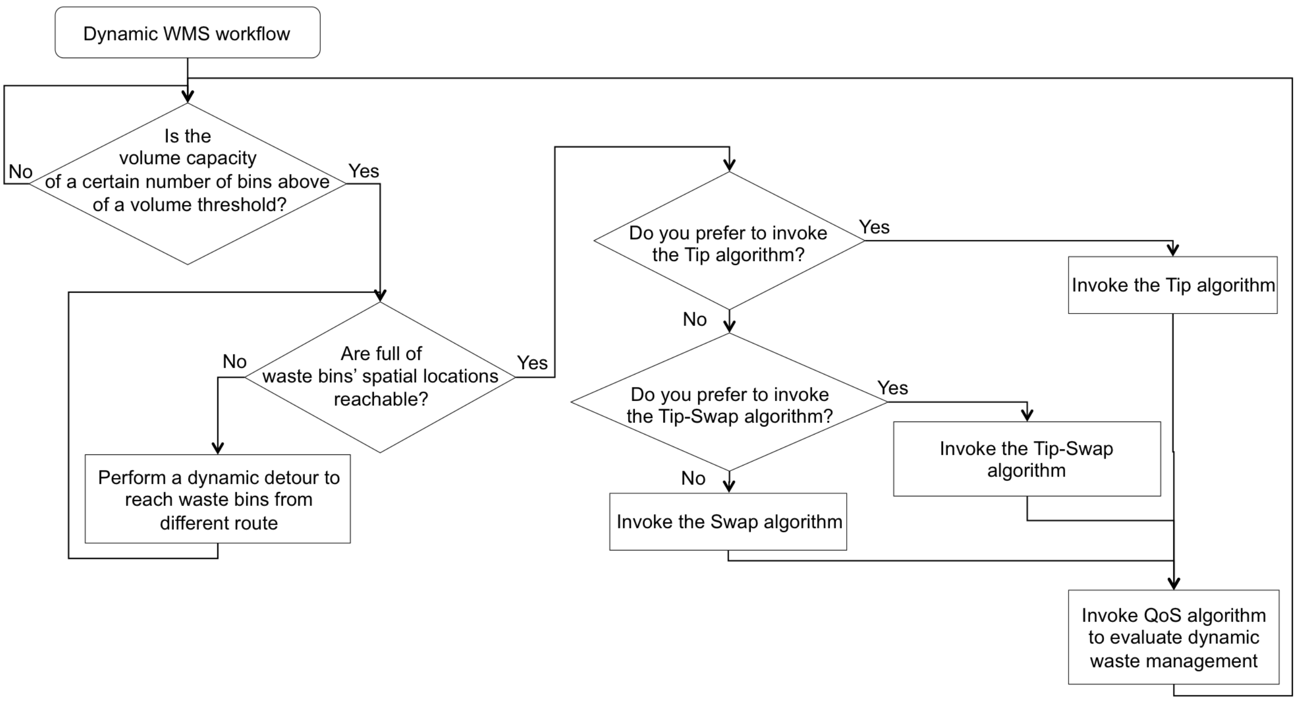
Figure 5 The Swap algorithm

Input: b, c, d //Bins, Trucks, Mobile Depots
Output: CT, TT, L, D, F, S
// Navigation algorithm has introduced in (Anagnostopoulos et al., 2015). Current
// research incorporates navigation algorithm into Swap algorithm.
Begin
If $(g_b \geq t_b)$ **Then** // If bin volume capacity is greater or equal to bin capacity
  $\{TT, L, D, F\} \leftarrow Navigate\ Truck\ to\ Bin$
  $CT \leftarrow Swap\ Bin\ to\ Truck$
If $(i_c \geq t_c)$ **Then** //If truck volume capacity is greater or equal to truck capacity
  $\{TT, L, D, F\} \leftarrow \{TT, L, D, F\} + Navigate\ Truck\ to\ Mobile\ Depot$
  $CT \leftarrow Swap\ Truck\ Bins\ to\ Mobile\ Depot$
End If
If $(j_d \geq t_d)$ **Then** // If mobile depot volume capacity is greater or equal to mobile depot capacity
  $\{TT, L, D, F\} \leftarrow \{TT, L, D, F\} + Navigate\ Mobile\ Depot\ to\ Dump$
End If
$S \leftarrow QoS(CT, TT, L, D, F)$
End

Figure 6 The QoS algorithm

Input: CT, TT, L, D, F
Output: S
Begin
If$\left((CT < m_{CT}) \cap (TT < m_{TT}) \cap (L > m_L) \cap (D < m_D) \cap (F < m_F)\right)$**Then** // If CT value is
// less than Gaussian CT PDF median value AND TT value is less than Gaussian TT PDF
// median value AND L value is greater than Gaussian L PDF median value AND D value is
// less than Gaussian D PDF median value AND F value is less than Gaussian F PDF median value
  $S \leftarrow High\ Satisfaction$
Else
  $S \leftarrow Low\ Satisfaction$
End If
End

Figure 7 Graphical representation of WMS workflow



Swap algorithm for UC-3 Model: In UC-3 model trucks are swapping full bins with empty bins. When bins of the trucks are full, trucks swap the full bins with empty bins from mobile depots. Subsequently, trucks continue to collect waste from the bins in the SC. When mobile depots bins become full they transport waste to dumps or recycling/processing units according to IS-1/IS-2. The algorithm for the UC-3 model is presented in Figure 5.

Algorithm Quality of Service Assessment: Quality of Service (QoS) Algorithm assesses the S metric, which defines the impact of the waste management service to the SC based on the CT, TT, L, D, and F metrics. Algorithm for the Quality of Service assessment is described in Figure 6. It should be noted that the discrete values of S metric are affected by the median (m) of the CT, TT, L, D, and F metrics. Specifically, m of the metrics is computed based on historical data observed during the training phase operation of the WMS. Therefore, to compute m and make an assessment to S metric we computed the Gaussian probability density functions (i.e., Gaussian PDF) of the CT, TT, L, D, and F metrics based on the historical data.

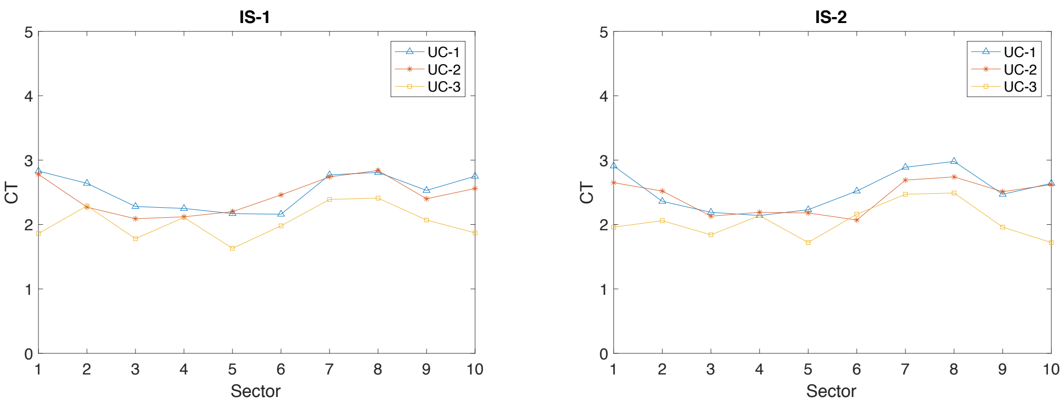
4.3 Graphical Representation of WMS Workflow

Adopted methodology is presented by incorporating a graphical representation, which explains the proposed dynamic WMS workflow. In Figure 7 we use a flowchart to present the significant steps of the adopted WMS workflow to be understood by greater audience and practitioners for implication. In addition, notations and variables used in the proposed algorithms and models are presented in Table 2.

Table 2 Notations and variables in algorithms and models

Description	Notation
b	Bin
c	Truck
e	Container
d	Mobile depot
g_b	Bin volume capacity
t_b	Bin capacity
i_c	Truck volume capacity
t_c	Truck capacity
j_d	Mobile depot volume capacity
t_d	Mobile depot capacity
CT	Collection time
TT	Transport time
L	Load
D	Distance
F	Fuel
S	Satisfaction
m_{CT}	Gaussian CT PDF median value
m_{TT}	Gaussian TT PDF median value
m_L	Gaussian L PDF median value
m_D	Gaussian D PDF median value
m_F	Gaussian F PDF median value

Figure 8 Results for CT metric



5 Results and Discussion

5.1 Results

We evaluated our system with real and synthetic data generated in the SC of St. Petersburg, as assessed in (Anagnostopoulos et al., 2015). Specifically, the models were fed with data captured from Google Maps and are covering a spatial area of 31.42026 square km, consisting of 1,214 GPS coordinates' points, from the centre of St. Petersburg SC, Russia. MATLAB software was used to evaluate the proposed models. To compute the mean and standard deviation of the CT, TT, L, D, and F metrics, which are used for the assessment of the S metric, a training phase of 30 days was accomplished. During that period, historical operational data were collected which enable the formation of distributions for the metrics. We assumed, without loss of generality, that the metrics are following a Gaussian distribution. Subsequently, we run the proposed WMS for another testing phase period of 30 days. During that period, the system was evaluated based on certain models and metrics. The results and the statistics are computed per waste collection route for the UC-1, UC-2, and UC-3 models for each of IS-1 and IS-2 scenarios. Specifically, in Figure 8 it presents the CT metric results. Median statistic measures of the CT metric distribution are presented in Table 3. Figure 9 presents the TT metric results. Median statistic measures of the TT metric distribution are presented in Table 4. Results for the L metric are presented in Figure 10. Table 5 presents the median statistics measures, of the L metric distribution. Figure 11 presents the results of the D metric. Median statistic measures of the D metric distribution are presented in Table 6. Similarly results for the F metric are presented in Figure 12. Table 7 presents the median statistic measures of the F metric distribution. S metric results are presented in Table 8. These results are inferred from all the values of CT, TT, L, D, F metrics. Note that for inferring the assessed values of S per IS and UC the *mode* statistic measure is used.

Table 3 Statistics for CT metric

CT	IS-1			IS-2		
	UC-1	**UC-2**	**UC-3**	**UC-1**	**UC-2**	**UC-3**
m	2,58	2,43	2,02	2,49	2,51	2,01

Figure 9 Results for TT metric

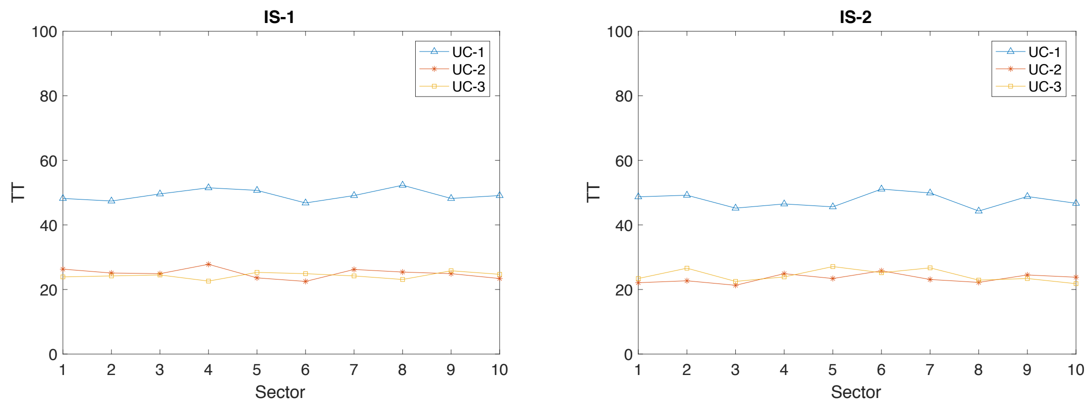


Table 4 Statistics for TT metric

TT	IS-1			IS-2		
	UC-1	**UC-2**	**UC-3**	**UC-1**	**UC-2**	**UC-3**
m	49,10	25,00	24,35	47,70	23,25	23,65

Figure 10 Results for L metric

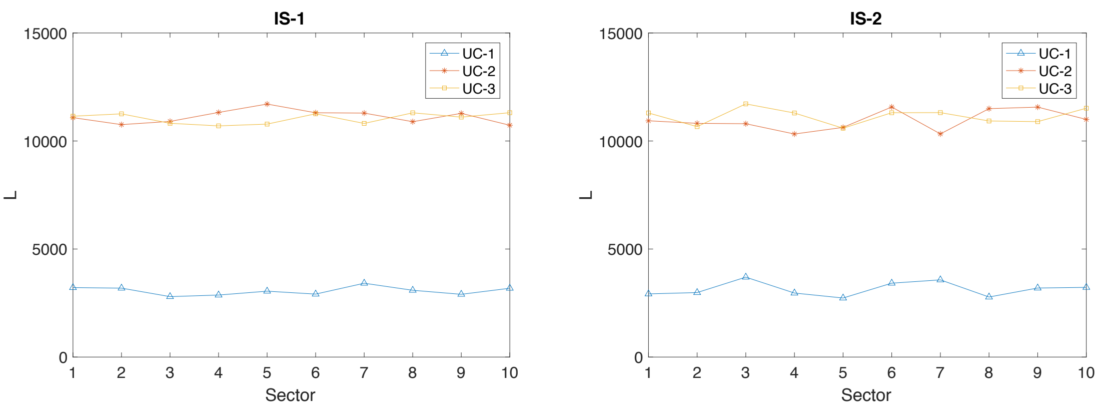


Table 5 Statistics for L metric

L	IS-1			IS-2		
	UC-1	**UC-2**	**UC-3**	**UC-1**	**UC-2**	**UC-3**
m	3069,50	11180,05	11126,95	3089,85	10875,95	11296,05

Figure 11 Results for D metric

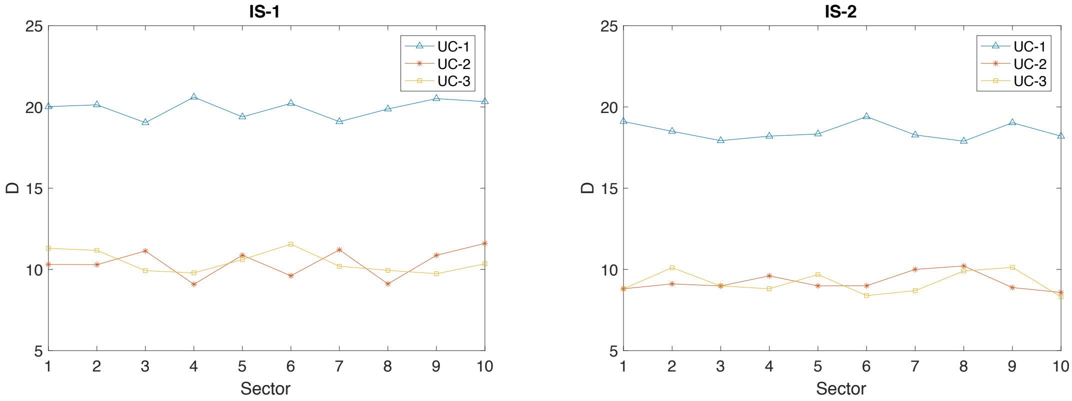


Table 6 Statistics for D metric

D	IS-1			IS-2		
	UC-1	**UC-2**	**UC-3**	**UC-1**	**UC-2**	**UC-3**
m	20,16	10,58	10,26	18,30	8,98	8,89

Figure 12 Results for F metric

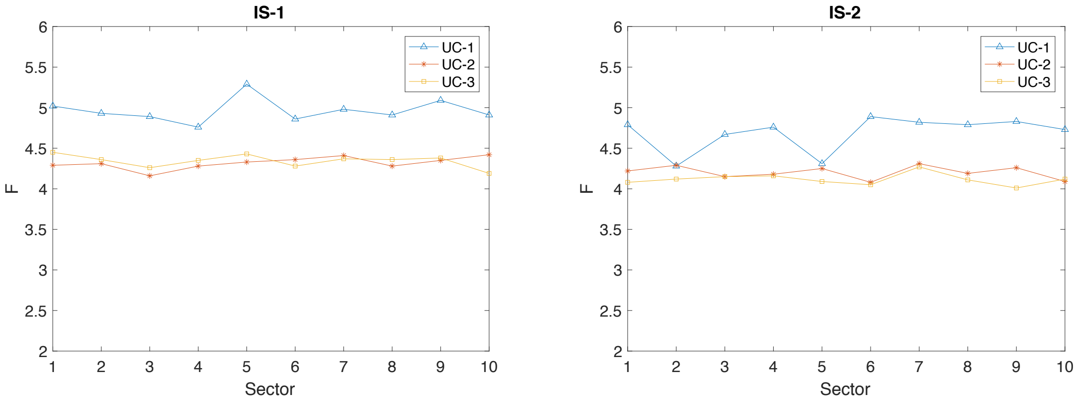


Table 7 Statistics for F metric

F	IS-1			IS-2		
	UC-1	**UC-2**	**UC-3**	**UC-1**	**UC-2**	**UC-3**
m	4,92	4,32	4,36	4,77	4,20	4,11

Table 8 Results for S metric

S	IS-1			IS-2		
	UC-1	**UC-2**	**UC-3**	**UC-1**	**UC-2**	**UC-3**
mode	*Low*	*Low*	*High*	*Low*	*High*	*High*

5.2 Discussion

In this section, we discuss the accuracy and validity of the results. Figure 8 and Table 3 present results and statistics for CT metric. Values for UC-1 and UC-2 are higher than UC-3. In addition, the value of UC-1 is higher than UC-2. This is explained due to CT process. Specifically, simulation parameter, used in UC-1, for the average time required tipping a bin ($\boldsymbol{k}$) is 2.5 minutes, which leads to higher value of CT. In UC-2 the $\boldsymbol{k}$ parameter is used,as in UC-1, but also the $\boldsymbol{l}$ parameter, which is the average time required to swap a container with value 1.5 minutes. Although UC-2 uses both parameters it is more CT efficient than UC-1 since there is a fusion on the values due to the capacity of bins and containers incorporated. UC-3 is more CT efficient than UC-1 and UC-2 since it is affected only by the average time required swapping a bin parameter ($\boldsymbol{n}$), which is 1 minute. All the CT values are not affected by the number of the dumps in the SC, so there are not biased by IS-1 and IS-2, since CT metric is affected only by the waste collection process between the bins, trucks and mobile depots.

TT results and statistics presented in Figure 9 and Table 4. Values of UC-2 and UC-3 are lower than value of UC-1. This is explained due to the use of mobile depots on both UC-2 and UC-3. Specifically, there is a fusion of TT values when both trucks and mobile depots are used. This is not the case in UC-1 where the trucks have to transport waste solely from collection points to dumps. In addition, TT values are higher for IS-1 than IS-2. This is explained due to longer distance have to be covered in the case of a single dump, like in IS-1, than the lower average distance has to be covered in the case of multiple dumps, which is the case of IS-2. For this reason, in IS-1 the case of UC-3 has lower values than the UC-1 and UC-2, while in IS-2 both UC-2 and UC-3 have lower values than UC-1 for the TT metric.

In the case of L metric results and statistics are obtained in Figure 10 and Table 5. L metric values are higher for UC-2 and UC-3 than UC-1 in both cases of IS-1 and IS-2. This is explained due to the fact that in UC-2 and UC-3 the volume capacity of the mobile depots is well aligned with the (***j***) simulation parameter, which is 12000 kilograms. In the case of UC-1, the distribution of L metric is based on the volume capacity of trucks parameter (***i***), which is 4000 kilograms.

Figure 11 and Table 6 present the results and the statistics for D metric. Value for UC-1 is higher than values of UC-2 and UC-3. This is explained since in the case of UC-1 trucks cover the whole distance between the location of the bins and the dumps. In the case of UC-2 and UC-3 trucks and mobile depots fuse the distance covered thus leading to a lower D metric values. In addition, in the case of IS-1 distance covered is on average higher than the distance covered in IS-2. This is because trucks and mobile depots in the case of IS-2 distribute the effort of the distance covered between multiple dumps.

F results and statistics are presented in Figure 12 and Table 7. F metric values are higher for UC-1 than for UC-2 and UC-3 since in the case of UC-2 and UC-3 trucks and mobile depots fuse the F metric distribution, while in case of UC-1 trucks consume more fuel to handle the waste collection process. In addition, in the case of IS-2, the F metric value is lower than the case IS-1. This is explained since in IS-2 there are multiple dumps distributed to the SC, which leads to less fuel consumption than with a single dump in the case of IS-1.

Results of S metric are presented in Table 8. Specifically, applying QoS algorithm to the distributions of the CT, TT, L, D, and F metrics leads to the S metric results. In the case of IS-1, UC-3 is inferred to have high satisfaction level while UC-1 and UC-2 are of low satisfaction level. Similarly, in the case of IS-2, both UC-2 and UC-3 reach higher satisfaction level than UC-1, which reaches a low satisfaction level. Qualitatively this means that IS-2 is an infrastructure scenario, which uses the dynamics of multiple dumps to achieve efficient results for the CT, TT, L, D and F metrics. In addition, UC-3 in both IS-1 and IS-2 achieves high satisfaction, which quantitatively means that UC-3 is more robust than UC-2 and more satisfactory than both UC-1 and UC-2.

We focused on the incorporation of an effective IoT-enabled model for waste collection, which is based on the adoption of high capacity waste trucks as mobile depots. Bin connectivity constraints are the limitations of the current study because they may affect the bin placement; for example, the output power of a communicating sensor would need to be set too high which may drain the battery faster. To overcome this limitation, the bin may be placed somewhere where energy consumption is more efficient to optimize comfort of residents.

6 Conclusion and Future Work

This research paper proposes a WMS, which incorporates certain waste collection swapping and tipping models. We prove that swapping models are more cost efficient than tipping models. Specifically, we introduced two infrastructure scenarios, IS-1 and IS-2, based on the number of dumps and recycling/processing units in the SC. In each IS we separate three use cases, UC-1, UC-2 and UC-3, to study efficient waste management. We treat waste management as an IoT-enabled system, which incorporates mobile depots as sustainable proxies. We also proposed three algorithms for the UCs, namely the tip algorithm for the UC-1 model, tip-swap algorithm for the UC-2 model and swap algorithm for the UC-3 model.

We defined certain metrics to evaluate the proposed system with synthetic data from the SC of St. Petersburg, Russia. Specifically, we introduce the CT, TT, L, D and F quantitative metrics and the S qualitative metric. The S metric takes as input the values of the quantitative metrics and gives an output of high or low satisfaction. It is inferred that UC-3 is more robust than UC-1 and UC-2 and achieves high satisfaction for both IS-1 and IS-2. In addition, UC-2 achieves high satisfaction only for IS-2, while UC-1 has low satisfaction for both IS-1 and IS-2.

We also focused on the limitations of the current study, which are that bin connectivity constraints may affect their placement. To overcome this limitation we proposed that the bin may be placed somewhere where energy consumption is more efficient to improve comfort of residents. Our future work focuses on optimizing the inference process of the proposed models by adopting a set of fuzzy logic inference controllers for each metric. In addition, we aim to perform a comparative study between a SC adopting such a model and the SC of St. Petersburg in Russia. Another interesting issue for further research is to incorporate the degree of consumer acceptance of the proposed models in future studies.

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