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Smart Waste Collection System Based on Location Intelligence

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Abstract

Cities around the world are on the run to become smarter. Some of these have seen an opportunity on deploying dedicated municipal access networks to support all types of city management and maintenance services requiring a data connection. This paper practically demonstrates how Internet of Things (IoT) integration with data access networks, Geographic Information Systems (GIS), combinatorial optimization, and electronic engineering can contribute to improve cities' management systems. We present a waste collection solution based on providing intelligence to trashcans, by using an IoT prototype embedded with sensors, which can read, collect, and transmit trash volume data over the Internet. This data put into a spatio-temporal context and processed by graph theory optimization algorithms can be used to dynamically and efficiently manage waste collection strategies. Experiments are carried out to investigate the benefits of such a system, in comparison to a traditional sectorial waste collection approaches, also including economic factors. A realistic scenario is set up by using Open Data from the city of Copenhagen, highlighting the opportunities created by this type of initiatives for third parties to contribute and develop Smart city solutions.

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1. Introduction

We are currently experiencing a fast development of Smart Cities where engineers, urban planners, architects and city managers are joining forces with the goal of boosting up the efficiency of municipal services and increasing benefits and convenience to their communities [1]. In this case, efficiency may be related to a wide spectrum of factors such as quality of life, economy, sustainability, or infrastructure management. ICT has been highlighted as

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one of the key enablers for Smart Cities/Societies regardless of the context or specific goals of each individual service, application or action under this umbrella [2].

In this paper, we describe how an integrated cyber physical system design, based on the combination of different disciplines in engineering, and taking advantage of municipal wireless access networks can lead to smart ways of improving the management of cities. The proposed system lays over the foundation of Geographic Information Systems (GIS), applied graph theory on graph optimization, and machine learning. It consists of an IoT based prototype with sensors measuring the waste volume in trashcans or containers, with the capability of transmitting information to the Internet via a wireless link. This data is used to optimize the management and strategies of waste collection logistics.

The system is simulated in a realistic scenario in the city of Copenhagen, and using freely available geolocation data of the municipality owned trashcans as Open Data [3]. The simulation covers a period of one month where trashcan filling and waste collection are modelled. The experiments are carried out performing an efficiency comparison of two different ways for waste collection: Traditional sectorial (not-intelligent) and dynamic on-demand based waste level status (intelligent). In addition, a preliminary assessment is performed evaluating whether the solution is economically sustainable on its own or not.

The outcomes of this work are an integrated system model for intelligent waste collection, and the quantification of its benefits and economic costs when deploying and using it for evaluating its feasibility as a real world Smart City application. In addition, this concrete use case illustrates the enormous potential of Open Data and the opportunities that a unified ICT infrastructure dedicated to Smart City oriented services can provide.

2. Background

The Smart City is a concept that has been widely used to describe the umbrella of new trends and goals pursued to make cities more efficient. These goals are very diverse such as to make greener cities by energy savings [4] or to improvement of people's quality of life [5]. Regardless of the application area or goals, one of the key enablers for this evolution is digital data and ICT infrastructure, and specifically in relation to the topic of this work, GIS based tools are highlighted to play an important role in decision support and data analysis [6]. Moreover, the development Internet of Things (IoT) and their applications have been acquiring relevance in Smart City solutions. In a nutshell, data gathered by sensors can be sent to remote servers where it is stored, processed and used for tracking, monitoring and ultimately making intelligent decisions for infrastructure or service management [7].

When the deployment and use of sensors becomes massive, the data collected together with its processing and storage can be directly linked to Big Data. Big Data is widely recognized to open new business models and data in this context is often referred to as the new gold. In addition, Open Data is considered a promoter of Big Data technologies such as IoT, and consequently the integration of both as part of cyber physical systems enhances the potential of a large spectrum of innovative Smart City solutions.

In relation to the application area of this work, waste collection systems and solutions have been a widely studied since they have direct impact on city management costs. However, these problems are very complex to solve due to its combinatorial nature. Examples of interesting solutions are [8] and [9] where routing and clustering algorithms to minimize the waste collection cost are proposed. In addition, sensing systems for measuring waste level in containers have been proposed in studies such as [10], elaborating also in the possibility that the system may lead to waste collection savings without any further analysis. Thus, our intention is not to create yet another solution in the context waste collection optimization by improving collection routing but to highlight the benefits and drawbacks of providing trashcans with some sort of intelligence, to optimize the selection of which cans should be collected daily.

3. System Description

3.1. Functionality overview

In a nutshell, the proposed waste collection system is based on waste level data from trashcans in a metropolitan area. The data collected by sensors is sent over the Internet to a server where it is stored and processed. The collected data is then used for monitoring and optimizing the daily selection of trashcans to be collected, calculating

the routes accordingly. Every day, the workers receive the newly calculated routes in their navigation devices. The key feature of this system is that it is designed to learn from experience and to make decisions not only on the daily waste level status but also on future state forecast, traffic congestion, balanced cost-efficiency functions, and other affecting factors that *a priori* humans cannot foresee. The rate at which trashcans are being filled can be analyzed based on historical data and the overflow predicted before it occurs. The optimized selection of trashcans to be collected is expected to reduce costs, improve collection efficiency or both, depending on predefined economic requirements. Fig. 1 shows the system overview.

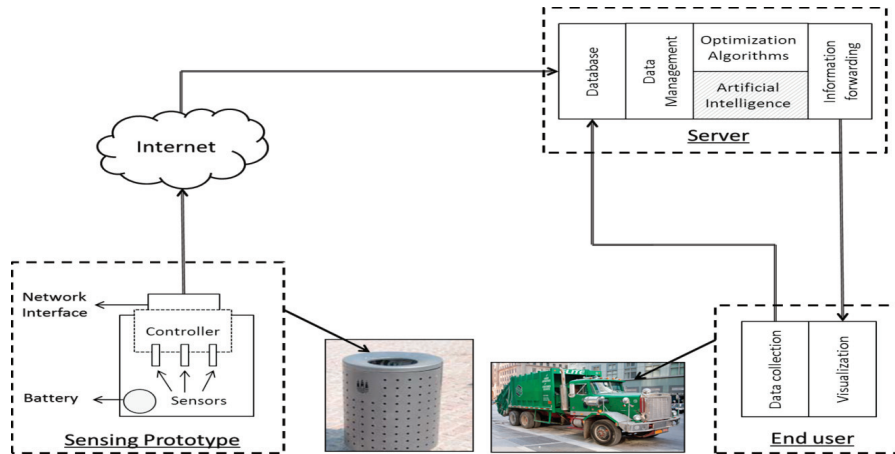


Figure 1. System overview of the smart waste collection system.

3.2. The system and its functions

A) The prototype:

- **Sensors:** The waste level is determined by measuring the distance from the top of the trashcan to the waste by sonar. The sonar used in the prototype is Ultrasonic Ranging Module (HC-SR04). It can provide measurement from 2cm to 400cm with 3mm accuracy, which adequate for typical trashcans. Additional temperature, humidity and motion, or weight sensors can be installed to increase the efficiency in the future.
- **Microcontroller:** The microcontroller used is Arduino Uno, which is based on ATmega328. It runs at 16MHz clock speed, and crank up to 1.5 Mips per MHz. It comes with on chip 2Kbytes of RAM and 32Kbytes of Flash Memory. The operating Voltage is 5V and power consumption 40 to 50 mA. The microcontroller is sufficient for collecting data from sensors and sending them to the Internet through a network interface. The choice of microcontroller was based on the required processing, memory, minimum power consumption, and lower price.
- **Access Network Interface:** The data collected must be sent to a remote server via a wireless link. In our prototype we used WiFi as a network access technology. We used CC3000 Shield with on board Antenna. The CC3000 provides an excellent coupling with the microcontroller used. The total cost of the whole prototype was approximately 45\$, price than can go down to around \$15-20 when massively produced.
- **Battery:** It is essential to optimize the battery usage to increase the lifespan of the devices. Sensing and data forwarding rates, and wireless technology used have a strong influence on energy consumption. In this particular case, data is collected and forwarded once day. The estimated device battery lifetime is at least a couple of years considering the used technologies and conditions.

B) Server:

- **Database:** Storage of all data collected by the sensors and the trucks, MySQL was employed for our setup.
- **Artificial Intelligence:** The forecast of waste levels and learning of how to select the daily cans to be collected is based on historical data. This module is highlighted in Fig. 1 because it has not been implemented for this work.

- Optimization algorithms: Everyday, after the trashcans to be collected have been selected, route optimization algorithms calculate the best route to follow. In this work, the routes are optimized in driving distance but there are also other possibilities such as to minimize driving time based on historical data on traffic congestion.
- Information adaptation and forwarding: The final routes must be sent to the workers in readable format by visualization devices, for example as a KML file.

C) End user:

- Visualization: The routes are sent to the end user and visualized in common devices such as mobile phones, tablets or navigation systems with data access. In this way the driver can easily follow the routes.
- Data collection: Additional data can be collected from the trucks such as GPS locations and timestamps in order to determine the traffic flow on the different streets. These and other data could be used by the Artificial Intelligence and Optimization Algorithms modules to learn and make better and more efficient can selections and routes.

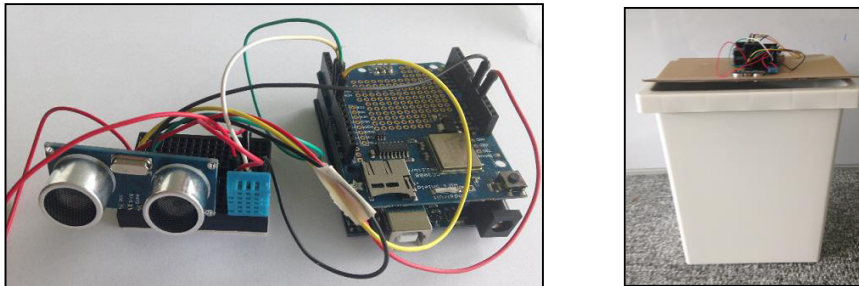


Figure 2: Prototype setup used in the experiment.

3.3. Algorithms

Shortest Path Spanning Tree (SPST) [11]: This algorithm is used to calculate the shortest distance between two points in the area (for example, two trashcans), combined with GIS data of the streets in the city. The street network can be represented as a graph where street segments are edges and the joining points are vertexes. Hence, it is possible to calculate a realistic shortest driving distance between points by applying SPST. The distances are necessary as an input for the route optimization process. For practical reasons, it is convenient to precompute the distance from all-to-all trashcans to speed up the route optimization process.

Genetic Algorithms (GA): Collection routes are essentially travelling cycles containing a given set of trashcans. The optimization of these cycles is a combinatorial optimization problem. When the objective function of this optimization is to minimize the driving distance (equivalent to minimizing the length of the cycles), the problem is well known as *The Traveling Salesman Problem* and closely related to *The Minimum Linear Arrangement Problem* which are NP-hard [12]. Due to the high number of route optimizations required to carry out the experiments, it was decided to use GA which are relatively fast in providing near-optimal solutions. A detailed explanation of how to use GA for this type of graph optimization problems can be found in [13].

K-means [14]: Clustering is also an NP-hard problem, especially complex to solve when involving hard clustering size constraints. However, the experiments carried out in this work do not have such constraints and K-means provides an easy and fast solution to the clustering problems to be solved.

4. Case Study

The experiments are carried out using real GIS data of the streets and municipality owned trashcans of the city of Copenhagen, Denmark. A total of 3046 trashcans are used, divided into 18 Collection Teams. Fig. 3 illustrates the geographic scenario; the dots represent the trashcans, each color corresponding to a different team. The rest of the data, collection strategies, and economic models required for carrying out the experiments are derived or assumed by the authors, and therefore by no means the provided results can be associated to any practices, management procedures or protocols currently performed by the city of Copenhagen in reality.

4.1. Scenario modelling

The following lines describe the models, assumptions and parameters necessary to carry out the experiments:

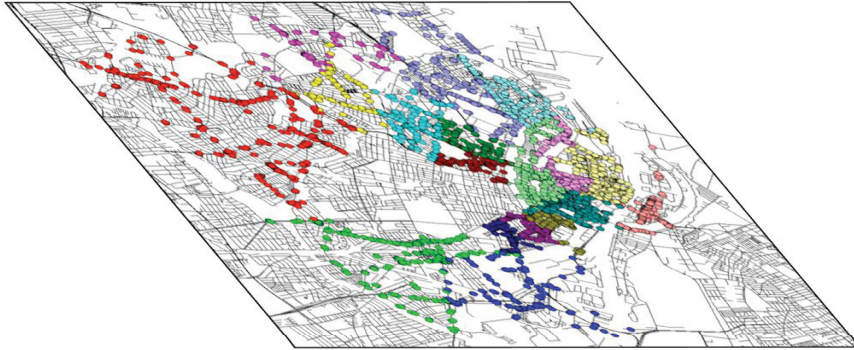


Figure 3. Street Network and Trashcans Geographic Overview.

- **Trashcans filling modelling:** No data in relation to how trashcans are being filled is available at this early stage of the project. Thus, a simple trashcan filling model was implemented based on Poisson distributions. Each individual trashcan i is assigned an average time to become full F_i where the Poisson average of the distribution is $\lambda=7$ days. In addition, each trashcan i is assigned a daily filling volume DF_i^d following a Poisson distribution of $\lambda=1/F_i$ where d corresponds to each concrete day in the simulation period. This modelling allows us to have some variance in terms of how trashcans are being filled.
 - **Collection modelling:** As previously introduced, there are two collection strategies based on the trashcans selected for each of the days.
 - Sectorial, the trashcans for each team area are clustered into subsets, and one cluster per day and team is collected. Neither sensing data nor intelligence is involved.
 - Dynamic, the trashcans to be collected are selected based on their filling states given by the sensors.
 - **Route Creation:** For each team, an arbitrary point was selected as headquarters and all routes must start and end at this point. Daily routes are created optimizing the driving distance for visiting all the selected cans for each day and team. There are 18 teams implying 18 parallel routes per day. Routes were created using the previously mentioned algorithms in Section 3.3, SPST to calculate the minimum driving distance between points in the area and GA to minimize the driving distance for visiting the selected cans and returning to the headquarters.
 - **Economic Models:**
 - Collection costs, C : Expenses in relation to waste collection. These include driving and worker time costs. Eq. (1a) illustrates how the cost of a generic route i (C_i) is calculated. C_{km} is the cost per km of driving, D_i is route's i driving distance, C_w is the cost per man hour, T_i is the time to complete route i , and p is number of workers per collection team. Eq. (1b) elaborates on how T_i is calculated, s being the average driving speed, and N_i the number of trashcans to be collected.
 - System's CapEx, S_{CapEx} : Cost related to the deployment of the system. Generically, Eq. (2a) illustrates the calculation of S_{CapEx} as the sum of the cost for deploying the devices (C_{dev}), cost for deploying the necessary access network (C_{acc}), and the cost of extra equipment such as servers or other devices (C_{eq}).
 - System's OpEx, S_{OpEx} : Cost related to the operation and maintenance of the system. Generically, Eq. (2b) shows how S_{OpEx} can be calculated as the sum of system's physical maintenance cost (C_m), cost of system administration (C_{sys}), cost of access network use (C_{net}), and costs related to physical facilities use/rent (C_{fal}).
- $$C_i = C_{km}D_i + pC_wT_i \quad (a) \quad T_i = \frac{D_i}{s} + t_cN_i \quad (b) \quad (1)$$
- $$S_{CapEx} = C_{dev} + C_{acc} + C_{eq} \quad (a) \quad S_{OpEx} = C_m + C_{sys} + C_{net} + C_{fal} \quad (b) \quad (2)$$
- **Performance Parameters:** These are used to quantify the efficiency of the different collection strategies tested.

- Route length: Driving distance required to collect the selected trashcans each of the days.
- Waiting time to empty full trashcans: Days the trashcans remain full being unavailable.
- Waste overflow: Waste that should be placed into the trashcans that cannot be accommodated due these being full. For the experiments, redistribution of waste to nearby trashcans when full is not considered.

4.2. The experiments

All the experiments were run simulating a period of five weeks, being the first one to stabilize the system results and the other four to collect results. Cans are collected once per day. In addition, the filling rates and daily filling volumes for all cans were pre-calculated for the simulation period before running the experiments. These were used for all the cases and scenarios, in order to ensure that the results correspond to exactly the same conditions (same waste volume generated and placed in the same cans). The two sets of experiments carried out are the following:

A) Strategy efficiency: Three collection strategies are compared in these experiments.

A.1 - Sectorial: The trashcans for each team are divided into seven clusters based on their geolocation, each cluster being collected one specific day of the week. Similar size clusters were created for each team, allowing a size variance of $\pm 5\%$ of the team's number of trashcans for simplifying the calculation process.

A.2 - Dynamic A: The collected trashcans were selected based on their filling state (the most full) and the number of trashcans collected was constrained to exactly the same number as the Sectorial case for each specific day and team. For example, if in "Team 1" and "Day 8" 43 trashcans were collected in the Sectorial case, also 43 were collected in the Dynamic A case for the same team and day. This constraint was applied in order to compare route distances under exactly the same number of collected trashcans.

A.3 - Dynamic B: The collected trashcans were selected based on their filling state (all which are full). The number of trashcans to be collected each of the days was not constrained, allowing more adaptability of the collection strategies to the daily trashcan status.

The assumptions made for the required parameter are: $C_{km}=\$0,5$, $p=2$, $C_w=\$10$, $s=30$ km/h, $t_c=5$ minutes.

Table 1 shows the results of the simulation of the routes as averages per collection day and a total of 18 parallel routes involving 3046 trashcans. Eqs. (1a) and (1b) are used to calculate the costs (money and time) for each route.

Table 1. Key collection parameters given as averages per collection day.

Method	Driving (Km)	Trashcans col.	Time (h)	Cost (\$)
Sectorial	46.23	435.14	37.80	779.18
Dynamic A	133.31	435.14	40.71	880.77
Dynamic B	137.24	491.86	45.56	979.88

Table 2. Efficiency parameters given as averages per collected trashcan.

Method	Waiting days when full	% of full trashcans when collected	Waste overflow (as trashcan capacity %)
Sectorial	0.80	0.53	0.30
Dynamic A	0.49	0.98	0.21
Dynamic B	0	1.00	0.07

Table 2 illustrates the efficiency results for the three strategies, expressed as averages per collected trashcan.

The results indicate that to base the collection strategies on trashcan filling status implies considerably longer driving than when the Sectorial approach is followed (Table 1), implying also higher daily collection costs. On the other hand, the efficiency clearly improves in terms of the waiting days to be collected when trashcans are full, and waste overflow. This is mainly due to the Dynamic approaches collecting (almost) all cans when they are full (% of full cans collected in Table 2). It is worth highlighting that it is possible reduce down to 0 the waiting days to collect full cans by increasing 10% the number of cans collected per day respect to the Sectorial approach, and applying the Dynamic B strategy. It may be anticipated that the waste overflow could be lowered even more when integrating the Artificial Intelligence module, since trashcan selection can be based on the trashcans which are expected to be full "tomorrow" by using historical data analysis instead of cans which are full "today" (Dynamic B strategy).

B) Economic feasibility:

B.1 - Calculation of the total costs of the three strategies in A) over a period of 2 years (estimated as the minimum device’s battery lifetime).

The total costs are the sum of collection costs (C), and system’s CapEx and OpEx, as presented in Table 3 and Eqs. (1a), (2a), and (2b) are used for the calculations. The assumptions made for the required parameter are: $C_{dev}=\$20$ per trashcan, $C_{acc}=0$, $C_{eq}=\$5000$, $C_{net}=0$, $C_{fal}=0$, $C_m=\$11.4$ per day, $C_{sys}=\$11.4$ per day. C_m and C_{sys} are derived from having one worker dedicated 8 hours per week to the task at a price of $\$10/\text{hour}$. C_{acc} , C_{net} , C_{fal} are set to 0 as an indication of the use of municipal access networks and ICT infrastructure that can be shared among all the smart services provided in the city. The results show that to deploy and maintain the system implies higher total costs. Therefore, although the efficiency improves, the price may be a constraint for city managers or decision makers to deploy such a system.

Table 3. Total costs over 2 year period.

Method	C (k\$)	S_{CapEx} (k\$)	S_{OpEx} (k\$)	Total Cost (k\$)
Sectorial	568.88	0	0	568.88
Dynamic A	642.96	65.92	16.68	752.76
Dynamic B	715.31	65.92	16.68	797.91

B.2 - Equal performance economic analysis: The previously commented results clearly indicate that to improving the collection strategies by deploying an intelligent system will incur into some economic expenses. In this experiment, the Dynamic strategies are compared to Modified Sectorial approaches to estimate their total costs when providing similar efficiency figures. The Modified Sectorial approaches are created by progressively reducing the number of clusters per Team from 7 to 6, 5, and 4. In this way, as the number of clusters is reduced, the trashcans are being collected more often. The experiments are limited to Team 1 with 291 trashcans due to high computational resources required to consider the whole city, however the results serve as an indication of the effect of the Modified Sectorial approaches over the complete scenario.

Fig. 4a. shows the average waiting days to be collected when trashcans are full and the waste overflow (as trashcan capacity %) for the previously mentioned cases. It can be observed that the same waste overflow for Dynamic B can be achieved by applying Sectorial approach with 5 clusters. However, the waiting days do not become 0 with any of the Sectorial strategies. Hence, it can be considered that the efficiency level of Dynamic B may be comparable (to some extend) to the Sectorial strategies with 4-5 clusters.

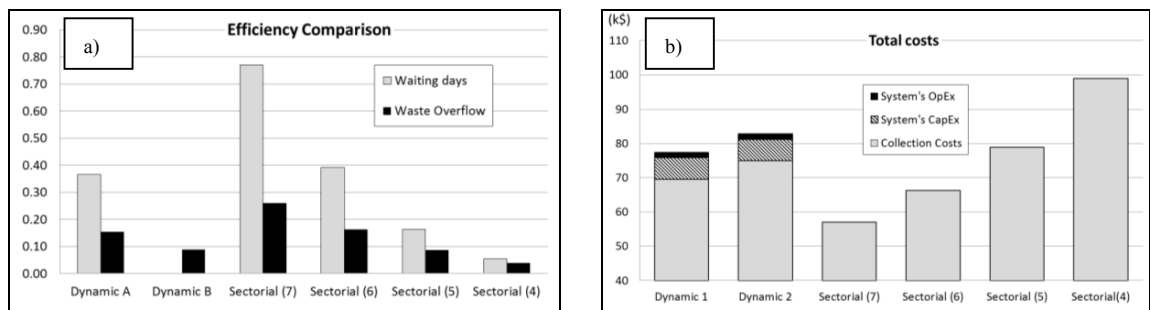


Figure 4. a) Efficiency Comparison for Team 1. b) Total Costs Comparison for Team 1 after 2 years.

Fig. 4b. presents the cost comparison for the different studied cases after 2 years. The values of S_{CapEx} and S_{OpEx} for Team 1 are calculated proportionally to its number of trashcans in relation to the total number in the city (ratio of 291/3046). The results indicate that the savings by applying the Dynamic B strategy may pay off (or be close to) the extra expenses for deploying and maintaining the system when compared to similar efficiency Sectorial approaches (4-5 clusters per team). Hence, it can be concluded that similar efficiency may imply similar total costs when using or not intelligent waste collection system under the studied cases. Consequently, considering that the Artificial

Intelligence module has not been implemented yet, the can selection is expected to be improved with the analysis of historical data (for example in terms of balanced cost-efficiency). Thus, there are good indications that when having a fully working system, an intelligent solution may outperform traditional strategies in both efficiency and costs.

5. Conclusion

This paper presents a practical Smart City use case of an intelligent waste collection cyber physical system. The system is based on an Internet of Things sensing prototype which measures the waste level of trashcans and sends this data over the Internet to a server for storage and processing. Based on this data, an optimization process allows creating the most efficient collection routes, and these are forwarded to the workers. The paper is focused on the efficiency and economic feasibility of the system, in order to motivate the potential interested parties to deploy intelligent solutions for common city services. The experiments are carried out on a Geographic Information Systems simulation environment, applying graph optimization algorithms and taking advantage of available Open Data about the city of Copenhagen, Denmark.

The results indicate that under the same conditions, basing the waste collection strategies on real time trashcan filling status improves the waste collection efficiency by guaranteeing that when trashcans become full, they are collected the same day, and by reducing by a factor of 4 the waste overflow that cannot be accommodated when trashcans are full. However, the distance required to drive is tripled, implying an increment on the daily collection cost between 13 - 25%.

In relation to the economic feasibility analysis, the improvement in efficiency by deploying and using the proposed system implies higher total costs. However, when comparing the total costs of the different collection strategies under similar efficiency figures, we have observed that the savings in collection costs for an intelligent solution may cover the extra expenses for deploying and maintaining the system (CapEx and OpEx) in a short term perspective of 2 years. Furthermore, once the system is deployed, the efficiency and collection costs could be further improved when historical data is available for trashcan selection optimization.

In relation to future work directions, being aware that the numerical results of the experiments are highly dependent on assumptions considered, a sensibility analysis on the different parameters may provide valuable information about the system's performance in under different conditions. Furthermore, the natural step to take is to test how the use of historical data analysis can improve the efficiency and collection costs of dynamic strategies. Afterwards, if the results are satisfactory, field trials are expected to be conducted.

References

- [1] Kunzmann K.R., Smart Cities: A New Paradigm of Urban Development. Crios, 1/2014, pp. 9-20, doi: 10.7373/77140
- [2] Kominos, N., Intelligent Cities: Innovation, Knowledge Systems, and Digital Spaces, 2002, Spon Press
- [3] Open Data Copenhagen: <http://data.kk.dk/>
- [4] T. C. G. on behalf of the Global eSustainability Initiative, The ICT behind cities of the future. *SMART 2020*, 2010.
- [5] Piro G., Cianci I., Grieco L., Boggia G., and Camarda P., Information centric services in smart cities, *Journal of Systems and Software*, vol. 88, no. 0, pp. 169 – 188, 2014.
- [6] Kostakos V., Ojala T., and Juntunen T., Traffic in the smart city: Exploring citywide sensing for traffic control center augmentation, *Internet Computing*, IEEE, vol. 17, pp. 22–29, Nov 2013.
- [7] Mitton N., Papavassiliou S., Puliafito A., Trivedi K. S., Combining Cloud and sensors in a smart city environment, *EURASIP Journal on Wireless Communications and Networking*, 2012:247, 2012
- [8] Nuortio T., Kytöjoki J, Niska H., Bräysy O., Improved route planning and scheduling of waste collection and transport, *Expert Systems with Applications*, Volume 30, Issue 2, February 2006, Pages 223-232, ISSN 0957-4174.
- [9] Byung-In K., Seongbae K., Surya S., Waste collection vehicle routing problem with time windows, *Computers & Operations Research*, Volume 33, Issue 12, December 2006, Pages 3624-3642, ISSN 0305-0548.
- [10] Vicentini F., Giusti A., Rovetta A., Fan X., He Q., Zhu M., Liu B., Sensorized waste collection container for content estimation and collection optimization, *Waste Management*, Volume 29, Issue 5, May 2009, Pages 1467-1472, ISSN 0956-053X
- [11] Spira, P. M., and Pan On, A., Finding and Updating Spanning Trees and Shortest Paths. *SIAM Journal on Computing* 1975 4:3, 375-380
- [12] Petit, J., Experiments on the minimum linear arrangement problem, *Sistemas Informatics*, 2001., vol. 8, pp. 112–128, 2001.
- [13] Gutierrez J. M., Imine M., and Madsen O. B., Network planning using GA for regular topologies, *Proceedings of IEEE International Conference on Communications, ICC 2008*, Beijing, China, 19-23 May 2008, pp. 5258–5262, 2008.
- [14] Steinbach M., Karypis G. and Kumar V., A Comparison of Document Clustering Techniques, *KDD Workshop on Text Mining*, 2000