# Methods for Sensor Placement in Waste Management

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A B S T R A C T

The present dissertation, developed within the Industrial Engineering and Management Master's program, intends to study an economically sustainable incorporation of information and communication technologies on the collection operations of solid wastes. More precisely, it's studied the implementation of ultrasonic sensors that, when installed inside the containers, are capable of measuring its filling level. The current collection routes are quite inefficient, since they are fixed routes that don't depend on the real waste levels. The use of this technology will provide information that enables the introduction of dynamic and more efficient collection routes, while the number of overfull containers is also reduced. However, the costs of implementing such technology are still very high. In this dissertation are studied criteria and strategies which may allow to identify what are the containers, of a certain population, in which their monitorization is more beneficial. Therefore, the main objective of this dissertation is to study the application of different methods for selecting a reduced number of containers to be monitored, in order to reduce the investment costs associated to the use of sensors, while maintaining the benefits of using this technology. For this purpose, it is analysed the collection operations of ERSUC – company that operates in the central west coast of Portugal –, in the municipality of Soure, from where it was concluded that monitoring only a fraction of the containers may allow a cost reduction of 11% when compared to all containers being monitored and of 21% when compared to the current situation.

## 1. Introduction

### *1.1. Problem Contextualization*

One of the major problems of Municipal Solid Waste Management (MSWM) today is the lack of efficiency on the collection of solid wastes and associated transportation. Since this the step where most of the costs reside in solid waste management, companies have been trying to find ways for tackling these inefficiencies with the integration of new information and communication technologies (ICTs). One example is the use of sensors that allow the measurement of the amount of waste existing inside a container in real time. By monitoring the real levels of waste, companies can develop models capable of responding to changes in the demand for collection and, consequently, they can optimize the collection routes and reduce the number of unnecessary pickups.

However, in his work, Gonçalves (2014) verified that the costs of installing the ultrasonic sensors in all containers were very high and wouldn't overcome the benefits of having them. The present dissertation comes as a result of Gonçalves' work and his conclusions. Even if this type of technologies allows us to better understand the waste collection systems and to gain insights from the data collected, they are still very pricey, and it is necessary to develop financially more sustainable strategies for integrating them into the waste collection activities.

For that, in this work, it will be analysed in which circumstances makes sense to have a sensor embedded in a container to measure its filling level, and a set of criteria, that takes into account the containers' characteristics will be identified.

Therefore, the main objective of the present dissertation is to develop methods for selecting a reduced number of containers to be monitored, in a given collection area. With this, it is intended to evaluate and compare how the different methods effect the day-to-day collection operations, under a dynamic collection policy. It's essential to perform a financial analysis, to understand if the proposed methods can help reducing the overall costs when compared to the current waste collection policy and to the scenario where all the containers are monitored.

In order to perform this study, it will be studied the real-case scenario of the paper/cardboard collection operations, in the municipality of Soure. These operations are carried out by ERSUC, which is a waste collection company that operates in the central west coast of Portugal.

### *1.2. Methodology of the Work*

In order to achieve the objectives mentioned, it was adopted the following methodology:

1) Contextualization of the solid waste management sector: The modus operandi was to start from the most-wide ranging topic and then start narrowing into the more specific subject matters that led to the identification of the problem under consideration.

2) Literature review: In this stage, it is performed a literature review on the aspects, practices and other topics worth considering when installing sensors in containers.
3) Development of the sensor placement methods: In this stage, the methods for selecting the containers are developed, taking into account the ideas and criteria extracted from the literature review.
4) Development of a dynamic collection policy: This stage consists on developing a dynamic collection policy that will be used to validate the methods proposed by simulating the day-to-day waste collection operations of each one.
5) Data collection: In this stage real data from ERSUC regarding each individual container will be collected and analysed. These data are used to describe the current situation, but also to statistically model the waste demand, which is necessary for simulating the day-to-day collection operations.
6) Testing the proposed methods with the real-case scenario data: The methods for selecting the containers are applied to the real-case scenario (its data were used as inputs) and, subsequently, the several different selections are run in the simulation environment, in order to obtain the results.

## 2. The Waste Management Sector

During the last 20 years, in Portugal, several sustainable measures were adopted that have directed the country to increase the reuse and recycling of waste materials, where the expansion of a separate collection for these recyclables played a major role (APA, 2019; Niza et al., 2014). However, these measures, even if important, often neglected the operational performance of such services, whose inefficiencies had led to a substantial aggravation of the collection costs, being important now to upgrade the collection models (APA, 2019).

In fact, waste collection is the phase that sustains any waste management system, being where the majority of the MSWM costs are located (Faccio et al., 2011; Kaza et al, 2018). These costs could be reduced, if the waste collection's resources were used more efficiently. The main reason why resources are not better used is a consequence of waste collection companies not knowing the real filling levels of the containers to be collected, resulting in trucks collecting partially full or even empty containers (Faccio et al., 2011; Ramos et al., 2018).

Currently, waste collection companies operate on the basis of static waste collection routes ("blind collection"), i.e., the routes which are performed are invariably the same ones, they are pre-defined routes that do not depend on the containers' real filling levels. Since the amount of solid waste generated by the communities is highly variable and hard to predict, assumptions about the quantities of waste existing inside a container are often incorrect (Faccio et al., 2011; Gonçalves, 2014; Johansson, 2006; McLeod et al., 2013; Ramos et al., 2018).


**Figure 1:** Waste collection routes with (b) and without (a) the ultrasonic sensor technology (adapted from Gonçalves, 2014).

With the installation of ultrasonic sensors in containers, it is possible to measure their levels of waste. This technology is, more and more, seen as a solution to reduce the uncertainty regarding the waste demand. This enables the transition from a blind collection to a dynamic collection, where routes are taken according to the real needs of a given moment (see Figure 1). With this, the distance travelled and the number of vehicles needed could, for example, be reduced, while the truck's load capacity is better exploited. Thus, waste collection companies can benefit from less fuel consumption and lower operational costs while reducing also the associated environmental impacts (Esmaeilian et al., 2018; Gonçalves, 2014; Ramos et al., 2018).

According to Lundin et al. (2017), when adopting this new type of solutions, waste collection companies still have valid concerns. They consider that the solutions that exist in the market are very expensive and is not clear to them if the benefits gained could compensate for the high investment costs that are required. According to the entities interviewed by the author, most them consider 70€ to be an appropriate price to pay for each sensor. However, the magnitude of the prices that some of the ultrasonic sensor providers charge are considerably greater than 70€. For example, Evox charges purchase prices between 140€ and 360€, and estimates installation costs between 5€ and 15€ per sensor, and also charges a rent of 1€ per month, per sensor. In his work, Gonçalves (2014), shown that for a network of 928 containers, equipped with Enevo sensors, it was possible to obtain savings of 14650€ annually. However, considering the rent prices of 13€ (i.e., 156€ annually, per sensor), the benefits had no chance of standing against implementation costs of 144768€.

It seems realistic that there's still work to be done in order to integrate these technologies in waste collection operations in a financially more sustainable way. In order to fill this gap, in this dissertation, it will be sought to understand the cost-benefit relation associated to the implementation of a sensor into a container. The value of using a sensor in a container will not be the same for each container and, in that way, it must be studied in which ones the sensor will be the most useful, i.e., in which ones the information they may provide, regarding waste demand levels, is more likely to be the most valuable for improving collection routes and scheduling. For that, containers' characteristics must be studied and several methods for selecting a reduced number of containers to be monitored, must be analysed.

## 3. Literature Review

### 3.1. Aspects regarding waste demand characteristics

In Zsigraiova et al. (2013), it’s emphasized how the waste collection problem (WCP) is a stochastic problem, and the authors criticize the fact that, in order to compensate for a lacking of reliable information regarding the filling-levels of individual containers, some works use the same average fill-up rate to model the generation of waste in the whole area under study. Mes et al. (2014) also treats the WCP as a stochastic problem, where future demand is known only in a probabilistic sense and is revealed over time through the use of sensors. The authors also consider important to learn with the historical fill-up levels in order to create more reliable predictions for the future. Other studies also acknowledge that the waste demand at each container must be dealt as having a probabilistic distribution and statistical analyses based on historical data may be used to improve solutions (Faccio et al., 2011; McLeod et al., 2013).

Several other works outline how waste demand rates (Krikke et al., 2008; Straightsol, 2014) and variability (Johansson, 2006; Mcleod & Charret, 2014; McLeod et al., 2013; Mes, 2012) affect remote monitoring’s utility for the optimization of collection routes and schedules. According to the authors, the value of having accurate information about waste levels increases for collection areas that have low deposition rates (require lower collection frequencies) and that experience more unpredictable rates (have a higher variability).

### 3.2. Spatial aspects regarding waste collection points

MSWM systems are clearly of spatial nature and they depend on the facilities locations and containers distribution (Zsigraiova et al., 2013). A higher dispersion of collection points results in relatively greater challenges and costs for waste collection companies (APA, 2019; Teixeira et al., 2014). The use of volumetric sensors allows for a greater savings potential in situations where sites are, on average, more isolated from each other since there are more possibilities of reducing the total distance travelled due to the dynamic routing (Mcleod & Charret, 2014; McLeod et al., 2013). With this, containers that are more isolated are also preferred to be monitored since unnecessary long-distance trips can then be avoided. This was the criteria adopted by Oxfam when some of the sensors they planned to use were damaged and decision-makers had to choose where to implement them in only 36% of the total number of sites (Straightsol, 2012, 2014).

### 3.3. Dynamic routing and scheduling practices to integrate with remote monitoring

Several works where it was implemented different dynamic and scheduling practices that might improve the integration of remote monitoring technologies, especially in the context of the problem in study, were also reviewed. Different authors agree that it can make sense to collect waste from containers, even if these are not near full capacity, in order to improve the collection vehicles’ capacity utilization and save future costs (Mes, 2012; Mes et al., 2014; Nourinejad et al, 2018; Omara et al., 2018; Ramos et al., 2018).

This is explained by the fact that it can be convenient to add partly filled-up containers to the collection process since sometimes their location is already included in (or is relatively close to) the assigned routes. Furthermore, as deposition rates increase, the better is to collect at lower filling levels and vice-versa (Nourinejad et al., 2018).

## 4. Methods for sensor placement

### 4.1. Proposed Methods

From the literature review, it was identified four main criteria for selecting when to monitor a container: low waste demand rates, high waste demand variability, high remoteness, and container not being an intermediate one.

The different methods described in the following sections for selecting the containers will apply these criteria to the population of containers. The first three methods will consist on a directly applying an individual criterion – waste demand rate, waste demand variability and remoteness. The fourth method is an algorithm that intends to indirectly apply some of the criteria – remoteness and the degree of how much intermediate a container is. Finally, the fifth method, will explore the application of the three first criteria simultaneously.

For the direct application methods, it will be defined a measuring unit for ranking the different containers in each criterion. In this way, for each criterion, an ordered list with all the containers is obtained, where the order is given by starting in the container that scored higher in that criterion and ending with container that scored the lowest. This means that a sample of the *k* containers that scored higher, in each criterion, can be selected.

#### 4.1.1. Method 1 – Waste demand rate of a container

It was concluded that it makes more sense to have a sensor in containers where the waste demand rate is lower. This means that the value of monitoring a specific container (the value of information) is inversely proportional to the waste demand rate of that container. The measurement unit that will be used to evaluate this criterion is the sample mean ($\bar{x}$) of the waste demands rates of the container – a container will be higher ranked for being selected as its sample mean decreases:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

#### 4.1.2. Method 2 – Waste demand variability of a container

It was concluded that when the deposition rate is uniform across time (lower variation of the deposition rate values), the need for a sensor is less, and when it is more floating (higher variation), the need for a sensor is higher. Therefore, the value of information is proportional to the waste demand variability of a certain container. In order to assess the waste demand variability of a container, it will be used the sample coefficient of variation of the observed values – the higher this measure, the more a container is preferable to be selected. This is a dimensionless measure that can be obtained by dividing the sample standard deviation to the sample mean:

$$\widehat{C_V} = \frac{s}{\bar{x}} \tag{2}$$

### 4.1.3. Method 3 – Remoteness of a container

This criterion is related with how much a container is isolated from the other locations of the collection network. It was seen that the more remote a container is, the more logical is to have it monitored, in order to prevent the cost of long distances being travelled unnecessarily. So, the value of information increases as the degree of remoteness of a container increases.

In order to evaluate the remoteness, it will be considered the road distances between locations, and two different options will be studied.

The first option will consider that the remoteness of a container depends solely on the distance to closest container. Considering *n* container locations and location 0 to be the depot, the remoteness of a container *i* is evaluated in the following manner:

$$r_i^{\,1} = \min\left(\left\{\frac{d_{i,0} + d_{0,i}}{2}, \dots, \frac{d_{i,n} + d_{n,i}}{2}\right\} \backslash \{d_{i,i}\}\right) \qquad i = 1, \dots, n \tag{3}$$

The second option evaluates the remoteness by calculating the average distance to all the other locations of the collection network (remaining containers + depot):

$$r_i^{\,2} = \frac{1}{2n}\left(\sum_{j=0, j\neq i}^{n} d_{i,j} + \sum_{j=0, j\neq i}^{n} d_{j,i}\right) \qquad i = 1, \dots, n \tag{4}$$

For both options, the higher the value of $r_i$, the more a container is preferable to be selected, according to its remoteness.

### 4.1.4. Method 4 – Cost Reduction Algorithm

Besides considering the criterion remoteness, method 4 will also attempt to consider how much intermediate a container is – a priori, containers that are "more intermediate" will have less chances of being selected by this algorithm. This is done since it was concluded that it can be advantageous for dynamic routing practices to collect the containers that are not near full capacity when the collection trucks will inevitably pass by them. Hence, in case such practice is carried, the value of information decreases for "very intermediate" containers.

Therefore, with the cost reduction algorithm, the placement of a sensor on a container will be guided by the fact that embedding a sensor in different locations might lead to different cost reductions on the total path necessary to visit the locations, and thus it would be more desirable to select the location which provides the larger cost reduction. The output of this algorithm is an ordered list that presents first the ones with a higher cost reduction.

It is considered *n* container locations plus a depot, a matrix $m_{ij}$ that represents the distances between all locations, and that all locations without sensor are covered by a fixed collection route with cost $C_{fixed}$. If now we want to know in which order the containers should be monitored, we can see, at each iteration *t*, which is the location *i* that when is "removed" – meaning that it turns to be a monitored container and is removed from the fixed collection route – will allow to obtain a collection route for the other (*n* – *t*) non-monitored locations, so that the difference $C_{fixed} - C_{n-t,i}$ is the maximum, for $i = 1, \dots, n + 1 - t$. In Figure 2 is presented the flowchart of the algorithm's functioning.

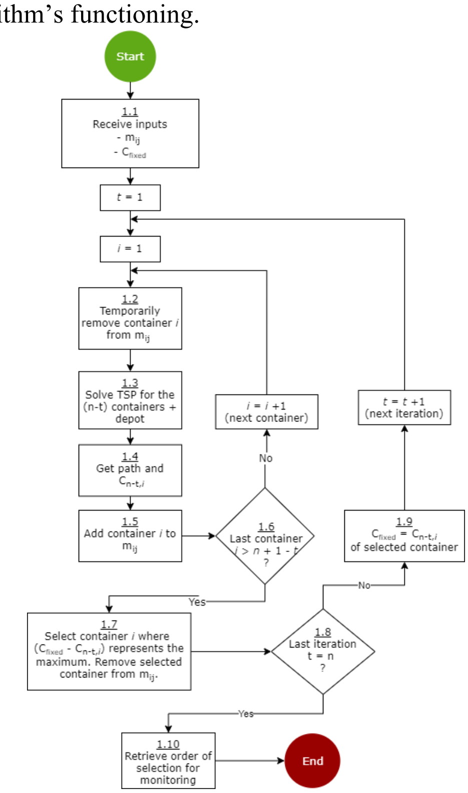


**Figure 2:** Flowchart of the cost reduction algorithm

### 4.1.5. Method 5 – Considering rate, variability and remoteness

The last method will consider the classification of each container, according to their behaviour in all the criteria that were presented in methods 1, 2 and 3. For example, if a container ranks among the top x% in the different criteria, a priori, they should be selected for being monitored.

## 4.2. Dynamic Collection Policy for Validation

Here, it is presented the dynamic collection policy that will be used to validate the methods proposed by simulating the day-to-day waste collection operations of each one (see Figure 3). With this policy:

→ Is intended to simulate the collection operations, where part of the population of containers is being monitored and communicates the filling levels in real time;
→ Routes are adapted to the waste demand by taking into account the filling levels of the monitored containers, and other aspects such as the historical data (rate and variance) regarding the complete population of containers:

- For the containers with sensor it's considered a specific threshold of collection
- For the containers without sensor it is considered a collection interval since the last visit

→ Containers to be collected are selected and then it is solved a Travelling Salesman Problem (TSP) to find the route to visit them;
→ The filling levels of the containers are determined by considering a stochastic function of the time, since last collection, i.e., the daily deposition rate is generated by considering the continuous probability distributions of each individual container;
→ Results such as the incurred costs and the number of overflows are computed;
→ Some inputs are: the matrix of costs between all locations, a graph that represents the topology of the road network, a list of the monitored containers, and, for each container, the threshold level, the required collection interval, and the parameters that will allow to model the waste demand of each container into a continuous probability distribution;
→ Other input is the required number of containers to be collected in each route, that is adapted to the geographical area in question. After critical containers are added (containers that must be collected today), it is added the next most critical containers and containers in-between (on the collection path) until this number is reached.

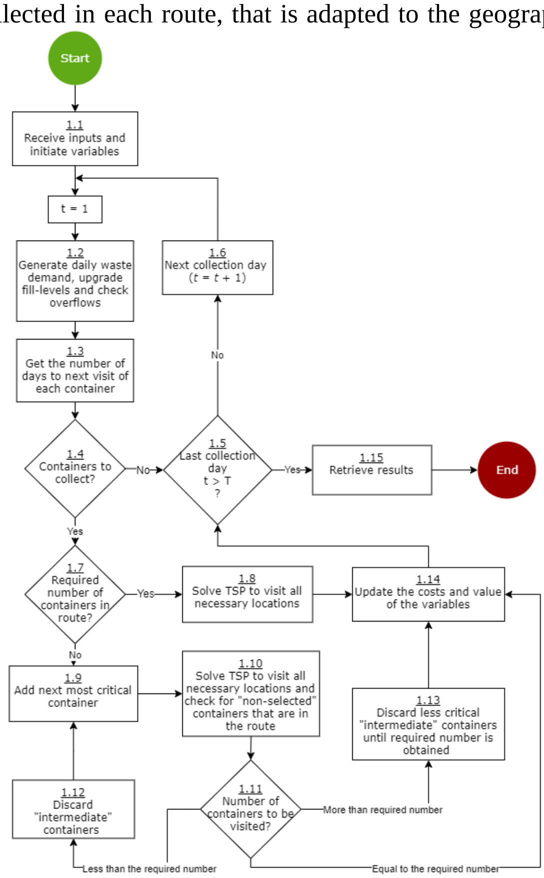


**Figure 4:** Flowchart of the dynamic collection policy algorithm.

## 5. Study of a real-case scenario

### *5.1. Waste collection in Soure*

The methods presented in the previous chapter will be validated on a real-case scenario. For that, the operations of ERSUC – Resíduos do Centro, S.A. will be studied. ERSUC is Portuguese waste management company responsible for exploring and managing a multi-municipal waste management system in the central west coast of Portugal. Their operations involve a total of 36 municipalities, covering 6700 km$^2$ and servicing a population of circa one million inhabitants. Nowadays, ERSUC possesses approximately 30 collection vehicles and has more than 13000 containers of separate collection, from where it collected 28513 tons of material, in 2018 (ERSUC, 2018). ERSUC is partner of this study and has shared several important data regarding their collection operations.


**Figure 3:** Network of paper-carboard containers in Soure.

It will be analysed, in particular, the paper-cardboard waste collection of the municipality of Soure, which compromises 98 containers and a depot, and is represented in Figure 4. It can be seen that the containers are divided in two sub-groups that correspond to two different routes: one of 50 containers (group A) – blue markers in the figure –, and other of 48 containers (group B) – green markers. It's also possible to notice that the containers are spread out across, practically, the whole area of the municipality of Soure (the shaded area in the figure); and that the depot is considerably far from the area of collection (the black marker in the right top corner).

In Table 1, some collection statistics of the year 2017, provided by the company, are presented for both groups.

**Table 1:** The collection of the 98 paper-cardboard containers, in 2017.

| | Group A | Group B |
|---|---|---|
| Number of containers | 50 | 48 |
| Number of collections | 52 | 53 |
| Average period between collections (days) | 7.0 | 6.9 |
| Maximum period between collection (days) | 14 | 11 |
| Minimum period between collection (days) | 3 | 4 |
| Average collection time | 6h14m | 6h25m |
| Average circuit distance (km) | 138.6 | 174.5 |
| Average collected quantity (kg) | 1234.2 | 752.8 |
| Average collected quantity per container (kg/container) | 24.7 | 15.7 |

Even if the period between collections can vary within each group, on average, the containers are collected once per week, resulting in 52 and 53 collections per year. By looking at the locations of the containers it's reasonable to think that ERSUC would benefit from having only one route for the whole collection. However, in that scenario the maximum collection time would be exceed for the collection crew, which performs shifts of 6 hours and 40 minutes maximum – note that the average collection time is close to that value but does not exceed it. In this way, two routes are required due to this legal restriction. Other reason that could force the inclusion of two routes would be the collection trucks' capacity not being enough to collect all the containers in one route. However, according to the data of 2017, ERSUC's trucks almost never reached full capacity (2200 kg).

Furthermore, the containers used by ERSUC have volume capacity of 2.5 $m^3$. Values for the density of the paper-carboard material within a container were empirically obtained and provided by ERSUC: 30 $kg/m^3$, in average. This means that the average collected quantity per container, for both groups, is far below from what a container could contain ($2.5m^3 \times 30\ kg/m^3 = 75$ kg).

### *5.2. Study of the Individual Demand*

#### *5.2.1. Gathering and analysis of each container's data*

It was seen that having knowledge about the waste demand characteristics of each container is very important to study in which ones the remote monitoring can be more beneficial. In order to overpass this problem, between April 1st and July 23rd of 2019, it was asked to the waste collectors of ERSUC to manual register the amount of waste inside a container at the moment just before its collection would take place; and to register also the amount inside the containers of the other materials that could be encountered in the same site, i.e., if, for example, the collection crew is collecting glass-waste containers, they would take a look into the containers of paper-carboard and of plastic-metal packaging wastes that would be on the same site, and register the waste level. This method involves analysing the content of the container in a visual manner, and is, of course, subjective and can only be performed in an approximate way. However, what is important it to just have a rough estimate of the waste level. Therefore, the worker registering the waste quantity would classify the container into the following values and intervals, constituting a Likert scale with six values, as seen in Table 2.

**Table 2:** Likert scale of visual measurements

| Status | Value assumed |
|---|---|
| Container is empty (0%) | 0% |
| Waste-level is between 0 and 25% | 12.5% |
| Waste-level is between 25 and 50% | 37.5% |
| Waste-level is between 50 and 75% | 62.5% |
| Waste-level is between 75% and 100% | 87.5% |
| Container is completely full (100%) | 100% |

The records made by the waste collectors are the raw data. These served to identify the waste level of a container, in percentage of the total container, on a specific day. By assuming that the filling level grows linearly between two dates without entries, it is possible to estimate the daily deposition rates of each individual container. With the application of this procedure to the whole period of observation, it is possible then to calculate, for each container, the average of the daily waste demand rates, as well the measures related to the variability. This is necessary because these measures are object of analysis in two of the proposed methods, but also since it is necessary to simulate the results of applying the methods, and thus these measures are used to attribute a continuous probability distribution to each container for modelling their waste generation.

#### *5.2.2. Statistical modelling of the waste demand – gamma distribution*

For modelling the waste generation, it will be used the gamma distribution which is a positive continuous probability distribution. A gamma-distributed random variable X with shape *k* and scale *θ* is denoted:

$$X \sim Gamma(k, \theta) \tag{5}$$

and has a mean $\mu = k\theta$, and a variance $\sigma^2 = k\theta^2$.

Therefore, the deposition of waste in a certain container C, in a day t, is considered to be a gamma-distributed random variable, and is denoted:

$$deposition(C)_t \sim Gamma(k, \theta) \tag{6}$$

By using the calculated means and variances from the observed data, it is then possible to determine the parameters *k* and *θ* for modelling the gamma distribution of each container.

### *5.3. Study of the road network*

For applying some of the methods and the dynamic collection policy it was also necessary to study the topology of the real-case scenario and to create a graph that represents it. This graph constitutes an auxiliary tool that will allow to know which of the containers are on the paths that go to other containers, i.e., which of them are intermediate.

For that, the distances between all containers were determined. After, the real road network was visually analysed, and, in Python, the positions of each location and the edges that illustrate all the direct connections between locations were represented. The graph for the area of Soure is presented in Figure 5. Note that what is important is not to visualize the graph but to call in the code.

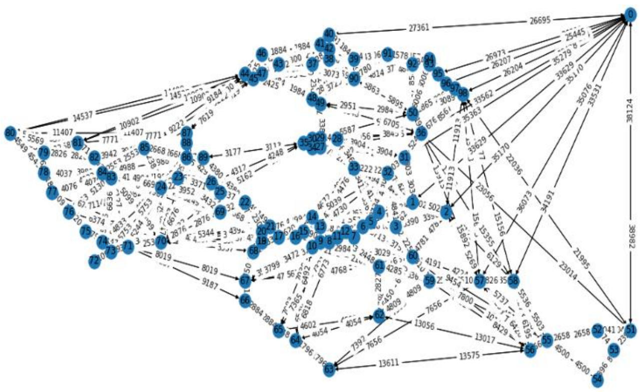

**Figure 5:** Graph of the Network of 98 Containers of Soure.

## 6. Results

### *6.1. Values and assumptions used*

Required number of containers to be collected: In order to consider the real time restrictions (shifts of 6h40m), and since the two existing routes involve the collection of 50 and 48 containers, it was defined that each collection route will involve the collection of 49 containers.

Overflow cost: It was not considered a cost for the overflow. Different scenarios for the overflow cost will be evaluated posteriori.

Period of the simulations: The simulations will run for 365 days.

Number of the simulations: Each scenario will be simulated 3 times in order to avoid outliers that could bias the results. It will be presented the average results obtained for the 3 runs.

Cost per kilometre: ERSUC considers 1€/km for each kilometre travelled, and so this is the value assumed during the simulations. This includes fuel consumption, the maintenance of the vehicle and the salary of the collection crew.

### *6.2. Study of the baseline scenarios*

Here, it is presented the results of 4 baseline scenarios:

- Baseline Scenario 1: It's the current waste collection policy, where the fixed routes A and B are performed with a 7-day interval.
- Baseline Scenario 2: Both routes A and B are performed with the collection intervals of the containers with higher frequency in each route (8 and 9 days respectively).
- Baseline Scenario 3: Routes are adapted to the collection intervals of each container. It is the limit of trying to apply the dynamic collection policy but with no data regarding the filling levels.
- Baseline Scenario 4: It's the application of the dynamic collection policy with full information – all containers are monitored.

In Figure 6 it is presented the collection costs *vs* the days in overflow. The measure days in overflow counts all the days that all the containers were in overflow.

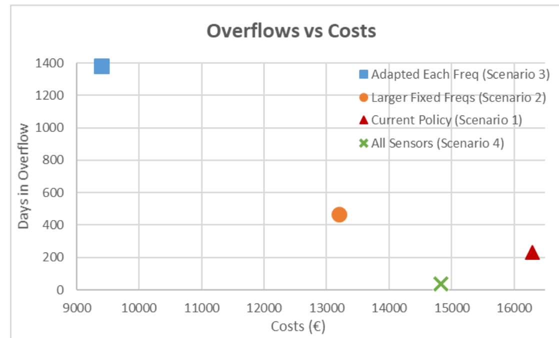


**Figure 6**: Scatter plot between costs and overflows of the baseline scenarios.

Looking to the different scenarios, one thing is practically inevitable: the higher the collection costs, the lesser the overflows and vice-versa, being the exception the case where all the containers are monitored.

By slightly increasing the collection interval of A and route B to 8 and 9 days (scenario 2), respectively, the costs decreased 19%, but the days in overflow doubled. In scenario 3, it's shown a great cost reduction (42%), but due to a great number of overflows, and thus it is certainly a scenario that won't be very desirable for the waste collection company.

As for the scenario where all the containers have a sensor (scenario 4), we can say that the dynamic collection policy presented was successively validated, as it managed to reduce both costs (in 9%) and overflows (in 84%), relatively to the current collection policy. With this dynamic collection, there were overflows in only 0.1% of the possible days.

### *6.3. Study of the partially monitoring scenario*

In this section, it is presented the results of the application of the proposed methods by dynamically collecting the waste. A sensitivity analysis is performed on the number of sensors to install (each case has a difference of 14 containers). In the presented figures, it will be also shown the results of the current policy (baseline scenario 1), and of scenarios 3 and 4, since the results of the partially monitored scenario will be in between these last two.

#### *6.3.1. Method 1 – Waste demand rate of a container*

The results for this method are in Figure 7. To notice any meaningful impact, the results will compare the order of selection previously described (blue line) to the results of the reverse order (orange line).

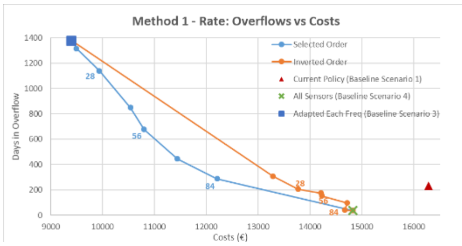


**Figure 7**: Overflows vs costs with a selection based on method 1.

It is possible to note that by starting to select the containers that are the slowest to fill-up (blue line), with a low number of sensors, there is almost no difference to the scenario where there are no sensors but the collection intervals were adapted (baseline scenario 3): costs are maintained at a very low value, but a very higher number of overflows exists. Whereas, when sensors are embedded first onto the containers that have the highest demand (orange line), there's a great reduction on the number of overflows but there's also a great increase on the collection costs and, with only 28 sensors, both the costs and overflows presented are less than the costs and overflows of the real case (cost decreases around 16% for the same number of overflows). These results show that, in fact, with the dynamic collection policy adopted, this is a criterion that presents visible influences on the collection costs and number of overflows. However, contrary to what was before being considered, depending on the overflow cost, it may also make sense to start embedding the sensors on the containers with the highest demand.

When sensors are placed on the containers that fill-up quickly first, collection travels will be more tailored to the real necessities of the demand of these containers and will impede them from overflow. Costs will increase due to more trips being undertaken, but there's also the benefit of anticipating more collections of the non-monitored containers, and so the probability that these may overflow is also reduced.

*6.3.2. Method 2 – Waste demand variability of a container*

The results of placing the sensors based on the coefficient of variation are presented in Figure 8. The pattern is very similar to what was seen by considering the average rates.

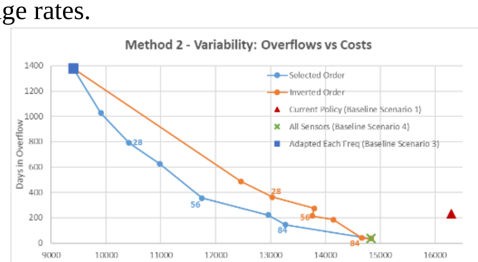


**Figure 8:** Overflows vs costs with a selection based on method 2.

However, it doesn't make sense that selecting first the containers with the lower coefficient of would provide a greater reduction on the overflows than selecting first the ones with a higher coefficient of variation. If we analyse the scatter plot between the coefficient of variation and the average rates (see Figure 9), we can see that the reason the variability shown a similar pattern is because the results were influenced by the average rates: by selecting first the ones with the higher coefficient of variation we are also selecting containers with low average rates; and by doing the opposite, i.e., by selecting first with the reverse order of the coefficient of variation, we end up rapidly selecting the ones with high average rates, and thus there is no evidence that this criterion influenced the results.

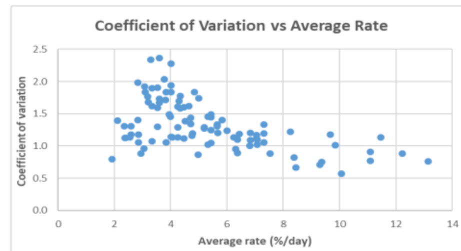


**Figure 9**: Scatter plot between the coefficient of variation and the average rates of the containers.

*6.3.3. Method 3 – Remoteness of a container*

In Figure 10 are the results of having selected the containers by the two options used to evaluate remoteness.

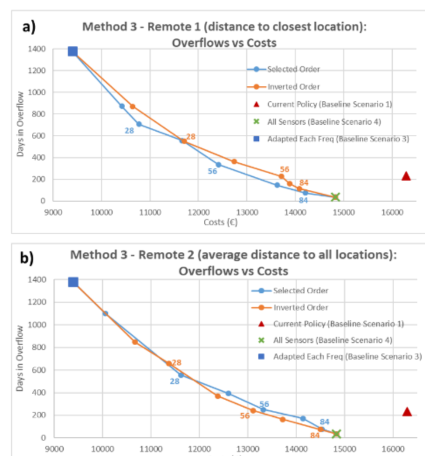


**Figure 10:** Overflows vs costs with the two options based on method 3.

The curves of the two options used to evaluate remoteness are roughly similar. It's possible to see that in the two cases, there is not much difference between the two curves (selected and inverted orders), and so it's very difficult to discern any effect. This suggests that there is not enough evidence supporting that the results were affected by this criterion.

*6.3.4. Method 4 – Cost Reduction Algorithm*

The results by this method are presented in Figure 11. Even if the evidence is not very strong, it seems that selecting containers by the order that the cost reduction algorithm provides is better than selecting containers with the reverse order: with the same number of sensors, the same number of overflows is obtained with less costs. It is considered that this method of selection shows a certain degree of impact.

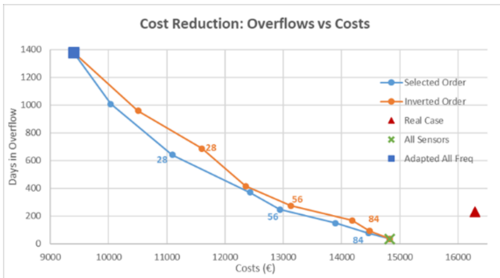


**Figure 11:** Overflows vs costs with a selection based on method 4.

### *6.3.5. Method 5 – Considering rate, variability and remoteness*

Due to the results of the previous methods, it was decided to study the combinations between high demand rates and high variability. However, with this method was not possible to obtain any significant results. It is being analysed a real-case and so it was not possible to find a significative number of elements across these two criteria – by simultaneously selecting containers in top 40% of those with higher demand rate and in the top 40% of those with high variability, it was only possible to obtain 4 containers.

### ***6.4. Financial Analysis***

For the financial analysis it is necessary to include not only the operational costs, but also the investment necessary with the sensor technology and to attribute a cost to each day in overflow. For the cost of the sensors, it will be used the average of the values given by Evox, i.e., 250€ for the purchase cost, 10 € for the installation and 1€ of rent per sensor, per month. For the overflow cost, it will be considered two cost schemes: a low value (10€) and medium value (35€). This analysis, for the partially monitoring scenario, will compare only the methods that presented relevant results: selected and reverse order for the waste demand and cost reduction algorithm. The target lines of the current policy (baseline scenario 1) and of the full monitoring (baseline scenario 4) will also be displayed for comparison. The results of the costs during a period of 10 years (duration of the sensors' battery life), for the low overflow cost and for the medium overflow cost are presented in Figure 12 and Figure 13, respectively.

It can be noted that monitoring all containers is better than keeping the current waste collection policy for a medium overflow costs (less 19% costs) but is worse for a low overflow cost (costs increased 2%).

Considering the dynamic collection policy adopted, allocating sensors by selecting the containers with the highest demands first i.e., by partially monitoring the population of containers with method 1 – high rates, seems to be the wisest choice. Depending on the available budget and on the overflow cost scheme considered, different allocations can be recommended to ERSUC. If the overflow cost is considered to be not very high (low cost), allocating a small number of sensors by this method can be the best solution for minimizing the costs (in the studied cases, 14 or 28 sensors – it is recommended 14 since it requires a lower investment) – the total cost is reduced in

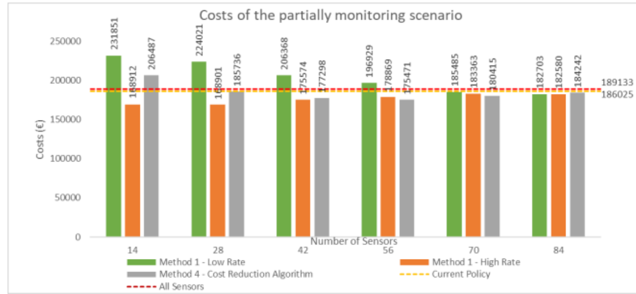


**Figure 12:** Total costs, in 10 years, for a low overflow cost.

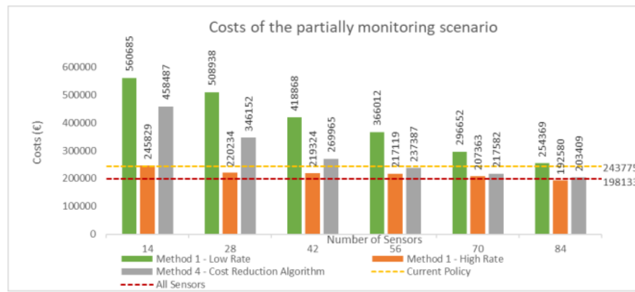


**Figure 11:** Total costs, in 10 years, for a medium overflow cost.

11% when comparing to installing 98 sensors, and is reduced in 9% when comparing to the current situation. If the overflow cost is considered to have a more adverse impact (medium cost), with a low budget, sensors can be allocated on 28 containers and most benefits are still attainable (it reduces 10% the costs relatively to the current situation but is 11% more costly than monitoring all containers). However, if there's sufficient budget, the most beneficial option is to allocate sensors in almost all containers by this method (in the studied cases, 84 sensors) – the reduction is of 3% when comparing to installing 98 sensors and of 21% when in comparison to the current policy.

## 7. Conclusions and Further Work

The objective behind this dissertation was to study the integration of ultrasonic sensors on the waste collection operations in an economically more sustainable way by proposing methods for the selection of containers. A dynamic collection policy was also developed in order to simulate the results of each method. It was studied the real-case scenario of Soure and used data regarding a total of 98 containers. From the analysis of this work, the following remarks are outlined:

- There's always a <u>trade-off between operational costs and overflows</u>.
- The <u>dynamic collection policy presented was validated,</u> since by monitoring all the containers is possible to have both less operational costs (decrease of 9%) and less overflows (decrease of 84%) than with the current collection policy. The financial analysis shown that is better to adopt sensors in all containers, than maintaining the current collection policy, for a medium overflow cost (reduction of 19%) but it is worse with a low overflow cost (cost increase of 2%).

• For the criteria remoteness (method 3) and variability (method 2), it was not perceptible any impact on the results. With the cost reduction algorithm (method 4) was detected a certain degree of impact.

• Method 1 was the only one that considerably impacted the results. Contrary to the initial assumption, it is best to start by monitoring the containers that experience the highest demand rates, instead of the ones the experience the lowest ones. With this option, considering a low overflow cost, the recommended number of sensors was 28 (compared to the scenario with sensors in all containers and to the current situation costs were reduced 11% and 9%, respectively), and with a medium overflow cost, the recommended number of sensors was 84 (compared to the scenario with sensors in all containers and to the current situation costs were reduced 3% and 21%, respectively). This means that, in fact, it's possible to maintain the sensors' benefits by partially monitoring a collection area.

• It's necessary to understand that the conclusions here drawn cannot be disassociated from the dynamic collection policy adopted. The author still believes that it makes sense to further study all the criteria identified in the literature review, but by using a different methodology, where it would be easier to detect the impact of each sensor embedded. It's probable that these criteria would work better in a scenario where routes are kept fixed to the containers that are not being monitored, and thus the sensor would only be used to decide if at the day of collection a container needs or not to be added to the fixed route. This proposal could also signify a smoother transition for the waste collection companies in adopting sensors, since they could see immediate results with little effort.

• It's also reasonable to say that different dynamic collection policies that are more well-thought and better tailored to a partially monitoring scenario, could be investigated in the future.

• A factor that has to also be taken into account is that the results could be different if it is considered another price model for the sensors.

• A difficulty encountered was when combining the different criteria (method 5). That part of the analysis wasn't very interesting, since it was being considered a real case and the presence (and intensity) of each criterion couldn't be modified. A more theoretical study regarding the criteria could benefit from manipulating the data and analyse the impacts on the results of each criterion.

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