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Intelligent Household Garbage Management: An Alternative Path to Climate-Neutral Europe

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Abstract

We consider intelligent household garbage management, where garbage containers are assumed to be digitalized with Internet-of-Things sensors that are capable of sensing the fill levels of containers and transmitting this data through LoRaWAN networks to a central server. We propose that the management is driven by these real-time signals. Thus, we give a number of algorithms for it. We give two algorithms that decide which containers can be scheduled for collections. Also, we give three algorithms that dispatch the trucks, subject to minimizing their CO_2 emissions. Finally, we give one algorithm that allocates fairly garbage costs to households. Our algorithms provide a stepping stone for further research in the future.

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Keywords: IoT and smart infrastructures; Sensoring and real-time information; Digitalization in mobility; Environmental impacts of logistics

1. Introduction

Greenhouse gas emissions are among the main factors for climate change. To reduce such emissions, in 2015, the UN introduced the 2030 Agenda for Sustainable Development. One well-understood path toward solving this challenge is to recycle garbage within circular economies. In fact, the EU has founded several such economies: the Circular Economy Package; the Circular Economy Action Plan; the European Green Deal. Nevertheless, despite their significant efforts in the last years, the European Environment Agency expresses concerns about reaching the agenda goals by 2030; see e.g. European Environment Agency (2021). In response, we consider an alternative and less-understood path to climate-neutral Europe: intelligent household garbage management (HGM). HGM has three main steps: (a) the collection of garbage from residential collection points, (b) the transportation of the collected garbage to sorting plants, and (c) the burning of sorted non-recyclable garbage at incineration plants. Optimizing HGM relates to minimising the CO_2 emissions generated by households.

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For example, the average German household carbon footprint (HCF) from waste is nearly 1 tonne (t) of CO_2 annual emissions (e/a): see Miehe et al. (2016). At the same time, there are nearly 40 million German households. Therefore, the overall HCF from waste is nearly 40 million t of CO_2 e/a. If we can optimize the HGM to give us around a 1% reduction in this amount then this would already be a huge improvement. Some recent works optimize HGM by motivating people to separate garbage more carefully: see e.g. Lian et al. (2020) and Rahman et al. (2022). However, they do not motivate households to generate less garbage. For this reason, we ask:

How can we motivate households to generate less garbage?

Household garbage generation (HGG) relates to lack of awareness, space limitations on recycling methods, inadequate policy, and lack of time and priority: see Nunkoo et al. (2021). Hence, minimising the amount of garbage generated due to these factors lies at the source of the HGM steps (a), (b), and (c). To tackle this problem, we draw additional inspiration from existing inadequate policies in Germany, according to which garbage collection companies (e.g. BSR, AWM) dispatch trucks on fixed schedules and rental agent companies (e.g. Vonovia, Degewo) do not inform regularly households of their garbage generating behavior. We, thus, ask:

How can we dynamically schedule containers for collections, efficiently dispatch garbage trucks through locations of scheduled containers, as well as fairly and regularly allocate collection costs to households?

Our response is to design a new data-driven solution: see Figure 1. This one uses IoT sensors (e.g. WILSEN.sonic.level) that are installed on the top lids of containers. The sensors use wireless connections (e.g. via Sigfox Germany) to transfer data in real-time about the fill levels of containers. The data is then used for management and feedback. The management consists of scheduling containers for collections and navigating trucks through locations of scheduled containers. The feedback consists of information about the levels of garbage generated by households and the allocations of garbage costs to them.

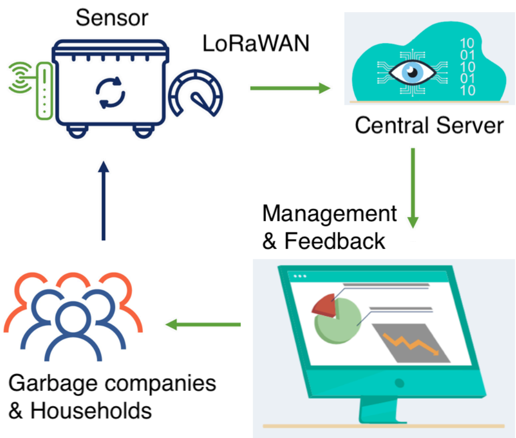

Fig. 1. The working cycle of our data-driven solution.

Our solution can thus (1) improve the awareness of households by keeping them in the loop, (2) provide regular feedback about their levels of generated garbage, and (3) allocate costs that are proportional to these levels. We hope that in response households can self-reflect on and become more cautious about their garbage-generating behavior in the future.

We discuss related work in Section 2. In Section 3, we then present the contributions. In Section 4, we look at the problem of scheduling containers for collections by using our solution. In Section 5, we study the problem of minimising truck emissions by using our solution. In Section 6, we study the problem of allocating garbage costs to households by using our solution. Finally, we discuss future work in Section 7.

2. Related work

In the last years, there is a growing interest in intelligent HGM. For example, companies such as Saubermacher, Nordsense, Sensoneo, and Mr.FILL have implemented similar IoT solutions for industrial markets. By comparison, our solution is for household markets. We note that household markets have a greater carbon footprint than industrial markets. For example, in 2014 Berlin, the CO_2 emissions related to households were nearly 65% of all CO_2 emissions related to households, transport, and industry: see Steinmeyer and Herrmann-Fiechtner (2017). Possible implementation paths for it can be borrowed from Kamm et al. (2020) and Ranjana et al. (2021). We use this solution for the scheduling of containers for garbage collections and also for "green" (i.e. minimal-emission) navigation of garbage trucks. Other works also analysed the efficiency of truck dispatching for garbage collection. Zhang et al. (2020) looked at the path planning of trucks. Gutierrez et al. (2015) focused on minimising the routing distance. Rajaprabha et al. (2018) used a Google Maps package to minimise the routing time. Buhrkal et al. (2012) studied minimising the routing cost. Lozano et al. (2018) investigated minimising both the routing time and cost. By comparison, we focus on scheduling trucks and minimising their associated routing gas emissions. Surprisingly, this has received little attention in the context of garbage collection. For example, Wu et al. (2020) studied minimising the emissions of trucks when collecting medical garbage. We note that household garbage is much more than medical garbage and the trucks for collecting the former are normally larger than the vehicles for collecting the latter. Therefore, we expect that optimising the dispatching of household garbage trucks would deliver greater environmental benefits than optimising the dispatching of the same number of medical garbage trucks.

3. Contributions

We next summarise our contributions. We consider a dynamic setting, in which, for some t from $\{1,2,...,+\infty\}$, $\mathbf{T} = \{1,2,\ldots,t\}$ is a horizon of t days. For example, for $t = 365$, $\mathbf{T}$ contains all days in a given year. We write τ for a generic day from $\mathbf{T}$. We next summarise our results.

- At the end of each day τ from $\{1,2,\ldots,(t-1)\}$, we consider a planning problem that concerns the scheduling of containers for collections on day $(\tau+1)$. For solving this problem, we propose two algorithms, i.e. Algorithms 1 and 2.
- At the end of each day τ from $\{1,2,\ldots,(t-1)\}$, we consider a routing problem that concerns the assignment to trucks of containers scheduled for collections on day $(\tau+1)$ and the navigation of trucks through the locations of their assigned containers, subject to minimising their total CO_2 emissions. We discuss that solving this problem optimally may require exponential time. In response, we present three inexact heuristics for solving the problem approximately, i.e. Algorithms 3, 4, and 5. We also evaluate these heuristics empirically.
- At the end of each day τ from $\{1,2,\ldots,(t-1)\}$, we consider an allocation problem that concerns the fair distribution of costs to households that are proportional to the levels of garbage generated by them. For solving this problem, we propose one algorithm, i.e. Algorithm 6.

4. Scheduling containers for garbage collections

We begin with the scheduling setting. Let us consider a set of garbage collection points. Each collection point contains normally a number of containers and each container can be of some different garbage type, e.g. "paper", "bio", "glass", "light packages", or "general". In practice, each point can contain multiple containers of a given garbage type. We refer to this as a *point type*. For a given point type, we say that it is *digitalised* on day τ if all of its containers are equipped with sensors that can transmit data on day τ.

Let us consider day τ from $\{1,2,\ldots,(t-1)\}$. The planning problem on day τ requires deciding which of the point types must be scheduled for garbage collections on day $(\tau+1)$. Such point types are either not digitalised on day τ but the garbage collection companies visit them on day $(\tau+1)$ anyway based on their existing schedules, or they are digitalised on day τ and all of their containers are full (or their fill level exceeds some threshold. see e.g. Wu et al. (2020)). For the purpose of solving this problem, we next summarise the point characteristics in Table 1.

Table 1. Point characteristics.

Description	Feature	Symbol	Domain/Value
number of types	garbage	w	D = $\{1,2,\ldots,+\infty\}$
generic type	garbage	ω	D = $\{1,2,\ldots,w\}$
set of w types	garbage	$\mathbf{W}$	V = $\{1,2,\ldots,w\}$
number of collection points	residential	m	D = $\{1,2,\ldots,+\infty\}$
generic collection point	residential	p	D = $\{1,2,\ldots,m\}$
set of m points	residential	$\mathbf{P}$	V = $\{1,2,\ldots,m\}$
location of p	point	l_p	D = $(-\infty,+\infty)^2$
generic container of ω at p	point	$c_{p\omega}$	D = $\{1,2,\ldots,c\}$
volume of $c_{p\omega}$	container	v_ω	V > 0
level of garbage in all containers of ω at p on τ	container	$F_{\tau p\omega}$	V ≥ 0 and V ≤ 1

In Berlin, garbage trucks run on fixed collection schedules. Thus, for a given point and garbage type, some truck performs one service (i.e. collects the garbage of all containers of that type) on some fixed weekday (e.g. Wednesday) or one service on each of some fixed weekdays (e.g. Tuesdays and Thursdays). We define these collection schedules. We also propose two scheduling heuristics that modify these collection schedules dynamically by using input from our solution.

Definition 1 (*Collection schedule*): For day τ from **T**, point p from **P**, and type ω from **W**, we let $\mathbf{S}_{\tau p\omega}$ contain the days between 1 and t^2 when collections for type ω at point p after day τ are scheduled.

4.1. Forward scheduling

Let us consider day τ from $\{1,2,\ldots,(t-1)\}$. If some point types are scheduled for collections on day $(\tau+1)$ according to their current schedules but not all of their containers are full by the end of day τ then the first heuristic pushes *forward* each of their future collection days by one more day. As a consequence, given at the beginning of the year collection schedules that are fixed for the entire year, it may modify these schedules as the year progresses and, thus, schedule fewer collections at the end of the year.

Algorithm 1. Forward scheduling.

Input: set of points **P**, set of types **W**, day τ, matrix of schedules $(\mathbf{S}_{\tau p\omega})_{m \times w}$, fill level matrix $(F_{\tau p\omega})_{m \times w}$	**Comments**: The fill levels are retrieved with our solution.
for each point p from **P** and garbage type w from **W** **do**	
if day $(\tau+1)$ belongs to $\mathbf{S}_{\tau p\omega}$ **then**	
if point p is digitalised wrt type ω on day τ **then**	
if $F_{\tau p\omega} < 1$ **then**	Some containers of point p wrt ω on day τ are not full.
for each scheduled day σ *from* $\mathbf{S}_{\tau p\omega}$ **do**	A modification step.
re-schedule σ for one day later	
return $\mathbf{PW}_{(\tau+1)}$	All point types that are scheduled for collections on day $(\tau+1)$.

Algorithm 1 implements this process. If a given point type is scheduled for collection on day $(\tau+1)$ according to its current schedule and digitalised on day τ but not all of its containers are full by the end of day τ then Algorithm 1 re-schedules each of its future collection days for one day later and, thus, modifies its schedule. As a result, if point-type containers get full less often than according to their collection schedules, then Algorithm 1 will schedule collections for them less often. Otherwise, it will follow their schedules.

4.2. Backward scheduling

Let us consider day τ from $\{1,2,\ldots,(t-1)\}$. If some point types are digitalised on day τ and all of their containers are full by the end of day τ then the second heuristic pulls *backward* each of their future collection days by as many days as their corresponding offsets between day $(\tau+1)$ and the first next collection days in their current schedules. As a result, given at the beginning of the year collection schedules that are fixed for the entire year, it may modify these schedules as the year progresses and, thus, schedule more collections at the end of the year.

Algorithm 2. Backward scheduling.

Input: set of points **P**, set of types **W**, day τ, matrix of schedules $(\mathbf{S}_{\tau p\omega})_{m \times w}$, fill level matrix $(F_{\tau p\omega})_{m \times w}$	**Comments**: The fill levels are retrieved with our solution.
for each point p from **P** and garbage type w from **W** **do**	
if point p is digitalised wrt type ω on day τ **then**	
if $F_{\tau p\omega} \geq 1$ **then**	All containers of point p wrt ω on day τ are full.
$\delta_{\tau p\omega}$ = first day from $\mathbf{S}_{\tau p\omega}$ minus $(\tau+1)$	
for each scheduled day σ *from* $\mathbf{S}_{\tau p\omega}$ **do**	A modification step.
re-schedule σ for $\delta_{\tau p\omega}$ days earlier	
return $\mathbf{PW}_{(\tau+1)}$	All point types that are scheduled for collections on day $(\tau+1)$.

Algorithm 2 implements this process. If a given point type is digitalised on day τ and all of its containers are full on day τ but it is not scheduled for collection on day $(\tau+1)$ then Algorithm 2 re-schedules each of its future collection days for as many days earlier as the corresponding offset and, thus, modifies its schedule. As a consequence, if point-type containers get full more often than according to their collection schedules, then Algorithm 2 will schedule collections for them more often. Otherwise, it will follow their schedules.

4.3. Heuristic comparison

Let us consider day τ from $\{1,2,\ldots,(t-1)\}$. If a given point type is scheduled for collection on day $\sigma > (\tau+1)$ according to its current schedule but all of its containers are full by the end of day τ, then Algorithm 1 will not schedule that particular point type for collection on day $(\tau+1)$. As a result, households who want to dump their garbage on day $(\tau+1)$ cannot do it in these containers because they are full. Instead, they have to wait until day σ. For this reason, they may be unsatisfied. This motivated the design choice behind Algorithm 2.

However, given fixed current point type collection schedules on day τ, the number of point types scheduled for collections on day $(\tau+1)$ with Algorithm 2 is at least as much as the number of point types scheduled for collections on day $(\tau+1)$ with Algorithm 1. Essentially, this follows because Algorithm 1 could re-schedule some of the point types scheduled for collection on $(\tau+1)$ for some days later whereas Algorithm 2 could re-schedule some of the point types scheduled for collections on some day $\sigma > (\tau+1)$ for day $(\tau+1)$.

Both Algorithms 1 and 2 run in $O(t^2mw)$ time for each day τ and $O(t^3mw)$ time for all t days. To see this, we observe that their computation for each day τ is dominated by mw iterations and, within each iteration, they may need to re-schedule $O(t^2)$ collections. Furthermore, as in practice m can lie in *10000-100000* (e.g. in Berlin), it might take years for the complete digitalisation of all point types. Nevertheless, Algorithms 1 and 2 can already be deployed on any partial digitalisation of some point types.

5. Navigating trucks for garbage collections

We continue with the navigation setting. Let us consider day τ from $\{1,2,\ldots,(t-1)\}$. Further, let us consider the set $\mathbf{PW}_{(\tau+1)}$ of point types scheduled for collections on day $(\tau+1)$. The navigation problem on day $(\tau+1)$ requires assigning the locations of point types from $\mathbf{PW}_{(\tau+1)}$ to trucks and navigating the trucks through these locations, subject to minimising the CO_2 emissions of the entire fleet of trucks. For the purpose of solving this problem, we next summarise the truck characteristics in Table 2.

Table 2. Fleet characteristics.

Description	Feature	Symbol	Domain/Value
number of garbage trucks	vehicle	n	D = $\{1,2,\ldots,+\infty\}$
generic truck	vehicle	g	D = $\{1,2,\ldots,n\}$
set of n steps	vehicle	$\mathbf{G}$	V = $\{1,2,\ldots,n\}$
begin location of g on τ	vehicle	$b_{\tau g}$	D = $(-\infty,+\infty)^2$
end location of g on τ	vehicle	$e_{\tau g}$	D = $(-\infty,+\infty)^2$
maximum number of $c_{p\omega}$ on τ for g	vehicle	$n_{\tau g\omega}$	D = $\{0,1,\ldots,+\infty\}$
quota of g wrt ω on τ	vehicle	$q_{\tau g\omega} = n_{\tau g\omega} \cdot v_{\omega}$	V ≥ 0

5.1. An objective for reducing emissions

We write $\mathbf{U}_{\tau}$ for the set of *locations* of point types from $\mathbf{PW}_{(\tau+1)}$. The collection ($\mathbf{U}_{\tau 1}$,...,$\mathbf{U}_{\tau n}$) is such that $\mathbf{U}_{\tau g}$ is a subset of $\mathbf{U}_{\tau}$ for each truck g from **G**, and the intersection between $\mathbf{U}_{\tau g_1}$ and $\mathbf{U}_{\tau g_2}$ is empty for each pair of different trucks (g_1,g_2). For each truck g from **G**, we write $\mathbf{R}_{\tau g}$ for the *route* of g. The route $\mathbf{R}_{\tau g}$ can be represented as a sequence that starts at $b_{\tau g}$, passes through the locations from $\mathbf{U}_{\tau g}$, and ends at $e_{\tau g}$. We suppose that truck g visits locations in the order induced by $\mathbf{R}_{\tau g}$. Further, we suppose that none of the garbage quotas of truck g for the different types of garbage is exceeded in $\mathbf{R}_{\tau g}$.

Let us pick truck g from **G** and a pair of locations (l_1,l_2). We write $t_{\tau g}(l_1,l_2)$ for the *shortest travel time* truck g needs when driving from l_1 to l_2 on day τ. The value of $t_{\tau g}(l_1,l_2)$ may depend on the road velocity of truck g or traffic congestion on day τ. Additionally, we write $e_{\tau g}(l_1,l_2)$ for the *amount of CO2* truck g emits when travelling time $t_{\tau g}(l_1,l_2)$ from l_1 to l_2 on day τ. Thus, for each route $\mathbf{R}_{\tau g}$, we let $x_{\tau g}(\mathbf{R}_{\tau g})$ denote the route *emission-by-time (ExT) value* of g on day τ which is equal to the additive sum of $e_{\tau g}(l_1,l_2) \cdot t_{\tau g}(l_1,l_2)$, where l_1 and l_2 are consecutive locations in $\mathbf{R}_{\tau g}$. Thus, our ambition is to minimise the sum of all ExT values on day τ:

$$ExT(\tau) = \sum_{g \in G} x_{\tau g}(R_{\tau g}).$$

5.2. Reducing emissions optimally

The complexity of minimising the ExT objective on day τ may be exponential in some cases. In fact, doing so might be at least as hard as deciding whether the objective value is at most some fixed strictly positive real number k. We prove that the latter problem belongs to the class of NP-complete problems. For this class, we refer the reader to Garey and Johnson (1990). For proving this result, we give a Karp reduction from the travelling salesman problem (TSP). For this problem, we refer the reader to Dantzig and Ramser (1959) and Beltrami and Bodin (1974).

Theorem 1. For positive k and an unbounded number of new locations on day τ, deciding whether the value of the ExT objective is at most k is NP-complete: see Aleksandrov (2022).

5.3. Reducing emissions heuristically

In response to the results in Theorems 1 and 2, we look at inexact insertion methods simply because such methods have proved useful for solving the TSP: see e.g. Rosenkrantz et al. (2009). More specifically, we propose the following three natural insertion heuristics for minimising the ExT objective, each running in $O(tnm^4)$ time.

Definition 2: (*Insertion decision*): For day τ from $\{2,3,\ldots,t\}$, consecutive pair (l_1,l_2) in route $\mathrm{R}_{(\tau-1)g}$ and location l, inserting l between l_1 and l_2 requires that truck g drives from l_1 to l and from l to l_2.

Algorithm 3 (*Least Emission Insertion*, *LEI*). For day τ from $\{2,3,\ldots,t\}$, consider $\mathbf{R}_{(\tau-1)g}$ for each truck g from **G**. While $\mathbf{U}_{\tau}$ is not empty do: if we can pick truck g from **G** and location l from $\mathbf{U}_{\tau}$ such that (1) $q_{\tau g\omega} \geq v_{\omega}$ holds and (2) hypothetically inserting l in $\mathbf{R}_{(\tau-1)g}$ would minimise the value of the ExT objective, then insert l in $\mathbf{R}_{(\tau-1)g}$ and continue with $\mathbf{U}_{\tau} \setminus \{l\}$; otherwise, send all trucks to their end locations, dump the garbage, and repeat.

Algorithm 4 (*Balanced Time Insertion*, *BTI*). For day τ from $\{2,3,\ldots,t\}$, consider $\mathbf{R}_{(\tau-1)g}$ for each truck g from **G**. While $\mathbf{U}_{\tau}$ is not empty do: if we can pick truck g from **G** and location l from $\mathbf{U}_{\tau}$ such that (1) $q_{\tau g\omega} \geq v_{\omega}$ holds, (2) the route time of $\mathbf{R}_{(\tau-1)g}$ is minimum among the trucks feasible for ω, and (3) hypothetically inserting l in $\mathbf{R}_{(\tau-1)g}$ would minimise the value of the ExT objective, then insert l in $\mathbf{R}_{(\tau-1)g}$ and continue with $\mathbf{U}_{\tau} \setminus \{l\}$; otherwise, send all trucks to their end locations, dump their garbage, and repeat.

Algorithm 5 (*Balanced Workload Insertion*, *BWI*). For day τ from $\{2,3,\ldots,t\}$, consider $\mathbf{R}_{(\tau-1)g}$ for each truck g from **G**. While $\mathbf{U}_{\tau}$ is not empty do: if we can pick truck g from **G** and location l from $\mathbf{U}_{\tau}$ such that (1) $q_{\tau g\omega} \geq v_{\omega}$ holds, (2) the number of locations in $\mathbf{U}_{(\tau-1)g}$ is fewest among the trucks feasible for ω, and (3) hypothetically inserting l in $\mathbf{R}_{(\tau-1)g}$ would minimise the value of the ExT objective, then insert l in $\mathbf{R}_{(\tau-1)g}$ and continue with $\mathbf{U}_{\tau} \setminus \{l\}$; otherwise, send all trucks to their end locations, dump their garbage, and repeat.

5.4. Reducing emissions empirically

We evaluated Algorithms 3, 4, and 5 in an early experiment. In our setup, there were 5 days (i.e. $t = 5$) and one garbage type (i.e. $w = 1$). Also, there were 5 trucks (i.e. $n = 5$) and 25 containers (i.e. $m = 25$) of type 1. The truck quotas for this type were equal to 25. The location source was the grid $[1000] \times [1000]$. Each truck's shortest travel time metric was the corresponding straight-line distance metric. The emission coefficients were sampled uniformly at random from $[1,2]$. The trucks began and ended at location $(0,0)$. For each τ from 1 to 5, we first sampled uniformly at random 5 new locations and assumed that each of these has 1 full container, and then ran Algorithms 3, 4, and 5. In this way, for each garbage truck, we measured its route emission, route time, and route workload.

Figure 2 shows our results. Achieving green navigation seems to require that some trucks visit more locations and, thus, travel longer than other trucks, but along routes of lower emissions. Indeed, "Least Emission Insertion" achieves the lowest value of the ExT objective. However, it dispatches some trucks to more locations than other trucks. "Balanced Time Insertion" achieves a greater value of the ExT objective because it tries to balance the route time per truck before the route emission per truck. Thus, it dispatches all trucks, but still, it assigns more locations to some trucks than to other trucks. "Balanced Workload Insertion" balances the number of locations per truck. As a result, it also dispatches all trucks, but it achieves the greatest value of the ExT objective.

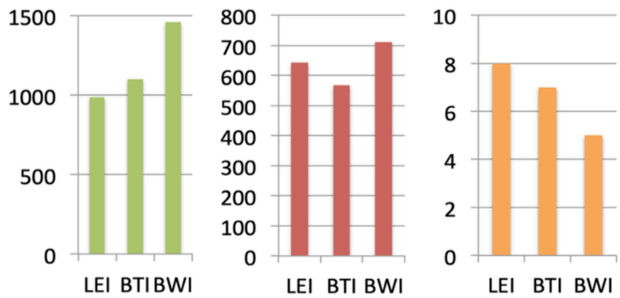

Fig. 2. Heuristics: Least Emission Insertion (LEI), Balanced Time Insertion (BTI), Balanced Workload Insertion (BWI), Plots: (left) maximum route emissions per truck; (center) maximum route time per truck; (right) maximum route workload per truck.

6. Allocating costs for garbage collections

We end with the allocation setting. For each point p from **P**, we let $\mathbf{H}_p$ denote the group of *households* associated with p. For example, people living in houses ofter have their own collection point whereas people living in apartments often share the same collection point. We write $c_\mathbf{T}$ for the *overall cost* the groups $\mathbf{H}_1,\ldots,\mathbf{H}_m$ need to pay respectively for garbage collections from points $1,\ldots,m$ on days scheduled from within **T**. For horizon **T** and group $\mathbf{H}_p$, we also write $c_{\mathbf{T}p}$ for the *contribution* of group $\mathbf{H}_p$ to $c_\mathbf{T}$.

In Germany, each group pays an annual contribution to the overall cost that is proportional to the square meters of their living area: see Berliner Mieterverein (2019). As a result, groups $\mathbf{H}_{p_1}$ and $\mathbf{H}_{p_2}$ that reside in living areas of the same size pay the same contribution to $c_\mathbf{T}$ (i.e. $c_{\mathbf{T}p_1} = c_{\mathbf{T}p_2}$), even when say group $\mathbf{H}_{p_1}$ generates over the course of **T** a strictly lower amount of garbage than group $\mathbf{H}_{p_2}$. This is unfair wrt the groups. To fix this, we propose to allocate to groups garbage costs that are proportional to the number of days when their garbage was collected.

If groups dump garbage less often then Algorithm 1 schedules collections less frequently and they pay less, but if they do it more often then Algorithm 2 schedules collections more frequently and they pay more. For each point p from **P** and each type ω from **W**, we write $\bar{c}(p,\omega)$ for the mean cost of collecting the garbage of type ω at point p, and $n(p,\omega)$ for the number of such collections on days from within **T**. For t days, Algorithm 6 computes each $c_{\mathbf{T}p}$ in $O(tmw)$ time. Finally, $c_{\mathbf{T}p}$ is proportional to the additive sum of $n(p,\omega) \cdot \bar{c}(p,\omega)$, where the sum iterates over ω:

$$c_{Tp} = \left[\frac{\sum_{\omega \in W} n(p,\omega).\bar{c}(p,\omega)}{\sum_{p \in P} \sum_{\omega \in W} n(p,\omega).\bar{c}(p,\omega)} \right] \times c_T .$$

7. Future work

In the future, we will look at other scheduling methods, that use time-series and historic data. Also, we will look at other navigation methods, that sample minimum spanning trees from the underlying location graph. Finally, we will run more extensive experiments.

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