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Abstract

We consider the problem of collecting waste from sensor equipped underground containers. These sensors enable the use of a dynamic collection policy. The problem, which is known as a reverse inventory routing problem, involves decisions regarding routing and container selection. In more dense networks, the latter becomes more important. To cope with uncertainty in deposit volumes and with fluctuations due to daily and seasonal effects, we need an anticipatory policy that balances the workload over time. We propose a relatively simple heuristic consisting of several tunable parameters depending on the day of the week. We tune the parameters of this policy using optimal learning techniques combined with simulation. We illustrate our approach using a real life problem instance of a waste collection company, located in The Netherlands, and perform experiments on several other instances. For our case study, we show that costs savings up to 40% are possible by optimizing the parameters.

Keywords: Inventory routing, Simulation optimization, Optimal learning, Transportation, Waste collection;

1. Introduction

During the last decades, there has been a growing interest in Vendor Managed Inventory (VMI). In VMI, the replenishment decisions are being made by a supplier based on various inventory and supply chain policies [1]. The combined decision on when to replenish the customers' inventories, how much product to deliver, and in which way to route the vehicles that execute the delivery, is also known as the inventory routing problem (IRP). Answering all these questions simultaneously is a challenging task, considering that the decisions taken at a certain moment in time for a given planning horizon influence the decisions made later within or beyond this horizon [2]. By now, various methodologies have been developed to cope with this challenge and to achieve higher service levels for customers, while simultaneously lowering the costs for the suppliers.

A common aspect in all solution methodologies for achieving these planning objectives is the requirement for suppliers to have full and accurate information about current and future customers' inventories and demand [3]. This information is vital for the decisions to be sound during the entire planning horizon. However, the inherent variability in the demand (and thus the inventories) makes it difficult to have a precise prediction, and hence creates an additional

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layer of complexity to the already difficult IRP. The problem becomes even tougher if we are dealing with companies serving a large numbers of customers. This typically occurs in urban areas, where customers are located closely to each other. Examples include vending machine replenishment [4], supermarket replenishment [5], and municipal waste collection [6]. The latter is also the topic of this paper.

A particular application of the IRP with a large number of customers, variability in the demand, and a long planning horizon, is the waste collection problem (WCP). In the special case in which the waste collection company plans the emptying of containers dynamically (as opposed to static or periodic scheduling and routing) and bases this planning on the amount of waste inside the containers (which can be known through the uses of sensors in each container), the WCP becomes a special case of the IRP. Strictly speaking, a WCP is a reverse IRP, because the purpose of visiting a “customer” is collecting rather than delivering something. However, the decisions dealt with are similar in both problems: which customer to visit and how to route the vehicles. Solution methodologies for IRPs also work for WCPs as long as they support decisions for uncertain demand (waste deposits) and a large number of customers (waste containers), which are usual settings for a WCP. In addition, a sound solution methodology for a WCP should be able to cope with a long planning horizon, since a short-term approach will postpone container visits to the next period as explained by Campbell et al. [7].

In this paper, we focus on a waste collection company, located in The Netherlands, with many customers within a relative small geographical area. These two characteristics make it possible to empty many containers during one day, especially when the waste deposits are frequent or large enough to fill the containers fast. In our study, a vehicle is typically able to visit more than ten and up to a hundred containers per day. We consider information about the current fill levels of containers to be available at any point in time. Furthermore, we consider that end-customer demand (waste deposits) are stochastic. This makes it difficult to design robust plans for all possible demand realizations. To solve the problem for a long planning horizon, a way of “learning” from historical demand (inventory levels) must be incorporated such that better predictions can be done for the future.

Taking into account the size of the container network, the stochastic nature of waste deposits, and the need to use a long planning horizon, on top of the interrelatedness of the multiple decisions, it is clear that not all solution approaches for the IRP are suitable. Modeling the planning decisions and solving the model for real-life problem settings and instances are challenging tasks. Exact solutions, such as mathematical programming, are not suitable to solve larger problem instances [8, 9]. Additionally, mathematical programming models usually assume deterministic demands. Stochastic modeling approaches, such as Stochastic Dynamic Programming and Markov Decision Processes, also become computationally intractable due to large state spaces and high-dimensional value functions that cannot be solved analytically [10]. For these reasons, different types of heuristic approaches have been proposed in the literature. In their review of various heuristics for the IRP, Abdelmaguid et al. [11] show that these heuristics involve parameters or settings that influence their performance. Even if ways of determining the parameters are given, they usually do not incorporate any form of coping with uncertainty; variability in demand realizations may thus diminish their performance.

In this paper, our main goal is to develop a fast and parametrized heuristic for solving the IRP for waste collection, together with a methodology to determine the best parameter settings for our heuristic. Since the performance and the quality of a particular heuristic heavily depends on choosing the right values of its parameters, we propose the use of techniques from optimal learning [12]. This paper makes the following contributions: (i) we propose a practical and sim-

ple heuristic for solving the IRP with many customers, (ii) we show how simulation optimization can be used for tuning the parameters of our heuristic in the best way for a given problem setting, and (iii) we provide insight into the dependency of the parameters of our heuristic with respect to several network characteristics (e.g., density of the container network, fluctuation in waste deposits, etc.). We illustrate our approach using a case study at the waste collection company “Twente Milieu”. This company has implemented the dynamic collection policy, where underground waste containers are scheduled to be emptied based on sensor information on the fill levels of these containers.

The paper is organized as follows. In Section 2, we briefly present the key points addressed in the scientific literature about the problem under consideration. In Section 3, we describe our model and present the assumptions of the IRP for waste collection. Following this, we explain our parametrized heuristic approach for solving the problem in Section 4. In Section 5, we describe the way an optimal learning algorithm can be applied to this problem and specifically to our heuristic. We present the experimental design and the insights of this study in Section 6. We end with conclusions in Section 7.

2. Literature

The problem we consider in this paper involves planning decisions in two logistical areas: transportation management and inventory control. Although each of them has often been studied separately, their decisions are interrelated and they share a common objective as can be seen in Figure 1. The integration of these two areas is known as the Inventory Routing Problem (IRP). In an IRP, three questions have to be answered: (i) when to visit a customer, (ii) how much product to deliver during the visit, and (iii) how to route the vehicles [7]. In this section, we present a brief review about the characteristics of diverse IRPs. Furthermore, we compare the benefits and drawbacks of different solution approaches when considering an IRP with many customers. Finally, we briefly discuss the IRP studies that have been done in the waste collection industry and describe how our study differs from existing studies.

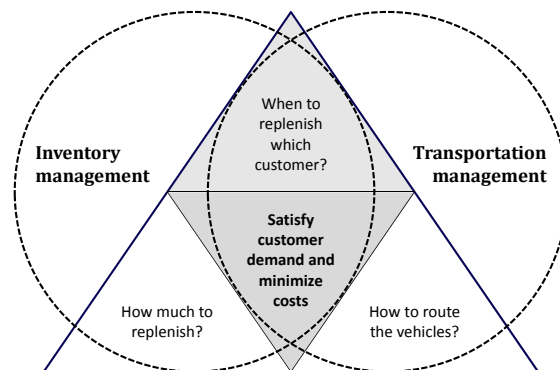


Figure 1: Decisions in an IRP and their relations

The IRP combines two problems classes: the Vehicle Routing Problem (VRP) and Vendor Managed Inventory (VMI). Some IRPs are considered as extensions of the VRP [13]. As the name states, the problem settings that govern a VRP are exclusively related to vehicles. Hence,

the objective is to minimize the duration and costs of the routes the vehicles travel [14]. In a VRP, a company limits itself to receiving customer orders and finding the best way to satisfy and deliver them. On the other hand, in an IRP, the customer orders are determined by the company, usually guided by some service level agreement. This case of customer stocks being replenished without an explicit customer order is known as VMI. VMI decisions focus on determining the size and time of replenishment. The combination of VMI and VRP decisions makes the IRP a challenging problem.

To cope with uncertainty in customer inventories, IRPs are usually solved dynamically (as opposed to static single time solving) within a given planning horizon. However, these frequent decisions have the effect that previous decisions influence current and future ones, as explained by Baita et al. [2]. Therefore, the length of the planning horizon has an impact on the way the problem should be conceptualized and tackled. For a thorough categorization of the characteristics of dynamic routing and inventory problems, we refer to Baita et al. [2] and Kleywegt et al. [15]. Here, we elaborate on only two of these characteristics: the planning horizon and the uncertainties in demand.

The planning period of IRP studies vary from a single period to an infinite horizon. Nevertheless, most researchers agree that the interrelatedness of decisions through time has an impact on the long-term planning objective. Since early studies of IRPs, authors have developed ways of measuring the long-term effect when using single period models. For example, Dror and Ball [16] solve a series of single period problems, model the long-term effect through the use of penalties, incentives, and expected changes in costs, and optimize the output of the single period problems in accordance to the long-term objectives. Chien et al. [17] also tackle the IRP long-term decision effects with single period problems, with the difference that they pass inventory and cost information from one period to the next one, and therefore make decisions taking into account information from other periods. The problem has also been studied the other way around: a long-horizon solution is developed first and then short-term plans are derived from it. For example, Campbell and Savelsbergh [18] develop a two phase rolling horizon approach. First, a monthly plan is generated, which is then split into short-term problems for daily scheduling. The plan is implemented only for the first few days of the planned month, after which a new plan will be generated. A similar rolling horizon approach is developed by Jaillet et al. [19], who build a two weeks schedule but only the first week is implemented. Just as these examples, most of the solving approaches in the literature typically decompose the entire IRP into short term problems and use some method to account for the long term objective.

The majority of models developed for multiple-period IRPs assume deterministic demand as seen in Andersson et al. [20]. However, it is often desirable that a planning system is able to cope with stochastic processes, especially when considering that the different realizations of real-life demand might prevent the plan of being executed as desired [21]. According to the classification scheme of Andersson et al. [20] and Coelho et al. [22], our problem can be characterized as a Dynamic and Stochastic Inventory-Routing Problem (DSIRP), with a finite horizon, one-to-many deliveries, multiple customer visits per route, order-up-to level inventory policy, using back-ordering, with a fleet of multiple homogeneous trucks. In the DSIRP, customer demand is known only in a probabilistic sense and revealed over time [22]. Frequently, stochastic IRPs are modeled as a Markov decision processes [15, 23, 24]. However, this approach might easily become computationally intractable due to the large state space. Iterative heuristics, linear reformulations, and scenario trees are ways to deal with this. Another commonly proposed methodology is simulation. For example, Cáceres-Cruz et al. [25] combine simulation with heuristics to solve the single-period IRP with stochastic demands. Reiman et al. [26] and Schwarz

et al. [27] combine simulation with traffic analysis and analytical models to develop policies that assure that the IRP objectives are attained in the long term. Theoretically, these approaches work well as long as the customers' usage can be forecasted accurately enough. When customers' usage evolves over time (which is usually the case), a sound planning methodology must be flexible enough to adapt to the changes. As Moin and Salhi [13] conclude, further research on how to capture the dynamic nature of the parameters involved in IRP models is needed.

Two recent studies on the DSIRP can be found in Bertazzi et al. [28] and Coelho et al. [29]. The authors provide various policies, implemented in a rolling horizon framework, with the objective to minimize inventory, distribution, and shortage costs. Related to our research, Coelho et al. [29] also study the impact of varying several system parameters, and solve relatively large instances (up to 200 customers). For a comprehensive review of the IRP literature, we refer to Andersson et al. [20] and Coelho et al. [22].

In comparison to the maturity of the IRP literature, the Waste Collection Problem (WCP) literature is still in a developing stage. The large share of the transport costs in the total cost of solid waste management systems is an incentive to study this problem [30, 31]. Karadimas et al. [32] quantify the costs of the collection phase to be 60% to 80% of the total costs of waste management in Greece. Some studies have deepened on the reasons for these costs, and have shown that the fuel consumed by the vehicles in the waste collection process strongly depends on the time of operation and the number of stops rather than the distance traveled [33]. Nevertheless, WCP objectives are not only about economic perspectives, but are also motivated by the positive environmental impact, in terms of CO₂ emission and traffic congestion [8]. This impact is even larger when applied to large and dense areas of fast population growth as reported by Vicentini et al. [34] in their study in Shanghai. These reasons encourage further studies on improving the efficiency of the planning and control in waste collection processes.

Most studies on waste collection processes have examined static problem formulations in which information is known in advance. Due to the assumption of known information, many authors have modeled the collection process as a variation of the vehicle routing problem (VRP) [35, 36, 37]. Although characteristics such as time windows, large number of containers, large demand (which is reflected in several visits to a disposal center during a day), and different types of waste have been conceptualized through VRPs in a large extent, the dynamism and stochasticity of the information for planning in WCPs have not [38]. Some authors propose the addition of some procedures to the basic VRP in order to cope with the constantly changing information. For example, Nuortio et al. [37] use a node routing approach through guided variable neighborhood search to cope with the highly variable amount of waste in the containers. Others use geographic information systems (GIS) and global positioning systems (GPS) to incorporate some aspects of uncertainty in the routing information [32, 33, 34].

Heuristics are commonly used as solution approaches for the WCPs due to the heavy computational demands of real-life instances. Usually, a combination of heuristics and optimization techniques is used to improve the quality of the solutions. For example, Chang and Wei [35] use a variant of the minimum spanning tree in combination with an integer programming model to improve vehicle routing efficiency. Teixeira et al. [39] use a three-phase heuristic that aims to create collection routes for every day of the planning horizon. Local search algorithms, such as tabu search, have also been applied [40, 41]. Karadimas et al. [32] apply an Ant Colony System, in which the ants (vehicles) search the area for optimal routes with respect to a known group of containers. The strength of the pheromone trail these ants leave is in relation with the quality of the solution value found. Therefore, good solutions are more likely to be followed by future vehicles.

There are some studies that explicitly consider the dynamism in terms of scheduling and routing. Simonetto and Borenstein [42] study solid waste collection in Porto Alegre, Brazil, and propose a dynamic planning methodology using simulation and heuristics. However, they consider a short-term horizon operational planning problem. Johansson [38] studies dynamic waste collection in the Swedish city Malmö. Analytical modeling and discrete-event simulation is used to assess different planning policies utilizing real time information from the containers (through level sensors and wireless communication technologies). Johansson [38] shows that dynamic collection policies (that take into account fill level information) outperform static policies (fixed routes and preset collection frequencies) in terms of distances traveled, labor hours, and costs. This last research is closely related to ours.

Much of the effort in the literature for waste collection and inventory routing problems has been spent on finding the best routes, throughout a given planning horizon with a given set of customers [43]. Also, sophisticated algorithms have been developed to handle the uncertainty in routing. However, less attention has been paid to managing the uncertainty in the selection of containers to be emptied. In the IRP for waste collection in a dense area with many customers and relatively small travel distances, selecting the right containers to empty might have a higher impact on the objective than the routing decisions. The focus of our work is the development of a fast and parameterized heuristic for solving the short term problem dynamically, taking into account the long term impact. In addition, we propose the use of optimal learning to (i) find the best configuration for the heuristic’s parameters and (ii) learn the relation of the parameters to different problem settings.

3. Problem description

In the remainder of this paper, we focus on the waste collection problem, where ‘inventories’ are emptied instead of being replenished, although our insights apply to the general IRP with many customers as well. In our waste collection problem, the company has to plan when to empty the containers and how to route the vehicles, such that the collection costs are minimized and customer satisfaction is maximized (tidiness of the environment). In this section, we provide a formal problem description and state our assumptions. To draw the parallel with common IRP formulations, we first present a time-discretized deterministic version of our problem. Next, we explain the stochastic and dynamic nature of our problem. Our parameterized heuristic to solve the stochastic and dynamic IRP is described in Section 4.

We have a set \mathcal{C} of containers that receive waste deposits and must be emptied during a planning horizon \mathcal{T} . These containers can be emptied at discrete points in time $t \in \mathcal{T}$, with t discretized to days. For each day t , $d(t)$ gives us the day of the week d , with $d \in \mathcal{D}$ and $\mathcal{D} = \{Monday, \dots, Sunday\}$. For each day of the week d , we have a maximum working time b_d . We assume the time b_d has been corrected to account for activities such as lunch breaks and fueling. Setting $b_d = 0$ means that day of the week d is not a working day. For the entire container network, information on the amount of waste $v_{i,t}$ a container i holds at a time t is available. Also, the deposit volumes $u_{i,t}$ for all containers $i \in \mathcal{C}$ and days $t \in \mathcal{T}$ are known. For the deterministic version of the problem, we assume that the deposits $u_{i,t}$ on day t take place after any collection. As long as container i is not emptied, the volume of waste in this container at later points in time can be calculated sequentially using $v_{i,t+1} = v_{i,t} + u_{i,t}$.

Every container i has a maximum waste-holding capacity of w_i . However, when a container is full, we consider “overflow” or extra waste in that container to be possible. This means that $v_{i,t}$ can be greater than w_i when, e.g., new waste deposits have to be placed next to container

i because the container is full. We denote the amount of overflow of container i at time t by $z_{i,t}$, which is defined as the difference between the waste $v_{i,t}$ collected from a container and its capacity w_i , i.e., $z_{i,t} = \max\{v_{i,t} - w_i, 0\}$.

To empty the containers and clean the overflow waste, a fleet \mathcal{M} of homogeneous vehicles can be used, each having a waste holding capacity of g . The collected waste within the truck is compressed. However, to keep notation simple, we here express the capacity g in terms of uncompressed waste. All vehicles depart from a given parking area and return empty to the same parking area at the end of a working day. To empty a vehicle, the vehicle must visit a waste disposal center. To keep the notation simple, we use i and j as index for all locations, i.e., for the containers as well as for the parking area and waste disposal center. In case we specifically want to refer to the latter two locations, we use p to indicate the parking area and q to denote the waste disposal center. The travel times $s_{i,j}$ between locations i and j and the handling times h_i for each location i are assumed to be known and deterministic for all vehicles. Handling times h_i can consist of loading waste into a vehicle ($i \in C$), or unloading waste at the disposal center ($i = p$), or parking ($i = q$).

For our problem, we take three types of costs into consideration: transportation, handling, and penalty costs. Transportation costs $c_{i,j}^s$ between locations i and j can be calculated by $c_{i,j}^s = \alpha^t s_{i,j}$, where α^t is a cost factor per unit of traveling time. Similarly, handling costs c_i^h for every location i can be computed by $c_i^h = \alpha^h h_i$ where α^h is a cost factor per unit of handling time. The penalty cost $c_{i,t}^p$ for the overflow waste of container i at time t is defined as $c_{i,t}^p = \alpha^p z_{i,t}$, where α^p is a cost factor per unit of volume of overflow waste and per time unit. A similar penalty formulation can be found in Chien et al. [17] and Kleywegt et al. [15]. These penalty costs are time dependent since the overflow waste increases if a container is not emptied in a timely manner. Note that $c_{i,t}^p = 0$ when $v_{i,t} \leq w_i$. The penalty costs can be considered as costs for ‘‘backlogging’’ in a normal IRP formulation.

We define a route $r \in \mathcal{R}$ to be the ordered group of locations that a vehicle visits during a day. A route starts and ends at the parking location, has at least one container to empty, has at least one visit to the waste disposal center, and the last visit to the waste disposal center should take place right before going back to the parking location. Hence, a proper route is of the form $r = \{p, i_1, i_2, \dots, q, i_k, i_{k+1}, \dots, q, p\}$. After a number of collections in a route $r \in \mathcal{R}$, a vehicle might get full and therefore must visit the waste disposal center in order to continue visiting more containers. We define a sub-route $r^s \subseteq r$ as the set of locations that a vehicle visits after departing from either the parking area or the waste disposal center until the next visit to the waste disposal center.

For the time-discretized deterministic version of the problem, we assume decisions are only made at the beginning of each day. We define $X_{i,r,t}$ as a binary decision variable equal to 1 if container i is emptied in route r at day t and 0 otherwise. We let $Y_{i,j,r,t}$ be a binary decision variable that is equal to one if location j is visited immediately after location i in route r at day t and zero otherwise. These decisions have to be made with the objective to minimize the sum of all costs over the entire planning horizon $t \in \mathcal{T}$. Our objective function is now given by

$$\min \sum_{t \in \mathcal{T}} \left[\sum_{r \in \mathcal{R}} \sum_{i \in C} c_i^h X_{i,r,t} + \sum_{r \in \mathcal{R}} \sum_{i \in C} c_{i,t}^p + \sum_{r \in \mathcal{R}} \sum_{i \in C} \sum_{j \in C} c_{i,j}^t Y_{i,j,r,t} \right]$$

The objective formulation is similar to that of Chien et al. [17] and Abdelmaguid et al. [11] with the exception that we do not have inventory (i.e., waste) holding costs. This objective function is subject to all typical IRP constraints, such as vehicle capacity constraints, routing

constraints, and sub-tour elimination constraints. Here, we only mention the constraints that are different for our problem.

- *Waste definition of the containers:* These constraints update the estimated volume of waste in a container and any overflow. Although they are similar to the inventory constraints, the difference with our problem is that we allow “backorders” or overflow waste and that there is no “partial delivering”, which means the container is completely emptied if visited.

$$\begin{aligned} v_{i,t+1} &= (1 - X_{i,r,t}) v_{i,t} + u_{i,t} & \forall i \in C, t \in \mathcal{T} \\ z_{i,t} &= \max\{v_{i,t} - w_i, 0\} & \forall i \in C, t \in \mathcal{T} \end{aligned}$$

- *Capacity of vehicles:* These constraints ensure that in each sub-route r^s , which is part of a route r , the capacity g of each vehicle is not exceeded:

$$\sum_{i \in r^s} v_{i,t} X_{i,r,t} \leq g \quad \forall r^s \in r \wedge r \in R, t \in \mathcal{T}$$

- *Working time:* These constraints ensure that the entire route r is done within the maximum working time (b_d) for a vehicle and crew on working day $d = d(t)$:

$$\sum_{i \in r} \sum_{j \in C} (s_{i,j} + h_i) Y_{i,j,r,t} \leq b_{d(t)} \quad \forall r \in R, t \in \mathcal{T}$$

Finally, our objective function is restricted by routing constraints that guarantee that a vehicle’s route is feasible (i.e., one visit to the disposal center per sub-route, a route starts and ends in the parking lot, no sub-tours) and that all decisions variables have a binary domain. These constraints are the same as in other problem formulations, such as those of Archetti et al. [44], Bard and Nananukul [45], and Savelsbergh and Song [46]. Although our problem shares many similarities with most IRP formulations, there are some specific characteristics of our problem:

1. There are no time windows for emptying the containers, but there is a starting and ending time for the working day, with a maximum working time b_d per day of the week d .
2. The capacity of containers can be exceeded with overflow waste. When emptying a container, it should be emptied entirely including the overflow waste. In IRP terminology, this corresponds to allowing backloging demand without partial deliveries.
3. Typically, a large number of containers has to be emptied on a working day (e.g., more than 100 containers per vehicle per day).
4. There are different “depots”, i.e., at least one parking location and one waste disposal center.

Furthermore, because waste deposits are not known up front exactly, we need to take stochasticity into account and to be able to plan dynamically. Deposit rates as well as deposit volumes are stochastic, and they might fluctuate due to changes in the environment (e.g., holidays, seasonal effects, and weather conditions). This uncertainty has an impact on the planning. For example, containers might get full faster during a working day than expected, such that we have to go earlier to the waste disposal center. Hence, we also need to allow for re-routing (re-planning) during the working days.

To cope with uncertainty in waste deposits, we replace the quantities $v_{i,t}, u_{i,t}, z_{i,t}$, with estimates $\hat{v}_{i,t}, \hat{u}_{i,t}, \hat{z}_{i,t}$. An estimate of the penalty cost per container is defined by $\hat{c}_{i,t}^p = \alpha^p \hat{z}_{i,t}$. To cope with uncertainty in the waste volumes, we replace the capacity g by a target capacity \bar{g} , which generally will be lower to buffer against uncertainty.

To allow decisions to be taken at different points in time, we use a continuous time formulation. A decision moment can occur (i) during the initial planning (morning) of a working day or (ii) during replanning situations triggered by some events during the day. These replanning situations may occur, e.g., after each collection, when there is a deviation with respect to the expected and realized collected volume, when some time for visiting the containers is not met, etc. This continuous time formulation has an impact on the way calculate the penalty costs. Every day, at midnight, we calculate the penalties similarly as mentioned before: $c_{i,t}^p = \alpha^p z_{i,t}$. However, when emptying a container during the working day, say at 10am, we only charge the corresponding fraction of penalties, i.e., $10/24\alpha^p$ per volume of overflow.

Different ways of solving the waste collection problem have been proposed in the literature as previously described in Section 2. However, large scale and complex instances as the one in consideration prevent the practical application of most of the exact methods due to computational limitations. In order to handle these characteristics in a timely manner, and to allow re-routing (re-planning) during a working day, a fast planning heuristic should be used. Moreover, a long planning horizon should be considered since a short term approach will postpone collections to the next period as explained by Campbell and Savelsbergh [18]. We propose a heuristic that uses a set of tunable parameters (i) to cope with the variability of the waste estimations $\hat{v}_{i,t}, \hat{u}_{i,t}$, and $\hat{z}_{i,t}$, and (ii) to generate a solution fast enough. We present this heuristic approach in the next section. In Section 5, we describe how optimal learning techniques can be used to optimize the tunable parameters.

4. Heuristic approach

As mentioned in Section 3, we use a heuristic approach to deal with the dynamic and stochastic nature of the problem and to be able to handle large problem instances. Although in this day-to-day planning, decisions are made for the immediate (short-term) time horizon, a consideration for the long-term performance must be done as well. The heuristic we propose uses a set of adjustable parameters, which regulate the immediate decisions, but have a direct impact on the cost function for the long planning horizon. The heuristic itself is used for an operational planning of the containers to empty based only on immediate handling and traveling costs. However, to analyze the long term performance (which includes penalty costs) in this operational planning, we propose the use of simulation optimization (Section 5). In this section, we explain our heuristic approach for the day-to-day planning.

First, we make a distinction between the different containers. We define a “MustGo” as a container that has to be planned into a route and has to be emptied during the current planning day. In addition, we define a “MayGo” as a container that might be planned into an existing route of MustGo’s if it is convenient to do so. Finally, we define a “NoGo” as a container that should not be planned to be emptied during the current planning day. This distinction is similar to that presented in Dror et al. [47] and Bard et al. [48]. At any decision moment, we use a parameterized heuristic that first categorizes the containers and initializes some parameters, then prepares routes according to the initialized values and categorization, and finally plans the routes to empty the different containers, as can be seen in Figure 2. We now describe each of these steps in more detail.

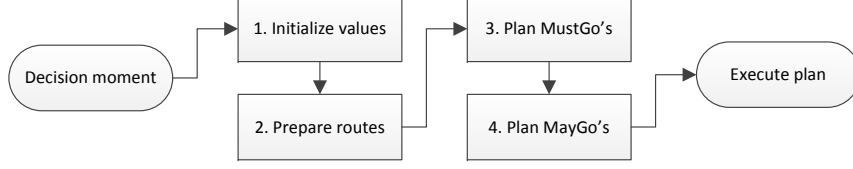


Figure 2: Heuristic steps

Step 1: Initialize values

With respect to the selection of containers, at any point in time t , we define $\hat{f}_{i,t}$ to be the expected number of days left before container i becomes full. It can be estimated as follows:

$$\hat{f}_{i,t} = t' - \frac{z(t, t')}{\hat{u}_{i,t'}}$$

where t' represents the number of whole days from day t until the container reaches overflow $z(t, t')$ for the first time. These quantities are given by

$$t' = \inf_{s'} \{z(t, s') \leq 0\},$$

$$z(t, s') = \sum_{s=t}^{t+s'} \hat{u}_{i,s} - (h_i - \hat{v}_{i,t}).$$

Using $\hat{f}_{i,t}$, we can categorize container i into a “MustGo”, a “MayGo”, or a “NoGo” container. We denote the set of MustGo containers as C^m and the set of MayGo containers as C^n . To define these sets, we introduce the adjustable parameters F_d^m and F_d^n for every day d of the week, with $d \in \mathcal{D} = \{1, 2, \dots, 7\}$, where $d = 1$ represents Monday. These two parameters represent a threshold on the number of working days on which container i must be full in order to consider it a MustGo ($\hat{f}_{i,t} \leq F_d^m$) or a MayGo ($F_d^m < \hat{f}_{i,t} \leq F_d^m + F_d^n$) container. As an example, suppose we have a five day work week (Monday to Friday). On a Thursday morning with $F_4^m = 1$, C^m contains all the containers that are expected to be full before Friday morning. On a Friday morning, with $F_5^m = 1$, C^m contains all the containers that are expected to be full before Monday morning. Besides the fluctuations in deposits over the days of the week, the length of the working week also give rise to use day dependent parameter settings.

With respect to routing, we define \bar{r}_t to be a lower bound on the number of sub-routes r^s to use from time t till the end of the current working day, and compute it as follows:

$$\bar{r}_t = \left\lceil \frac{\sum_{i \in C^m} \hat{v}_{i,t}}{\bar{g}} \right\rceil$$

For every vehicle $m \in \mathcal{M}$, a route r is initialized as long as the vehicle is needed. Hence, at time t we define the number of routes as $|\mathcal{R}| = \min(|\mathcal{M}|, |C^m|, \bar{r}_t)$. Since the decision moment could have been triggered by two cases (as mentioned in the beginning of this section), we have the following two cases for initializing all routes $r \in \mathcal{R}$:

1. If the route is empty ($r = \emptyset$), usually the case when the decision moment is at the beginning of the day, then we let $r = \{p, q, p\}$, where locations p and q denote the parking area and the disposal center respectively.

2. If the route r is not empty, which is the case when re-planning occurs during the day, we empty it in a non-preemptive way. By non-preemptive we mean that the current visit of a vehicle (when the re-planning occurs) is not removed from the routes. In order for the initial routes to remain feasible, this current visit to a container will be followed by a visit to the waste disposal center and a return trip to the parking area.

With the set of containers C^m and C^n , and the initialized set of routes \mathcal{R} , we proceed to the next steps in our heuristic.

Step 2: Prepare routes

For this step, we use a common classification of customers in the VRP construction heuristics: the seed customers. Seed customers are customers that have a special characteristic (e.g., longest distance from depot, largest demand, etc.) and are the nucleus around which the routes are constructed [49]. We define C^s to be the ordered set of seed containers that will be used to plan a route, such that one seed container is used per route (i.e., $|C^s| = |\mathcal{R}|$). Note that, even though a route can consist of more than one sub-route r^s , we use one seed per route $r \in \mathcal{R}$, which we assign to the first sub-route r^s .

The seed containers are selected from the set of MustGo containers C^m , such that $C^s \subseteq C^m$. In our heuristic, seed containers are chosen based on the largest minimum distance from the parking location and the other seed containers. These seed containers serve the functions of (i) spreading the vehicles over the network, (ii) realizing insertion of containers close as well as far from the parking location into the schedules, and (iii) balancing the workload per route to anticipate the insertion of MayGo containers.

Step 3: Plan MustGo's

In this step, the remaining unplanned MustGo containers have to be planned, as long as capacity and time restrictions allow for this. For assigning a container $k \in C^m$ that is not a seed container, i.e., $k \notin C^s$, we use a cheapest insertion heuristic.

The MustGo containers can be assigned to any route r and hence to any vehicle. To do so, an insertion cost c_{k,i,j,r^s}^{insert} of container k between the visits of locations i, j per sub-route r^s is calculated. This insertion cost depends on the additional time required to visit the container at a certain point in a vehicle's route, and it is calculated by

$$c_{k,i,j,r^s}^{insert} = c_{i,k}^t + c_{k,j}^t - c_{i,j}^t + c_k^h, \quad \forall r \in \mathcal{R} \wedge \{i, j\} \in r^s | r^s \subseteq r. \quad (1)$$

Besides the traveling and handling times, we also take into consideration the capacity of a vehicle in each sub-route r^s when deciding where to insert a container. If the additional volume of waste that comes from container k exceeds the target capacity \bar{g} of the vehicle executing sub-route r^s , then additional visits to the waste disposal center are planned within that sub-route (thus creating a new sub-route $r^s \subseteq r$ in that vehicle's route). The insertion costs (1) are updated with the time required for these additional disposal visits accordingly. After the insertion costs for all possible positions in every route have been calculated, the best position to insert a container k is chosen according to the cheapest insertion heuristic [18]. Note that this step could easily be improved using more advanced construction and improvement heuristics. However, since our focus is on parameter tuning, we keep things simple here.

Step 4: Plan MayGo's

After all MustGo containers have been scheduled, there might be vehicles that can still load more waste from other containers. In order to improve the capacity utilization of these vehicles, we add MayGo containers to their routes.

With respect to the insertion of MayGo's, a container $k \in C^n$ is merged into a vehicle's route r according to the cheapest insertion heuristic. However, a different cost definition from the previous step is used this time, since we might or might not add a container k to an existing route. In the IRP literature, a common way of defining costs for a potential customer is by using the ratio of additional required traveling and handling time (which in step 3 of our heuristic was defined as insertion cost c_{k,i,j,r^s}^{insert}) and the estimated volume required by this customer [50]. We define this cost ratio as

$$c_{k,r,t}^{ratio} = \frac{\min_{i,j \in r^s | r^s \subseteq r} c_{k,i,j,r^s}^{insert}}{\hat{v}_{k,t}}, \quad \forall k \in C^n, r \in \mathcal{R}. \quad (2)$$

However, in this way of defining costs, the more distant a container's location is, the more unlikely it is that this container will be considered for insertion into a route. To handle this situation, we use a relative improvement criterion denoted as $\Delta_{k,r,t}^{ratio}$. We compare the resulting ratio of (2) with a historical smoothed average of this cost ratio \bar{c}_k^{ratio} and define the relative improvement criterion as

$$\Delta_{k,r,t}^{ratio} = \frac{c_{k,r,t}^{ratio}}{\bar{c}_k^{ratio}}, \quad \forall k \in C^n, r \in \mathcal{R}. \quad (3)$$

This improvement criterion is defined for the minimum additional time in every route, and for all routes $r \in \mathcal{R}$. A large positive value of $\Delta_{k,r,t}^{ratio}$ represents a good opportunity that we should take. Nevertheless, the smaller the ratio $c_{k,r,t}^{ratio}$, the more attractive it becomes to consider container k for insertion, since the additional time it takes to visit the container is relatively small compared to the volume of waste we collect.

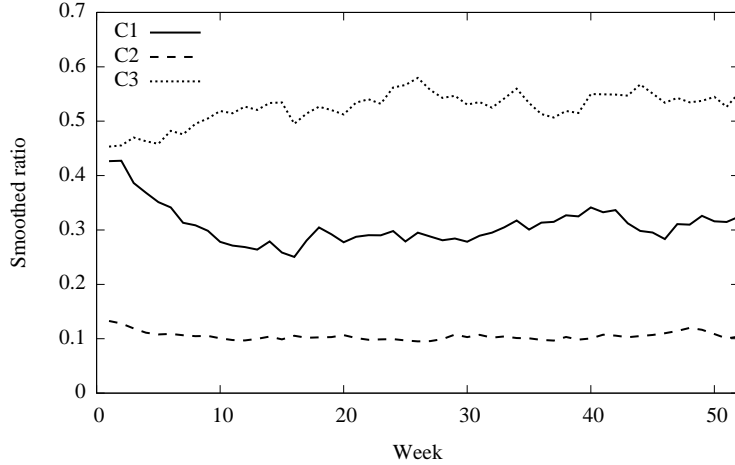


Figure 3: Smoothed ratios for three containers

To illustrate the situation with the cost ratios mentioned above, consider Figure 3. This figure shows the smoothed ratios \tilde{c}_k^{ratio} for three different containers. Container 3 (C3) is a remotely located container, container 1 (C1) is located closely to the parking area and waste disposal center, and container 2 (C2) is somewhere in between. The ratio of C1, is the lowest of the three because, as seen from (2), it requires less time for a visit. If we only would use the ratio as it is, we will always favor C1 in comparison to C3. Containers at remote locations would never be selected even if it would be better to include them now than in a new route another day. This is the reasoning behind the relative improvement criterion $\Delta_{k,r,t}^{ratio}$ defined in (3).

Although adding MayGo containers increases vehicle utilization, it might also lead to unnecessarily long routes (since the set of MayGo containers is not defined by location) or that unnecessary work is carried out on a working day (since visits could be postponed to subsequent days for more efficient collections). Evidently, this efficiency depends on how the MayGo set C^n is defined. A good value for F_d^n , the parameter that makes the distinction between a MustGo and a MayGo container, has a positive influence on both waste-capacity and routing efficiency. Adding too many containers (e.g., until all vehicle capacities are met) can also contribute to the aforementioned inefficiency. To have a control over this situation, we introduce a limit F_d^l on the amount of containers that can be emptied per working day. This limit is expressed as a fraction of the total number of containers $|C|$. After $F_d^l \times |C|$ containers (including MustGo's) have been planned on a day d , no more MayGo containers can be added to a vehicle's route. Another option, which we do not consider here, would be to add a bound to the cost ratio (2) or the improvement criterion (3).

To summarize, we developed an easy to implement heuristic for the dynamic waste collection problem. The heuristic uses adjustable parameters $\{F_d^m, F_d^n, F_d^l\}$ ($\forall d \in \mathcal{D}$) and historic cost information \tilde{c}_k^{ratio} , which incorporates knowledge about long-term performance to its immediate decisions. To tune the parameters, we propose the use of optimal learning techniques. In Section 5, we briefly explain how optimal learning can be applied to our heuristic through the use of discrete-event simulation.

5. Optimal learning

The heuristic proposed Section 4 is appealing from a practical point of view because of its easy interpretation. From a network of containers, we empty those that are expected to be full within a certain number of days, and visit them in an efficient route. We might also empty additional containers that are more convenient to empty now than later. We fill the routes with these MayGo containers until a predefined limit on the number of containers is reached. The heuristic optimizes the collection process given its parameter settings and considering only the handling and traveling costs. The performance of the heuristic and the value of the overall objective function (as presented in Section 3) heavily depends on the chosen input parameters. In this section, we describe the use of optimal learning techniques to choose the best input parameters.

In an optimal learning problem, we efficiently collect information through measurements to improve future decision making. The problem arises in both offline and online settings. In an offline setting, we have a measurement budget for finding the best possible decision, after which we implement the best one. In an online setting, every decision is implemented and we have to live with their costs, but we want to learn as we go. Optimal learning is an issue primarily in applications where observations or measurements are expensive [51]. Online learning for our waste collection problem would mean that the company uses the planning approach, with given parameter settings, during some period of time and observes the resulting performance to

improve future decision making. These real life experiments form expensive measurements for the company. Here, we focus on offline learning, where the expensive measurements come in the form of a time consuming simulation run (experimenting through computer simulation). This problem is also known as simulation optimization, and can be defined as the process of finding the best parameter settings among all possibilities without explicitly evaluating each possibility. The objective of simulation optimization is to minimize the resources spent while maximizing the information obtained in a simulation experiment [52].

Mathematically, the problem comes down to finding alternative x out of a set of alternatives \mathcal{X} , such that the value $f(x)$ of this alternative is minimized. The value $f(x)$ follows from a simulation run and therefore the outcome is subject to noise, i.e., measurement n of alternative x will result in an observation $y_x^{n+1} = f(x) + \epsilon$, with ϵ being the measurement error. In our case, alternative x defines a particular setting for the parameters $F_d^m, F_d^n, F_d^l (\forall d \in \mathcal{D})$. The ‘‘correct’’ settings of these parameters may vary per day d of the week. Intrinsicly, the right choice for these parameters is influenced by the variability of the waste deposits. In the remainder of this paper, we assume five working days per week, i.e., $\mathcal{D} = \{1, 2, \dots, 5\}$. Now, alternative x can be defined as a matrix of the following parameters

$$x = \begin{bmatrix} F_1^m & F_2^m & \dots & F_5^m \\ F_1^n & F_2^n & \dots & F_5^n \\ F_1^l & F_2^l & \dots & F_5^l \end{bmatrix}.$$

Recall (Section 4) that these parameters are defined as

F_d^m Threshold on the number of days on which a container is expected to be full in order to consider it a MustGo during day d .

F_d^n Threshold on the number of days on which a container is expected to be full in order to consider it a MayGo during day d .

F_d^l Limit on the amount of containers that can be emptied during day d . This limit is expressed as a fraction of the total number of containers $|C|$.

We use the following domains, based on preliminary experiments and expert opinion $F_d^m \in [0, 4]$, $F_d^n \in [0, 4]$, and $F_d^l \in [0, 1]$. The objective of our learning problem is to minimize the expected value of the objective function after performing N experiments

$$\min_{x \in \mathcal{X}} \mathbb{E}^N [f(x)],$$

where \mathcal{X} represents the feasible area given by the 15-dimensional domain formed by F_d^m, F_d^n , and F_d^l , for all $d \in \mathcal{D}$.

Now, suppose we discretize the domain of each parameter into 10 distinct values. We then have 10^{15} possible parameter configurations. Evaluating all of them, using a sufficient number of replications for each parameter configuration and using a sufficiently long run length, would not be feasible in reasonable time.

To solve the learning problem, a wide variety of methods are available, coming from the fields of Ranking and Selection (R&S) and Bayesian global optimization (BGO), see Powell and Ryzhov [12] for an overview. The choice for an efficient learning technique depends on various problem characteristics, e.g., online or offline measurements, binary, discrete or continuous parameters, high or low dimensional state space, etc. Because even the discretized version of

our problem would result in a larger number of alternatives than we could measure, we require policies that are able to generalize across the state space. In this paper, we use two policies that are able to achieve this: the Sequential Kriging Optimization (SKO) from Huang et al. [53] and the Hierarchical Knowledge Gradient (HKG) from Mes et al. [54].

The policies SKO and HKG take advantage of Bayes Theorem, which assumes we have a prior belief (a prior predictive distribution) for the cost function $f(x)$. Bayes rule is used to form a sequence of posterior predictive distributions for $f(x)$ based on this prior and the successive measurements. Let μ_x^n and $(\sigma_x^n)^2$ be the mean and variance of the predictive distribution after n measurements. Both policies assume the true mean μ_x of $f(x)$ conforms to a Gaussian process, i.e., $f(x) \sim \mathcal{N}(\mu_x, (\sigma_x)^2)$. With every measurement n , with $y_x^{n+1} \sim \mathcal{N}(\mu_x, \sigma_x)$, we update our prior belief to a posterior belief. The measurement policy aims to choose the measurements (x^0, \dots, x^N) in such a way that the implementation decision x^{N+1} minimizes $\mathbb{E}^n [f(x^{N+1})]$ (in a minimization problem), where \mathbb{E}^n denotes the conditional expectation given what we have learned through the n measurements. For more information on BGO, we refer to Powell and Frazier [51] and Frazier et al. [55].

SKO is an extension of the well known Efficient Global Optimization (EGO) policy [56] to the case with noisy measurements. SKO works from a feasible region (set of alternatives) that is continuous, connected, and compact. New alternatives to measure are based on a so-called “expected improvement function”, which strikes a balance between exploitation and exploration. This method works with input coming from a black-box system, meaning that it does not require a closed-form formulation of the objective function. For the reasons above, we consider this technique suitable for our problem. HKG is an extension of the knowledge-gradient policy for correlated normal beliefs (KGCB) from Frazier et al. [55] and uses discretized state space aggregation to achieve generalization. The advantage of HKG over SKO is that it is able to handle problems with categorical attributes (e.g., number of working days), and to cope with complex dependencies between the parameters [54]. However, the disadvantage of HKG is that it is only applicable to problems with, say, up to several thousands alternatives. We compare HKG and SKO with a pure exploration policy (random sampling), which we denote by EXPL.

In conclusion, optimal learning techniques can provide us with knowledge of the best input parameters for our heuristic in the long run. In addition, through the use of simulation, we analyze the variability in the waste deposits and record observations that give insight in heuristic’s performance and its dependency on the chosen parameter values.

6. Numerical experiments

Through numerical experiments, we analyze the dependency of the parameters of our heuristic with respect to several network characteristics. We use real-world information about a waste collection company located in The Netherlands to create different test instances for these experiments. In Section 6.1, we describe the settings considered for the experiments. In Section 6.2, we present the numerical results and give insights into the sensitivity of our algorithm to the parameter setting.

6.1. Experimental settings

Our experimental settings are based on a case study performed at the waste collection company “Twente Milieu”, located in The Netherlands. This case study is described in detail in Mes [43], where a simulation study is carried out to study the benefits of a dynamic collection policy

compared to the current static way of scheduling. After the study of Mes [43], the dynamic planning methodology has been implemented at the company and major savings have been reported.

To evaluate the impact of specific parameter settings, we use a similar simulation model as described in Mes [43]. However, instead of using specific discrete-event simulation software, we now implemented the model in Delphi, a general-purpose programming language. We re-implemented the simulation model to (i) reduce computation time and (ii) connect the optimal learning policies HKG and SKO (implemented in Matlab and Delphi) to the simulation. In addition, to focus on the topic of parameter tuning, we consider a simplified collection problem here. In contrast with Mes [43], we assume (i) deterministic deposit volumes (still stochastic interarrival time between deposits), (ii) constant mean deposit rate and volume over the days in the week, and (iii) accurate sensor information on the volume of waste inside the containers. To provide general insights, we also consider variations to the real life setting, by varying the network density (depending on the size of the network and the number of containers located in it), the number of vehicles available to collect the waste, and how fast the containers fill up (rate and volume of waste deposits). An overview of the different network settings is given in Table 1.

Table 1: Network settings

Name	Size (min)	#Cont.	#Veh.	Volume (liter)
NL-C100-V25	150x150	100	1	25
NL-C100-V35	150x150	100	1	35
NL-C500-V20	150x150	500	1	20
NL-C500-V25	150x150	500	1	25
NS-T1-V15	30x30	500	1	15
NS-T1-V25	30x30	500	1	25
NS-T2-V25	30x30	500	2	25
NS-T2-V50	30x30	500	2	50
NR-VN	Real	378	2	41.23
NR-VL	Real	378	2	61.85

We consider three types of networks: (i) a large virtual network in a square area of 150x150 minutes driving time, (ii) a small virtual network in a square area of 30x30 minutes driving time, and (iii) the real network. For the virtual networks, we randomly place the customers within the square area, and place the parking area and waste disposal center on one of the diagonals at 1/3 and 2/3 of its length respectively. The large network instances correspond to regional networks (e.g., a province from The Netherlands) and the small network instances correspond to urban networks (e.g., a large city with suburbs). The size of the real network is comparable to the 30x30 minute network. For the large virtual network, we consider instances with 100 and 500 customers. For each combination of network size and number of containers (large with 100 customers, large with 500 customers, small with 500 customers, and real with 378 customers), we generate one instance with respect to the container locations.

For the small virtual network, we consider instances with one and two trucks. For all virtual network instances, we consider two levels for the volume of waste deposits. The larger settings for waste volumes are chosen such that the vehicles are able to handle all demand, not necessarily without penalties, and that there is no excessive overcapacity of collecting vehicles. With the latter, we mean that it is not possible to handle all demand if we shorten the work week with one day. The deposit rates (number of deposits per day) follow a Gamma distribution with a

deterministic deposit volume per deposit as shown in Table 1. For the real network instance NR-VN, the stated deposit volume of 41.24 liter is an average over all 367 containers, since the deposit volumes differ per container, see Mes [43]. The deposit volume for the real network instance with larger volumes (NR-VL) represents an increase in deposit volumes of 50% at every container. For all virtual networks, the Gamma distributed deposit rates have a mean of 10 deposits per day and a variance of 80. For the real network, the deposit rates have a mean of 9.5 and a variance of 55.86.

In order for our optimal learning technique to choose the best settings for our heuristic in terms of long-time performance, we use as key performance indicator the weighted cost per volume of waste collected, which we denote by CL . The costs consist of traveling, handling, and penalty costs. The penalty costs α^p per day per liter of overflow are chosen such that they represent an equal trade-off between traveling half the diameter of the network (back and forth) and emptying a full container. We index the travel costs per minute to $\alpha^t = 1$ and set the handling costs per minute to $\alpha^h = 0.5$. The handling time per container is 4 minutes and 15 minutes at the waste disposal center. The capacities are $w_i = 4000, \forall i \in C$, $g = 90,000$, and $\bar{g} = 85,000$. We have five working days of 7.5 hours (excluding breaks), starting from 7:30am. We initialize each simulation run with uniformly filled containers between 0% and 75%. We use a warm-up period of eight weeks, and a simulation run length of 24 weeks.

Our numerical analysis consists of three parts. First, we perform a number of simulation experiments of the different networks, manually adjusting the parameters to gain insight into the parameter sensitivity, where we use the same parameter settings for all working days d . For each of these experiments, we use 100 replications. Second, we test the learning policies to gain insight into the speed of convergence of these policies. For all policies, we consider the domains as mentioned in Section 5. Third, we report the optimized parameter settings for each network using the policy SKO with 5,000 measurements for each of the network settings. For all the learning policies, we use 10 replications for each simulation experiment, i.e., one measurement consists of 10 replications of a simulation experiment with given parameter settings.

For the policy HKG, used in the second part of our numerical analysis, we need (i) to define the variance λ of the measurement error ϵ , (ii) to discretize the domain, and (iii) to define an aggregation structure. First, we set $\lambda = 0.1$. Next, we discretize the parameters F_d^n and F_d^m in intervals of length 0.5, resulting in 9 values for F_d^m and 11 values for F_d^n . For the parameter F_d^l , we include some prior knowledge. First, we know that, under ideal circumstances, about 30% of the containers can be emptied within one working day using the two trucks, which means that any setting of $F_d^n > 0.3$ has a similar effect. Second, when $F_d^l > 0$, day d will be a working day and at least some containers will be emptied. If that is the case, F_d^l should not be set too low. Therefore, we use the following domain: $F_d^l \in \{0, 0.12, 0.14, \dots, 0.3, 1\}$ with 11 different values. For the aggregation structure of HKG, we introduce one additional parameter $F^w \in \{4, 5\}$, which represents the number of working days, i.e., the number of days d for which $F_d^l > 0$. We perform aggregation on one state variable at a time, achieving an almost exponential decline in the size of the state space. For all parameters, we use the same settings for all working days, except for the number of working days d with $F_d^l = 0$, which is determined by the factor F^w . An overview of the aggregation structure is given in Table 2, where a ‘*’ corresponds to a state variable included in the aggregation level and a ‘-’ indicates that it is aggregated out.

6.2. Numerical results

To gain insight into the effect of different parameter settings, we perform a number of experiments. First, we study the effect of the MayGo parameter (F_d^n) on the costs CL , while fixing

Table 2: Aggregation structure

Level	F_d^w	F_d^l	F_d^n	F_d^m	Size of the state space
0	*	*	*	*	$6 \times 11 \times 11 \times 9 = 6534$
1	*	*	*	-	$6 \times 11 \times 11 \times 1 = 726$
2	*	*	-	-	$6 \times 11 \times 1 \times 1 = 66$
3	*	-	-	-	$6 \times 1 \times 1 \times 1 = 6$
4	-	-	-	-	$1 \times 1 \times 1 \times 1 = 1$

$F_d^m = 1$ and $F_d^l = 1$. The results for the different networks can be found in Figure 4. Note that we use the same parameter settings for all working days d . For the 150 min network, we observe decreasing costs with increasing MayGo level. This decrease is even more apparent in case of higher volumes. Higher volumes result in a larger share of the penalty costs in the total costs; higher values for F_d^n reduce these penalty costs. The same observation also holds for the 30 min network. However, for the low volume cases (NS-T1-V15 and NS-T2-25), this decrease is realized up to a value of $F_d^n = 3$. An even higher value for F_d^n , in combination with relatively low deposit volumes, simply results in an unnecessary high number of emptyings per day.

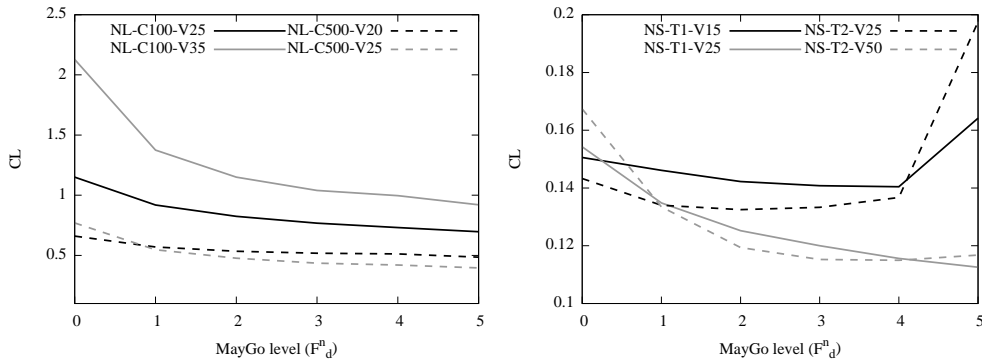


Figure 4: Illustration of parameter dependency for the 150 min (left) and 30 min (right) network

Next, we study various combinations of all parameters using the real network instance, see Figure 5. Again, we observe an initial decrease in costs with increasing MayGo level. With the normal deposit volumes (NR-VN) we eventually see an increase in costs, because we are emptying more containers than necessary. In the right figure of Figure 5, we vary the MustGo level F_d^m in combination with several other parameter settings. Here, N1 stands for $F_d^n = 1$, N ∞ stands for $F_d^n = \infty$, L1 stands for $F_d^l = 1$, L0.22 stands for $F_d^l = 0.22$, and P4 stands for a four times larger penalty factor α^p . Clearly, a large MayGo level without a limit on the number of jobs (N ∞ L1) results in high collection costs. The reason is that we have overcapacity in the real network. Hence, a high MayGo level results in too many emptyings. When $F_d^n = 1$, we first see a decrease in collection costs with increasing F_d^m . However, when $F_d^m > 2$ costs increase again due to emptying more than necessary. Clearly, the settings with $F_d^l = 0.22$ result in lower collection costs. With N ∞ L0.22, it seems that the best value for F_d^m is zero. When more weight is put on penalties (N ∞ L0.22P4), a value around $F_d^m = 1.5$ seems to perform best.

The results from Figure 4 and Figure 5 clearly demonstrate that the right choice of parameter

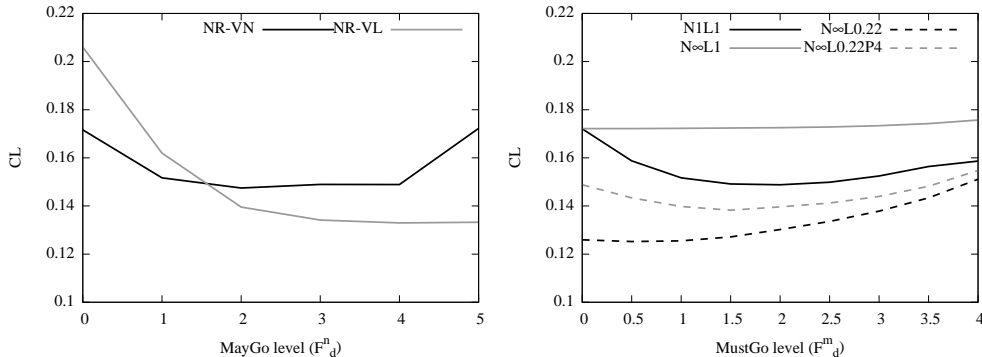


Figure 5: Illustration of parameter dependency for the real network instance

settings heavily depends on the network characteristics. Generally, a high MayGo level is preferred as long as we are not emptying too much, which can be influenced by setting the limit F_d^l appropriately. The MustGo level should not be set too high, to allow flexibility in routing.

Next, we study the performance of HKG and SKO to determine the right parameters settings for the real network instance (NR-VN). During test runs, it appears that SKO has problems fitting a Gaussian process to the simulation outcomes because we are dealing with extreme values. Setting the parameter F_d^l too low results in huge penalties and setting the parameter F_d^m too high results in high travel costs. With SKO, these extreme values play a role in fitting the Gaussian process prior. As a result, we have a less reliable fit at the area of interest. Obviously, HKG also loses measurements on these extreme values. However, their influence on the fit (via the aggregation function) is limited since HKG automatically puts a low weight on them. Similar conclusions on the effect of extreme values are drawn by Mes et al. [54]. To cope with this problem, we use a lower bound in our simulation output, given by a policy with $F_d^m = 0, F_d^n = 0, F_d^l = 1 (\forall d \in \mathcal{D})$. We compare HKG and SKO with pure exploration (EXPL). In addition, we plot the performance of the optimized parameter settings (OPT), which we determine in the last part of our numerical analysis. The results are shown in Figure 6.

The optimal learning policies HKG and SKO require significantly less measurements to find suitable parameter settings compared to pure exploration (EXPL). HKG convergences quickly to reasonably good parameter settings. Besides the problem with extreme values, SKO also experiences difficulties due to the dependencies between the parameter settings: there is a substitution effect in the parameters F_d^n and F_d^m , and a low level of F_d^l makes the choice for the other parameters irrelevant. Therefore, SKO requires more measurements to converge to reasonable settings.

The main drawbacks of HKG are that (i) it requires discretization to a limited set of parameter value combinations (at most several thousands) and (ii) it requires some insight into the problem to design an aggregation structure and to set the measurement variance λ . Due to the limited number of parameter value combinations, HKG will not converge to the optimal parameters settings, as shown in Figure 6. The strengths and weaknesses of HKG and SKO give rise to a combination of the two policies. We could use HKG to quickly identify the promising areas within the search space and then use SKO on these areas. Using HKG, it seems that 200 measurements is sufficient to come up with reasonable parameter settings. The time required for

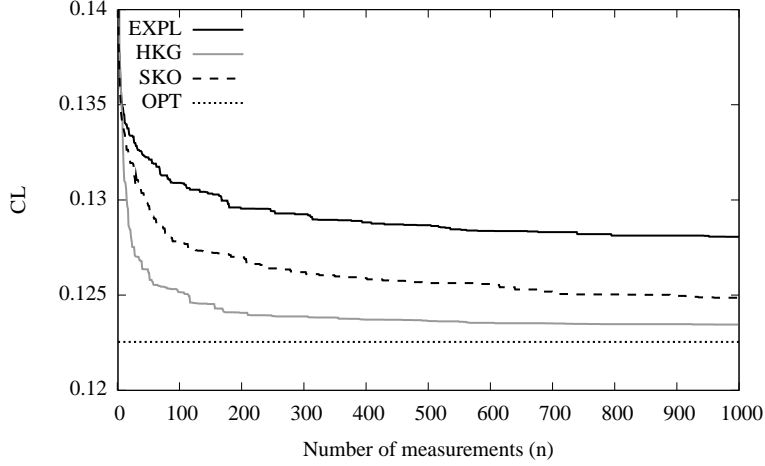


Figure 6: Convergence results using the real network instance

one measurement, consists of the time required by (i) the optimal learning policy (HKG or SKO) and (ii) the 10 replications of the simulation. On average, this takes about 10 seconds (2.53 GHz Intel Quad Core) in the experiments of Figure 6 using HKG and SKO. This means that it would take slightly more than half an hour to perform the 200 measurements, which seems reasonably fast for periodic, or even daily, adjustment of the parameter settings. Note that the time required for the learning policies is negligible compared to the simulation time. Now, suppose that, due to time limits, the company has a budget of 200 measurement. Then the savings in total costs of using HKG instead of EXPL are 4.5%.

We conclude our numerical analysis by running SKO on each network instance, using 5,000 measurements. The results are shown in Table 3. The values for the MayGo are not shown in Table 3 because we observed that in all cases, a high value for the MayGo works best (most instances result in parameter settings with $F_d^n > 4$). Note that in most cases a value $F_d^l > 0.3$ practically means no limit on the number of containers that can be emptied on one day, and the settings for F_d^m have no effect on the performance when $F_d^l = 0$ for the same day d . We draw the following conclusions. First, in some of the ‘small volume’ instances, it is beneficial to reduce the number of working days with 1 or 2 ($F_d^l = 0$ for two days), preferably somewhere in the middle of the week. In those cases, the MustGo level on the working days is set high to make sure the most urgent containers are emptied first. In the other ‘small volume’ instances, the limit F_d^l is set relatively low for all working days. Remarkably, in most cases, the limit on Fridays (F_5^l) is set relatively low. The explanation is that on Fridays the size of C^m (set of MustGo containers) is very large, because it includes all containers that are expected to be full before the end of the weekend when $F_d^m \geq 1$ (recall that the threshold F_d^m is defined in terms of working days). The set C^n of MayGo containers practically includes all other containers. To prevent doing too much and to focus on the most urgent containers, the limit F_5^l is set relatively low. In the real network instance (NR-VN), the limits F_d^l are set relatively low and closely matches the current way of working of the waste collection company, that uses $F_d^l = 0.22$ for all working days. Also the MustGo levels F_d^m are set relatively low in the real network instance to allow flexibility in the routing options. This flexibility in routing becomes more crucial when penalties are relatively

low, which will be the case in networks with overcapacity (relative small volumes).

Table 3: Optimized parameter settings

	CL^{opt}	CL^{ori}	$Sav.$	F_1^l	F_2^l	F_3^l	F_4^l	F_5^l	F_1^m	F_2^m	F_3^m	F_4^m	F_5^m
NL-C100-V25	0.70	0.92	24%	1.0	0.2	0.7	0.0	0.4	3.8	3.5	1.4	2.5	1.2
NL-C100-V35	0.80	1.35	40%	0.9	0.6	1.0	0.8	0.6	3.0	2.6	0.9	0.2	0.4
NL-C500-V20	0.40	0.57	30%	0.6	0.0	0.4	0.1	0.1	2.2	3.7	1.8	2.3	3.6
NL-C500-V25	0.39	0.55	29%	0.1	0.2	0.3	0.2	0.1	1.2	1.2	1.4	1.1	4.0
NS-T1-V15	0.11	0.15	23%	0.4	0.0	0.5	0.0	0.4	3.4	2.6	1.3	3.8	3.9
NS-T1-V25	0.11	0.13	18%	0.9	0.4	0.8	0.3	0.2	2.7	1.2	0.4	0.4	2.4
NS-T2-V25	0.10	0.13	22%	0.1	0.1	0.1	0.1	0.1	0.5	0.3	0.7	1.8	1.1
NS-T2-V50	0.11	0.13	17%	0.2	0.6	0.3	0.3	0.8	1.6	0.6	1.9	0.4	3.7
NR-VN	0.12	0.15	19%	0.2	0.1	0.2	0.2	0.2	0.8	0.8	0.9	0.3	0.7
NR-VL	0.14	0.16	16%	0.2	0.2	0.3	0.3	0.3	1.8	2.1	1.8	2.0	3.0

Besides the expected optimal parameter settings (after 5,000 measurements), Table 3 also shows the average performance CL^{opt} of using the optimal parameter settings, and the performance CL^{ori} of using the default settings for our policy (all parameters equal to one). Both, CL^{opt} and CL^{ori} are based on 1000 replications. Even though the default parameter settings work reasonably well in most network settings, the performance can be improved considerably (up to 40% cost reduction) by tuning the parameters appropriately. Note that when considering more realistic networks, where we take into account personnel costs and daily fluctuations in deposits, this tuning of day-dependent parameters becomes even more important.

7. Conclusions

We proposed a planning methodology for dynamic waste collection, taking into account the long-term consequences of the decisions. In addition, we provided insight into the applicability of our approach using a case study at a waste collection company. The methodology is applicable to the general class of Inventory Routing Problems with many customers.

The proposed dynamic collection policy has been implemented at the waste collection company and major savings have been reported. Our heuristic is easy to implement in existing routing applications and is easy to work with. To cope with changing environments, our heuristic is equipped with a set of tunable parameters. We have shown that the performance of the heuristic heavily depends on the parameter settings. Even when the network of customers is physically the same, a change in other characteristics, such as the number of vehicles available or mean volume of waste deposited, requires different parameters. In practice this means that in case of, e.g., the start of a holiday period or changing weather conditions, the parameters have to be adjusted. Through numerical experiments, we have shown that by changing the parameters from their default setting to an optimized setting, costs reductions up to 40% are possible.

To tune the parameters, we proposed two optimal learning techniques, namely HKG and SKO. Based on the simulation outcomes, both policies sequentially decide which combination of parameter values to simulate. Both policies are able to generalize observations across the state space; in SKO this is achieved by fitting a Gaussian process through the observations and in HKG by using a family of aggregation functions. This generalization makes it possible to find reasonable parameter settings using a limited number of simulation runs. We have shown that

in most cases a few hundred measurements would be sufficient to find near optimal parameter settings, making the approach suitable for daily planning purposes.

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