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USING SIMULATION TO ASSESS THE OPPORTUNITIES OF DYNAMIC WASTE COLLECTION

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Abstract

In this paper, we illustrate the use of discrete event simulation to evaluate how dynamic planning methodologies can be best applied for the collection of waste from underground containers. We present a case study that took place at the waste collection company Twente Milieu, located in The Netherlands. Even though the underground containers are already equipped with motion sensors, the planning of container emptying's is still based on static cyclic schedules. It is expected that the use of a dynamic planning methodology, that employs sensor information, will result in a more efficient collection process with respect to customer satisfaction, profits, and CO_2 emissions. In this research we use simulation to (i) evaluate the current planning methodology, (ii) evaluate various dynamic planning possibilities, (iii) quantify the benefits of switching to a dynamic collection process, and (iv) quantify the benefits of investing in fill-level sensors. After simulating all scenarios, we conclude that major improvements can be achieved, both with respect to logistical costs as well as customer satisfaction.

1 INTRODUCTION

The collection of waste is a highly visible and important municipal service that contributes to environmental pollution and traffic congestion, and involves large expenditures. Twente Milieu, a waste collection company located in The Netherlands, wishes to increase its corporate social responsibility and therefore searches for innovative and more efficient collection strategies. Twente Milieu is an important player in the field of waste collection and the maintenance of public areas. Its main activity is the collection of household refuse and in this area the company wants to improve the truck planning and container emptying as to save on fuel consumption, reduce CO_2 emission, and increase customer satisfaction.

Twente Milieu operates different types of containers. The most important types are mini containers and block containers. Mini containers are located at every house and have to be emptied on pre-specified days, because residents have to put the containers along the side of the road. This is not the case with block containers, which are meant for a larger number of households and which are mostly located at apartment buildings or within the city centre. Since

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2009, Twente Milieu also makes use of underground containers. At first, these underground containers mainly replace the block containers installed at apartment buildings and commercial buildings (e.g., at restaurants), but their use is now extended to all sorts of living areas. The underground containers offer several advantages: (i) they have a relative big storage capacity of 5m^3 which is roughly five times as big as the traditional block container, (ii) they are only accessible with an id-card which prevents illegal waste deposits, (iii) due to solid locking it decreases odour nuisance, and (iv) only a small part of the container is visible which makes the container suitable for use in public areas and contributes to an attractive environment.

Currently, Twente Milieu is unsatisfied with the average fill rate of the underground containers upon emptying. It is expected that, on average, the underground containers are less than 50% full upon emptying. As a result, one would expect that it is possible to reduce the emptying frequency, which results in less mileage of the trucks and less CO_2 emissions. The current planning methodology for emptying the containers is based on static and cyclic schedules. These schedules describe, for each container, at what days it should be emptied and how often, e.g., every Tuesday, or Wednesday once in the two weeks. Since deposit volumes fluctuate heavily, a static planning methodology requires a relative large amount of slack capacity. As a result, the average fill level upon emptying will be relatively low.

For the mini containers, a static planning approach is required because citizens have to place their containers at the street. However, for the underground containers, this approach is no longer necessary. Moreover, the containers are equipped with sensors that inform the company each time the container lid is opened. Twente Milieu expects that the introduction of a dynamic planning methodology, that employs this sensor information to estimate the fill levels, results in less frequent emptying and higher customer satisfaction. The additional advantage of using a dynamic planning methodology is the possibility to adapt the schedules to weather conditions or public holidays, to incorporate for example odour nuisance in warm periods, and to cope with changing patterns in deposit behaviour. Finally, it is expected that additional efficiencies can be achieved by investing in fill level sensors, which provide more accurate estimates.

In this research we look at the different possibilities for a dynamic planning methodology with the aim to increase logistical efficiency and customer service. More specifically, we aim to find a method for container selection and routing that satisfies Twente Milieu's standard to save resources and to contribute to a cleaner environment. The goal of this research is the following:

> *To asses in what way and up to what degree a dynamic planning methodology can be used by Twente Milieu to increase efficiency in the emptying process of underground containers in terms of logistical costs, customer satisfaction, and CO_2 emissions.*

To reach this goal, we formulate the following research questions:

1. How should a dynamic waste collection strategy be designed?
2. What would be the benefits of changing to a dynamic waste collection strategy?
3. What would be the added value of investing in fill-level sensors?

To answer these questions, we use a simulation. According to Law (2007), simulation is a suitable tool to evaluate complex real-world systems which cannot be analysed analytically and where experimenting with the real system is impossible or too expensive. Besides the fact we face such a system, we use simulation because it allows us to (i) analyse a wide range of interventions, (ii) perform sensitively analysis, and (iii) benchmark to current way of working with the proposed new planning methodology.

The remainder of this paper is structures as follows. First, we present related work in Section 3. In Section 4 we present the underground container project in more detail. The various possibilities for a dynamic planning methodology are presented in Section 5. In Section 6, we present our simulation model and we present our numerical results in Section 7. We end with conclusions and recommendations in Section 8.

2 RELATED WORK

The problem we face is related to the so-called Vehicle Routing Problem (VRP) and, more specifically, the Inventory Routing Problem (IRP). First, we provide a short review on related research in these areas after which we present related research in the area of waste management. We end this section with a statement of our contribution.

In general, the problem we consider here belongs to the broad class of Vehicle Routing Problems (VRP). The VRP involves the design of an optimal set of routes for a fleet of vehicles in order to serve a given set of customers. The VRP arises naturally as a central problem in the fields of transportation, distribution and logistics (Dantzig and Ramser, 1959). It has been studied extensively during the last few decades, with solution methodologies ranging from exact mathematical programming techniques to heuristics. For an overview of approaches developed for the VRP we refer to Toth and Vigo (2001).

A specific instance of the VRP which is related to our problem, is the periodic vehicle routing problem (PVRP) where customers may require service on multiple days during a given planning horizon. The challenge is first to determine service frequencies (e.g., a customer will be serviced twice per week) or service patterns (e.g., a customer will be serviced every Monday and Thursday), and then to solve the VRP each day using the assigned customers of that day. Early formulations of the PVRP were motivated by municipal waste collection and are developed by Beltrami and Bodin (1974) and by Russell and Igo (1979). Usually, the PVRP is solved heuristically and often using a two-stage approach consisting of a construction and improvement step. Chao et al. (1995) review some of these early heuristics, and propose a new heuristic to overcome issues of poor local optima. More recently, Cordeau et al. (1997) propose a tabu search algorithm for the PVRP. In all of these works, the service frequencies are pre-determined. Variants in which the service frequency is a decision variable can be found in Newman et al. (2005), Mourgaya and Vanderbeck (2007), and Francis, Smilowitz and Tzur (2006). For a literature review on the PVRP and its extensions, we refer to Francis, Smilowitz and Tzur (2008).

A distinguishing feature of our problem compared to the PVRP, is that the service frequency is not something we have to determine at the beginning of a given planning horizon. Instead, each day we have to select the customers to visit using actual sensor information. In a way, the static planning methodology as currently used by Twente Milieu, can be seen as a solution to the PVRP. The problem class that combines vehicle routing with inventory management is the so-called Inventory Routing Problem (IRP). In an IRP, the following trade-off decisions are considered:

- At which point in time should a customer be delivered to fill up its stock? (selection)
- How much ought to be delivered in that situation? (demand determination)
- What is the best order and therefore route to deliver the set of selected customers? (routing)

The IRP differs from the VRP because it is based on the usage of customers rather than just the number of customer orders. As a result, solution methodologies for the IRP are suitable for planning the emptying's of sensor-equipped waste containers. The containers, ideally, should be full upon emptying, but at the same time they should not overflow. Our problem can be seen as a reverse IRP, or an IRP where the product to be replenished is empty space (air); we collect waste by filling the containers with empty space. The most important decision here is when to serve a customer.

Solving an IRP is difficult and even gets more complicated with the number of customers (Campbell et al., 1998). A crucial decision in IRPs is the choice which customers to include in the routes of the current period. With this short-term decision, we have to take into account the long-term effects of this decision since a short-term approach might postpone as many customers as possible to the next period (Campbell et al., 1998). Therefore, Campbell et al. (1998) propose two solution methodologies, (i) an integer program with a relative long horizon where subsets of delivery routes and aggregation of time periods are used to keep the program computationally tractable and (ii) an infinite horizon Markov decision process (MDP). Jaillet et al. (1997) take a rolling horizon approach to tackle the differences between short-term and long-term solutions. They do this by determining a schedule for two weeks, but only implementing the first week. A common heuristic approach for the IRP is to distinguish between customers that have to be served in the current period (which we indicate as MustGo's) and those that might be served (which we indicate by MayGo's). To determine which customers should be served first, Golden et al. (1984) use the ratio of tank inventory to tank size. When this ratio is smaller than some threshold, customers are excluded from service for that day. Campbell et al. (1998) use a ratio of urgency to extra time required for the selection of customers. In this paper, we use a similar approach with MustGo's and MayGo's. For a further literature review on inventory routing, we refer to Andersson et al. (2010).

A growing amount studies are dedicated specific to waste collection strategies. As McLeod and Cherrett (2008) state, efficient waste collection strategies are not only vital from economic perspective, but also from an environmental perspective with reductions in emission and traffic congestions. The common approach to model the waste collection process is to use the VRP; see, for example, Chang and Wei (2002), Kim et al. (2006), and Nuortio et al. (2006). Nuortio et al. (2006) propose a stochastic variant, because the amount of waste in the bins is highly variable. For solving the problem, they use a node routing approach. This approach makes it possible to consider each bin separately. Kim et al. (2006) describe a VRP that uses time windows. These time windows include stops for lunch breaks and disposal operations. For solving the problem, they use a clustering based algorithm. McLeod and Cherrett (2008) describe the routing and scheduling problem as an capacitated VRP, which has constraints on vehicle capacity and working hours and they propose different ways to solve this waste collection problem, such as tabu search, a genetic algorithm, and fuzzy logic methods. Karadimas et al. (2007) also point out the importance of an efficient collection process, because 60-80% of the total costs are spent during the waste collection process. To solve the problem, they use an ant colony system. Here, artificial ants (trucks) are searching the area for the optimal route for a given set of container locations. This is done by initially random cycling through the area and leaving a "pheromone trail" in the intensity of the found solution value of travelled kilometres. A route with a high pheromone density is more likely to be followed by the other artificial ants so that better routes are found. Chalkias & Lasaridi (2009) use a geographic information system (GIS) in their optimization of municipal solid waste collection. For the formulation of a model, they collected data about roads and bin locations. They state that the success of decision making depends largely on the quality and quantity of the available data, in which the geodatabase can be very helpful. One remarkable conclusion is that fuel consumption relates more to the time of operation and the number of stops than to distance travelled. The reason for this is that most of the time is spent for loading and emptying.

In our problem, the travel distances are relatively small and drivers appear to have enough driving experience within the region such that the routing aspect has a lower priority. Instead, our focus is mainly on the selection of containers to be emptied in the current period. In this area, the most closely related research as that of Johansson (2005). This work focuses on the dynamic collection of waste from 3300 containers (aboveground) in the Swedish city Malmoe. Similar as in our research, they use discrete event simulation and analytical modelling in order to access the performance of the waste collection procedures proposed. They conclude that dynamic routing decreases the operating costs and hauling distances, increases the length of the collection cycle per container, and causes a reduction in labour costs. The containers considered by Johansson (2005) have two infrared optical sensors that provide real-time access on the fill status of each container, which can be used to access a MayGo level and a MustGo level. If the inventory in a container reached its MustGo level, it should be emptied within a fixed period of time. Containers with a waste level below the MayGo level were not allowed to be included in the emptying routes. Different policies where considered varying from static to dynamic. They conclude that with relative large systems (>100 containers), the 'most' dynamic variant (dynamic scheduling, dynamic routing, and always using MayGo's) performs best. It is further concluded that the highest savings of this dynamic policy are achieved in unstable environments with high demand fluctuation.

As seen in the short summary of existing literature on waste collection, most articles are about routing problems; finding the optimal route along a set of containers. For Twente Milieu, the main emphasis is put on the selection of containers to be emptied since driving distances are relatively small and drivers are familiar with the area they drive in. This means that existing literature in the area of waste collection is less applicable to our problem. Also in the area of inventory routing, relative much attention is given to the routing aspect. Especially in dense areas, where the travel distances are relatively small, the selection of customers might even be more important than the routing decisions. The main focus of this paper is on customer selection; especially in the area of waste collection, this is a new research area. The theoretical contribution of this work is to show how models for the IRP can be used to improve the waste collection process and to quantify the benefits of such an approach.

3 CASE DESCRIPTION

To be able to make a thorough suggestion about how a dynamic way of planning should look like and how it should be implemented, it is important to have a good understanding of the current way of working. This section describes the different aspects Twente Milieu deals with in relation with the process of emptying the underground containers. We start with a description of the company (Section 3.1) and the underground container project (Section 3.2). We then present the planning methodology as currently used by the company (Section 3.3) and end with our main findings from the data analysis (Section 3.4).

3.1 COMPANY DESCRIPTION

Twente Milieu is a government-oriented enterprise owned by six municipalities located in the The Netherlands. The main activity of Twente Milieu is waste collection and processing, but Twente Milieu also operates in the cleaning of streets and sewers, mowing of verges, road ice control, and the control of plague animals. Twente Milieu belongs to one of the largest waste collectors in the Netherlands when it comes to the number of household connected to their network. In 2009, Twente Milieu was serving a total population of ca. 399,000 inhabitants; the vast majority of them (77%) living in the three bigger cities Enschede, Hengelo, and Almelo. In 2009, ca. 215,000,000 kg of refusal was collected; this amount is expected to increase in the near future.

The mission of Twente Milieu is to offer high societal value at low costs and the preservation of natural resources. To do so, Twente Milieu tries to reduce waste wherever possible, encourage citizens to segregate waste, and to increase recycling opportunities in various manners. Twente Milieu has the vision to become and stay on of the pioneers in effective, fair, and societal responsible waste collection. This also forms the drive for the underground container project and the desire to become one of the first Dutch waste collectors that are actually working with a dynamic routing methodology in order to reduce costs, increase customer satisfaction, and to reduce the CO_2 footprint.

3.2 THE UNDERGROUND CONTAINER PROJECT

The underground container project is one of the most prestigious and ambitious projects of Twente Milieu. As mentioned in the introduction, the underground containers have a number of advantages over mini containers and block containers. However, there are still several advantages that are not fully exploited yet, namely that fact that (i) we no longer need to make appointments with citizens on the timing of emptying's and (ii) the sensors provide information that enable Twente Milieu to retrieve deeper insights into the speed of the container fill process.

In March 2011, Twente Milieu operates 677 underground containers. This number increases continuously and it is expected that within a few years this number increases to 1500. Most of the containers are equipped with a motion sensor which counts the number of lid openings. Once a day, the number of lid openings is communicated, using GPRS, to a central container registration system. Furthermore, the containers are equipped with a digital lock that can only be opened by a participant-owned RFID-card. This enables the future introduction of Diftar, which stands for differentiated tariff for waste deposits. Most of the container locations have one container per location. However, there are also locations, mainly at large apartment buildings, that have two or more containers at one spot.

Twente Milieu has five trucks available for emptying the underground containers. There are a number of drivers capable of driving these trucks; this requires some experience with driving a large truck through the small streets of city centres, and it requires experience with the crane that hoists the container out of the ground. Given the expected growth to 1500 containers, additional trucks will be acquired within the next few years.

3.3 CURRENT PLANNING METHODOLOGY

Currently, the scheduling of container emptying's and the routing of trucks is done on a static bases with some deviations in the routes incorporated. The static planning methodology describes for each container on what days it should be emptied. Most containers are emptied on a weekly basis, some of them once in the two weeks, and some twice per week. Changes in the emptying schedule are rarely made, except on Fridays to avoid overflow in the weekends. Every Friday morning, a list with lid openings per container is printed to judge whether there are any additional containers that need to be emptied before the weekend. Another source of deviation from the static schedule is due to the drivers' freedom to pick more (or less) containers based on his experience. Since the resulting collection process heavily depends on personal perception and experience, switching drivers or hiring new drivers during holiday periods becomes problematic. In addition, it is difficult to cope with changes in the network, such as the addition of new containers.

Figure 1 - Truck emptying an underground container

The truck driver starts his working day at 7.30 am when he receives a list with containers to empty that day. The exact order in which he empties these containers is determined by the driver himself without planning or navigation support. This is possible since drivers are familiar with the static set of customers that have to be emptied on the different days. All trucks depart from a central depot. When the driver arrives at a container location, he empties it with the use of a remotely controlled crane. At the same time as the emptying of the containers, the driver checks whether the surrounding area needs cleaning. Any possible failures or other irregularities to the container are reported to the service department; the driver does not fix these problems himself. Emptying one underground container takes around four minutes. When the waste from the container is disposed into the truck, a press is activated to reduce the volume of waste with a factor five. In the current way of working, a truck can empty, on average, close to thirty-five containers before its capacity is reached. When the truck is full or when the driver has finished his complete route, the driver goes to the waste processing centre, called Twence, to dump the waste. The truck is weighed at arrival and departure. The difference between these two is the total weight of waste collected from the containers. After a tour through one city, first a trip to the waste processing centre has to be made, before continuing to another city. This is because the different municipalities have to pay for the discarding of the waste. At the end of the day, the trucks have to return empty to the depot. On average, the trucks will visit the waste processing centre twice per day. A normal workday has eight hours from half past seven until four o'clock, with a lunch break of half an hour.

3.4 DATA ANALYSIS

For our simulation study, we need input data with respect to fleet characteristics, driving- and handling times, distances, and information on deposit frequencies and volumes. Most of the data is readily available. However, the information on deposit frequencies and deposit volumes requires a further analysis, which we describe in this section.

To get information on the deposit frequencies and volumes for each of the containers, we make use of the container registration systems (different systems are in use since Twente Milieu uses different types of underground containers). These registration systems record for each connected container, the number of times the lid of the container is opened and closed again. During our analysis, we found several errors and inconsistencies in the registration systems. In addition, these registration systems provide only information on lid openings whereas we also need information on the volume of waste disposals. Therefore, we had to collect more information via a number of other channels:

1. Deposits at the waste processing centre
2. One week of weighing the emptying's
3. One week of visual checks for (almost) full containers
4. Interviews and brainstorm sessions with employees

First, we retrieved the data on lid openings in 2009 for all containers from the registration systems. This gives us an idea about the waste disposal frequency for all these containers. Second, we combined this data (for a part of the network) with records from the waste processing centre. This enables us to relate lid openings with the average weight of a disposal. Third, we performed an experiment for one week with a collection truck that is able to weight the containers upon emptying. This provides another source to relate the lid openings with the average weight of waste disposals. From this analysis, it became clear that average weight per deposit differs a lot for the different containers.

Figure 2 shows the wide spread of the number of lid openings in relation to the weight measured. The arrow in Figure 2 shows the weight of waste for containers that have approximately the same number of lid openings of 75 times. We see large differences ranging from 115kg to 475kg. It should be noted that some of the deviations can be explained from the fact that some containers require a manual reset of the counter for lid openings, and sometimes drivers forget to do this. Further, it is more likely that the density is different per unit of weight, which will decrease the previously mentioned observation. Still, the huge differences would result in unreliable estimates of the container volumes solely based on the number of lid openings.

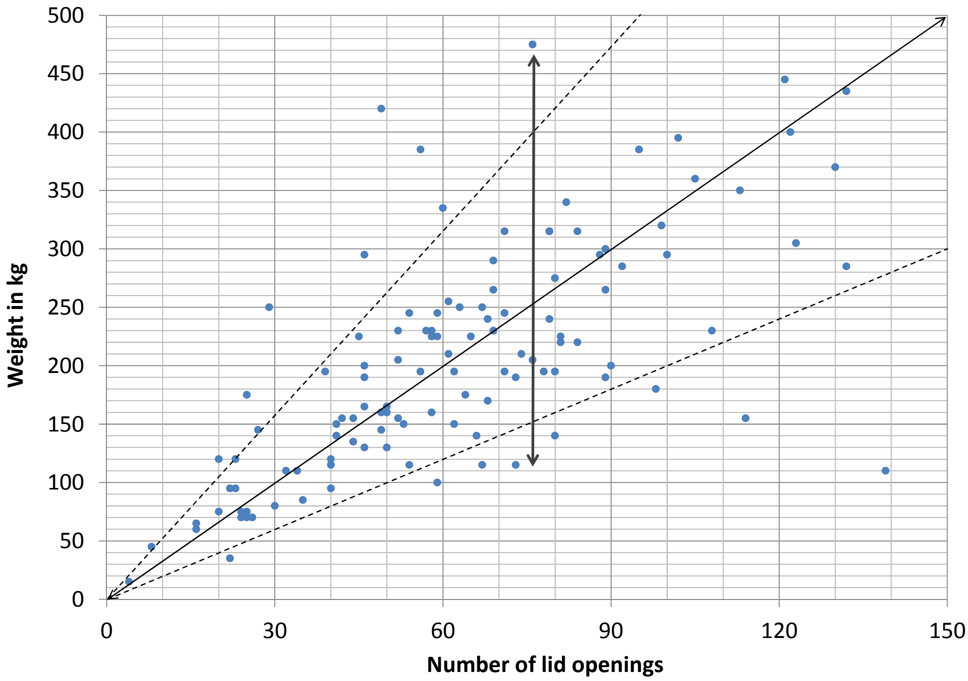

Figure 2 - Weight of waste as a function of the number of lid openings

At this point, we are still not able to relate lid openings to volume. Assuming more or less equal deposit volumes, the number of lid openings provides an indication of the fill level. Currently, the company assumes that every time the lid of the container is opened and closed again, the output ratio is raised by 1%. This means that a container is considered to be 'full' after 100 deposits. To verify this, we perform a one week field experiment in which we visually check the actual volume stored in containers that are full or almost full. This provides us with insight on the ratio between lid openings/weight/volume. From our analysis, it appears that the 1% assumption is not correct and the deposit volumes differ a lot per container. However, based on our one week field experiment, we expect that the deviations in deposit volumes are relatively small compared to the variations in weight, which means that the density varies.

To summarize our findings, we obtained the following insights:

- On average, one cubic meter of waste weighs 110 kilos, the average volume of a deposit is 48 litre, and the average fill level upon emptying is 50%. The effective capacity of 5m^3 containers is only 4000 litre because the top part of the container is filled in the shape of a cone. On average, containers are emptied 56.63 times on a yearly basis. This conclusion will be helpful in the verification phase of the system performance of the simulation model.

- There are huge differences in deposit volumes between the different container locations. For example, containers near stores have higher deposit volumes than containers for households. Also, there are huge differences in deposit frequencies between containers that are on the same location. This indicates that the alignment of the containers influences the speed of the filling process (closest to the entrance is full earliest).

- The number of deposits seems to fluctuate heavily from weekday to weekday and from week to week. Seasonal fluctuations became visible as well. Regarding seasonal patterns, we see a weekly pattern (relative many deposits on Monday and few deposits on Sunday), a less visible monthly pattern (slightly more deposits at the beginning of the month), and huge random variation from day to day. These deviations already provide a good argument to switch to a dynamic routing approach, since a static planning approach would empty too less in peak periods and too much in other periods.

Although we do not include all the data resulting from our data analysis, we do provide some of the results in our section on input settings (Section 6.2).

4 PROBLEM DESCRIPTION

We face an infinite horizon planning problem in which we have to empty N different containers at different points in time. Container i receives waste deposits with an average volume of a_i per day. Upon a given decision moment, an estimate of the actual waste volume in container i is given by v_i. The capacity of container i is Q_i. The expected number of days left before container i becomes full is given by d_i, which is given by $d_i = (Q_i - v_i)/a_i$. When the container is full, new deposits to this container are placed outside the container (overflow) which will be cleaned after emptying this container. To empty these containers, a fleet of M homogeneous trucks is available, each having a capacity of K. We introduce r as the number of routes to use, and L as a maximum on the number of containers to empty per day.

We use the common distinction between MustGo's and MayGo's. MustGo containers have to be emptied and the MayGo containers may be emptied if they can efficiently be incorporated in the routes. We introduce the following sets: (i) C consisting of all containers, (ii) C^m containing all MustGo's, and (iii) C^n containing all MayGo's. We define MustGo's as those containers i for which $d_i \leq D^m$, with D^m being a threshold on the number of working days. Here we explicitly state working days since we have to take into account the weekends since no emptying's will be done on Saturday and Friday. As an example, if $D^m=1$, we select all containers that are expected to be full before the next working day. On a Thursday morning, C^m contains all containers that are expected to be full before Friday morning. But on a Friday morning, C^m contains all containers that are expected to be full before Monday morning. The MayGo's are defined similarly, having $d_i \leq (D^m+D^n)$.

For the purpose of this simulation study, we make the following assumptions:

- Each truck can only be assigned to one job at a time and a job can be assigned to at most one truck. Each truck has finite capacity.

- Truck drivers have a maximum working time per day. Lunch breaks are ignored (we reduce the time of a workday with the time required for breaks) as well as additional trips required for fuelling. All trucks depart from the depot and return to the same depot at the end of the day.

- Containers are always entirely emptied. There are no time windows for empting the containers. When a container is full, deposits are placed next to the container, which we denote as overflow.

- All times are considered to be deterministic. This involves time for traveling, loading, and unloading at the waste processing centre.

- Costs for trucks and drivers are not taken into account. As a result, the algorithm might decide to use multiple vehicles and drivers for only a few hours per day.

- A natural approach to model the waste deposits would be to use a Poisson arrival process. However, the huge variance in deposit frequencies cannot accurately be described by a Poisson distribution. To model the arrival process, we use a Gamma distribution for the number of deposits per day, and then uniformly distribute the arrivals over the day. A chi-square test with $\alpha=0.05$ does not result in a reject of our hypothesis that the number of deposits per day follows a Gamma distribution (see Section 6.2). The size of the deposits (deposit volumes) also follows a Gamma distribution (see Section 6.2).

The expectations of using a dynamic routing methodology are rather high. First, it should increase customer satisfaction and avoid waste overflow. Second, it should reduce the operational costs of emptying the containers. The initial objective was to empty the containers as close to their due dates as possible achieving an increase in service level (the percentage of containers emptied on time). However, emptying a container that is far from full might still be efficient when a truck just passes this container. Therefore, the main objective is to reduce the mileage of trucks in the long run, the total working time required to empty all containers, and to increase customer satisfaction with respect to waste overflow. Variability in the waste disposal pattern has to be minded in the new approach, since it is already expected that the true demand of waste collection might vary strongly because of external events like weekly, monthly, and seasonal patterns, special occasions, and holidays. Given the problem description and the assumptions made in this section, we now present the planning approaches themselves.

5 PLANNING METHODOLOGIES

Independent on the type of planning methodology we use, we always create a planning at the beginning of a day for the whole day. The advantage of this that it is relatively easy to execute and truck drivers know the work they have to do on that day (just as in the current situation). However, we still need to be able to perform replanning since plans might become infeasible during the day. The latter might be the result of travel delays or of collecting more garbage than expected, which requires scheduling a trip to the waste processing centre earlier. In next two subsections we describe the static planning methodology as currently used by the company (Section 0) as well as our proposed dynamic planning methodology (Section 5.2).

5.1 STATIC PLANNING METHODOLOGY

Currently, a static planning methodology is used. This policy is described in Section 3.3. For the purpose of our simulation study, we need to model this policy. We have to model it in such a way that static plans are created automatically, based on experimental settings such as the number of containers, deposit frequencies, and volumes.

In essence, static plans are based on a desired time between emptying's (delivery frequencies). This time between emptying's is computed by dividing a target fill level upon emptying by the expected daily deposit volume. Then, this time is rounded to half a week, one week, or two weeks. So, containers are emptied twice per week, once per week, or once in the two weeks. Next, all emptying's are assigned to specific days in such a way that the workload is spread equally over the days insofar possible. Finally, manual adjustments are being made to cope with negative aspects of rounding the time between emptying's. In addition, at the beginning of each day, a planning employee might add additional emptying's to avoid overflow. Especially on Fridays, this manual adjustment takes place to avoid overflow in the weekend.

Obviously, the above description, which involves human intervention, is difficult to model in a simulation environment with changing settings for deposit behaviour and number of containers. Therefore, we choose to model it slightly different. First, we determine the time between emptying's as done before. However, we do not round this time. Instead, after each emptying, we set the time for the next emptying equal to the current time plus this desired time between emptying's. Second, to resemble a balanced workload, we determine a fixed number of containers to empty per day, given by L. Each day, we sort the containers based on their planned emptying time, and then select the first L of these containers to empty. The result is that the required time between emptying's is not used exactly, but this procedure avoids explicitly taking into account the weekends. The main difference with the real static plan is (i) that the time between emptying's is not rounded and (ii) no manual adjustments take place. We expect that this model still provides a good match with the current way of working since the manual adjustments in reality are just necessary to cope with the rounding of time between emptying's.

5.2 DYNAMIC PLANNING METHODOLOGY

In the dynamic planning option, we daily select containers based on their estimated fill levels. For solving this problem, we might use an exact approach such as a Mixed Integer Linear Program. However, our problem has some characteristics which make a successful application of such an exact approach very unlikely. First, our problem involves multiple vehicles (up to 7 trucks), multiple depots (2 parking areas and 1 waste processing centre), and a large number of customers (expected to grow to 1500 containers within a few years). Further, our problem requires a long-term planning horizon, since a short-term approach will postpone deliveries to the next period (Campbell et al., 1998). Finally, we face dynamic environment with stochastic travel times and stochastic waste disposals which may require replanning during the day. In addition, we have to deal with weekly and monthly patterns, and special days (e.g., holidays). Given the scale and complexity of our problem, exact approaches are not suitable and we decided to use a heuristic approach. An illustration of this heuristic can be found in Figure 3.

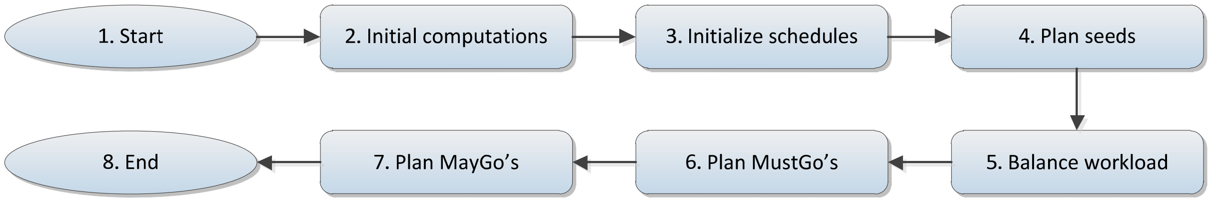

Figure 3 - Steps in our heuristic

We now explain the different steps of our heuristic.

1. The planning heuristic is started by two events: (i) initial planning in the morning and (ii) replanning during the day. Replanning can be triggered by several events, e.g., after each collection, after visiting the waste processing centre, periodically, or when the deviation from the planning exceeds some threshold (deviation with respect to volume or time).

2. The initial computation involves, (i) estimation of the days left d_i for all containers, (ii) determination of MustGo's C^m, (iii) determination of the number of trucks to use W ($W \leq M$), and (iv) determination of a lower bound on the number of routes to use, $r = \lceil \sum_{i \in C^m} v_i / (W * K) \rceil$.

3. For all trucks we decided to use (see Step 2), we initialize their schedules. For trucks currently having an empty schedule (typically the case with planning at the beginning of the day), their initial schedule would be from the parking area, to the waste processing centre, and ending up at the parking area again. For trucks with a non-empty schedule (we are doing replanning during the day), we empty their schedule in a non-pre-emptive way. To keep the initial schedules feasible, a collection job will be followed by a visit to the waste processing centre, and a visit to the waste processing centre will be followed by a return trip to the parking area. We use these initial schedules to insert new collection jobs in the next steps.

4. We extend the initialized schedules (see Step 3) with seed customers. We decided to use one seed customer per route and divide the routes over the trucks. Seed customers are chosen based on the largest minimum distance from the depot and the other seed customers. We use the seed customers to (i) spread the trucks across the area, (ii) realize insertion of collection jobs from containers close as well as far from the depot, and (iii) balance the workload per route to anticipate the insertion of MayGo's.

5. As an optional step, we assign MustGo's to the trucks in a balanced way. This means that we loop over all trucks and assign jobs to them one by one. Obviously, this will not be the most efficient way with respect to the MustGo insertions. However, it becomes particularly useful when we are going to extend the routes with relatively many MayGo's (see Step 8). MustGo's are added to the routes according to the cheapest insertion heuristic (see Campbell and Savelsbergh, 2004), where the insertion costs depend on the additional time required for the insertion. Note that additional visits to the waste processing centre are scheduled automatically when necessary; the time required for these additional visits is also included in the insertion costs. The first time we do not find a feasible insertion for some truck, we stop this procedure and continue with Step 6.

6. For all remaining MustGo's, we try to assign them using the same cheapest insertion heuristic as used in Step 5, but now by considering all insertion positions for all trucks and routes.

7. When all MustGo's are scheduled, there may be some space left in the trucks to empty other containers. By adding MayGo's, we make use of this free capacity to improve the routing efficiency. Also the MayGo's are scheduled using the cheapest insertion heuristic. However, this time we use another cost criterion which we explain later on. A high value for D^n has the benefit that we can choose between a large number of MayGo's. However, emptying them all will not always be the most efficient option. Therefore, we use the limit L on the number of emptying's per day.

8. We execute the planning and perform replanning when needed (see Step 1).

To schedule the MayGo's, a common choice in Inventory Routing Problems is to use a ratio of the additional travel time required to empty this container and its volume, see for example Golden et al. (1984). The problem with using such a ratio is that the more remotely located containers are unlikely to be considered as a MayGo. The criteria we use here is the relative improvement of the before mentioned ratio compared to a smoothed historical average of this ratio. A large positive value represents a one-time opportunity we should take. We do this based on a ratio of the additional time it takes to empty the container (both travel and handling time) to the waste volume in the container. A small ratio indicates a high amount of waste compared to the additional time; this means the smaller the ratio, the better. This procedure selects containers for which the emptying costs today are expected to be lower than at some later point in time.

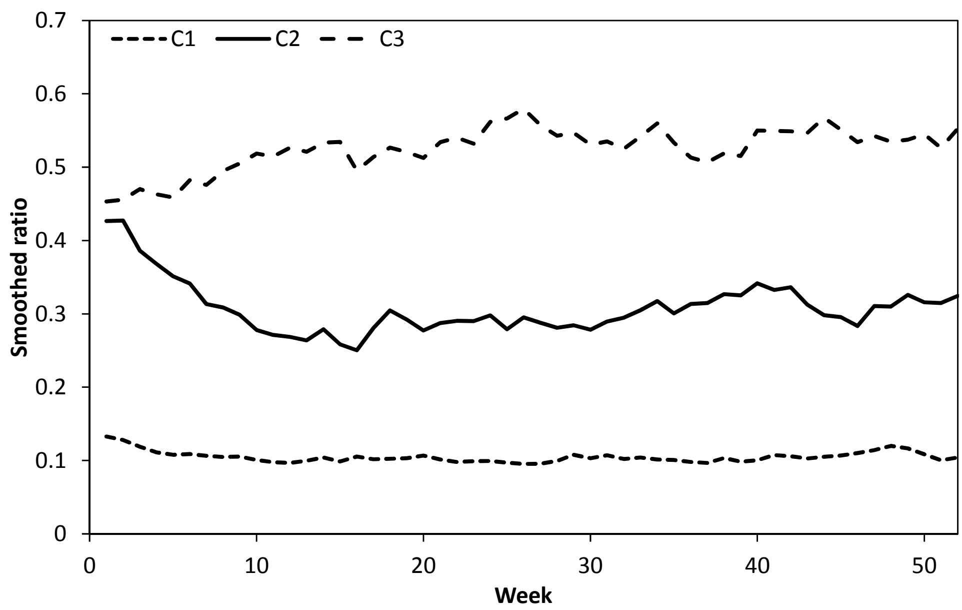

Figure 4 - Smoothed ratios for three containers

Figure 4 shows the smoothed ratios for a number of underground containers. Here, C3 is an isolated container, C1 is a container close to the waste processing centre, and C2 somewhere in between. The ratio of a container at a favourable location is much lower compared to one at an isolated location. This makes sense since containers at a location with more containers in the neighbourhood require less additional driving than containers at remote locations. This results automatically in smaller ratios. Figure 4 also support our choice to select MayGo's based on their improved ratio. Otherwise, containers at a remote location would never be selected, while the costs for emptying these containers might be relatively low today. Finally, Figure 4 also indicates we need at least several weeks as warm-up period for our simulation (see Section 6).

6 SIMULATION MODEL AND EXPERIMENTAL DESIGN

In this section the simulation model will be described that will be used to evaluate different routing and container selection methods as presented in the previous section. Subsequently, we present the structure of the simulation model (Section 0), the experimental settings (Section 6.2), experimental factors (Section 6.4), performance indicators (Section 6.5), and the replication-deletion approach (Section 6.6). We end with some notes on the verification and validation of our model in Section 6.3.

6.1 STRUCTURE

A schematic view on the structure of our simulation model can be found in Figure 5. The simulation is driven by the object "Citizens" which generates waste disposals. The planning and scheduling of emptying's is done with the object "Waste collection company". The events upon which both objects operate are controlled by the "Event controller". The actions of citizens (waste disposals) and of the waste collection company (trucks emptying the containers) are displayed on an animated network. The object "Waste collection company" contains the methods that actually execute all steps necessary to develop an emptying schedule. This object needs the input of the experimental settings, keeps track of the performance of the different planning methodologies, and provides this as output data. The input of the simulation will be discussed in Section 6.2. The output, in the form of performance indicators, will be discussed in Section 6.5.

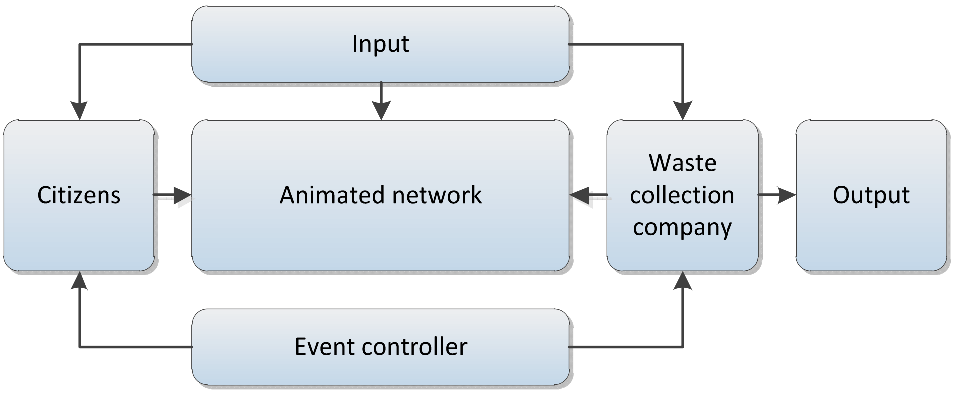

Figure 5 - Structure of the simulation model

To make the simulation model more accessible for usage, we added visualization in the form of an animated network. This does not contribute to the actual output of the model, but it increases the understanding of the operation of the model. The animated network consists of a map of the area Twente Milieu operates in. The underground containers are all marked on that map. Displaying a part of a 3D globe on a 2D map requires some transformations. For this, we use the Universal Transverse Mercator coordinate system (UTM) to transform the GPS coordinates of all containers into XY coordinates. In our case, this projection is somewhat easier because all container locations are in the same zone (32U). In addition, also the planned routes are displayed on this map, although this is done based on straight lines. We use separate colours for the different routes. Also, MustGo's are displayed in red whereas the others are displayed in black. A screen capture of our simulation model can be found in Figure 6.

We implemented our discrete-event simulation model in the software package Tecnomatix Plant Simulation. Tecnomatix Plant Simulation is a computer application developed by Siemens PLM Software for modelling, simulating, analysing, visualizing and optimizing production systems and processes, the flow of materials, and logistic operations (Plant Simulation, 2011).

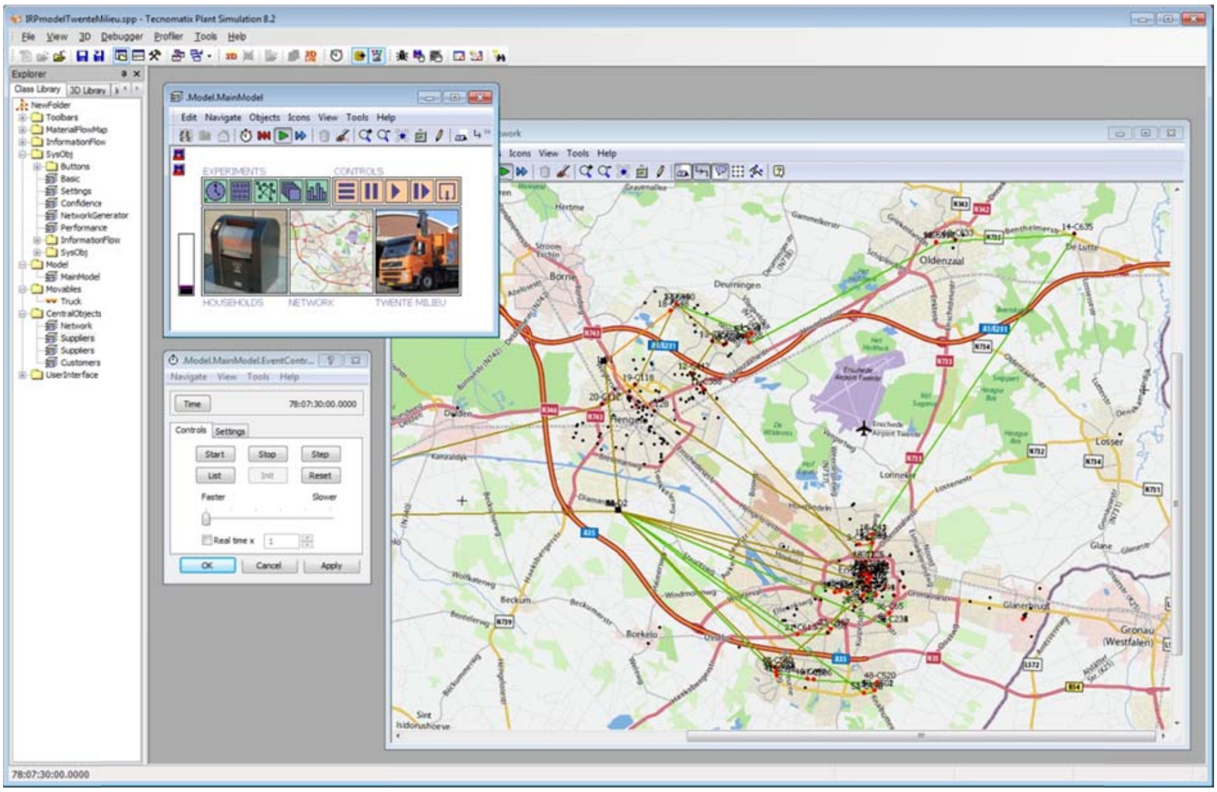

Figure 6 - Screen capture of the simulation

6.2 SETTINGS

For the settings of our simulation model we have to choose a reference point in time since new containers are installed on a weekly basis. For this use the situation as is was at the end of March 2009. At that moment, Twente Milieu operated in total 520 underground containers. From these containers, only 378 are equipped with sensors. In the near future, all containers will be equipped with sensors. But for now, we limit ourselves to the 378 containers for which historical sensor data is available. In our simulation experiments, we also consider a situation with 700 containers, as we discuss later on.

For every container, we need the following input: (i) the two parameters for the Gamma distribution for generating the number of deposits per day, (ii) the two parameters for the Gamma distribution of the volume of each deposit, (iii) the capacity, and (iv) the handling time. Obviously, these settings will differ per container. Instead of showing the settings of all containers, we here show the results for a typical container:

- Deposit frequency: Gamma(1.62, 5.88)
- Deposit volume: Gamma(248.78, 0.17)
- Capacity: 4000 litre

- Handling time: 4 minutes

As default scenario, we use two trucks (M=2) which we use every workday (W=2) independent on the amount of emptying's for that day. The capacity of these trucks is 18.000 litre of compressed waste. Given the compression factor of 5, this comes to a capacity of 90.000 litre of uncompressed waste. The handling time at the waste processing centre is 15 minutes. Workdays are Monday till Friday from 7:30am to 3pm where we subtracted the lunch breaks from the end of the workday (see Section 0).

The travel times between each of the container locations are derived from the Google Maps API, using the GPS coordinates of the 378 containers as input. The main assumption here is that the truck speed is equal to the speed of passenger cars. In the urban areas Twente Milieu operates in, this assumption is reasonable. To give an idea about the network, the average travel time between two container locations is 14 minutes with a maximum of 43 minutes. The largest distance between two containers is 51 kilometre.

In the static planning approach, the planned time to empty a container depends on the last time this container was emptied. As a result, we need to do something at the start of the simulation. At the start of the simulation, we randomly fill the containers (see Section 6.5) and calculate the days left d_i for each container. As long as there are containers that have not been emptied before, we give priority to these containers, starting with those having the lowest value of d_i. For the static planning approach, we further use a target fill level of 75%.

For the dynamic planning methodology, we have to determine the threshold D^n and D^m for respectively the MustGo's and MayGo's. Based on some preliminary experiments, we choose $D^n=1$ and $D^m=5$. As mentioned in the next subsection, we also consider a dynamic policy that only empties the MustGo's. For this policy we use $D^n=2$.

As mentioned in the beginning of Section 5, all planning options might require replanning during the day and we mentioned several possibilities for this. In our simulation we choose the following. After each emptying that is not immediately followed by a visit to the waste processing centre, we look if the effective capacity of the next container to empty still fits in the truck. If not, we perform rescheduling only for this truck. To avoid excessive replanning, we work with a truck slack capacity of 5000 litre in our planning methodology.

As mentioned in Section 3.4, deposit frequencies fluctuate heavily. We saw large random fluctuations per day as well seasonal patterns. To simulate the seasonal patterns, we multiply the mean deposit volume for each day with some factor. This factor follows a sinus curve with a given amplitude *FA* and a period of 4 weeks. We assume that the company is not aware of this sinus curve. Hence, within one period, there will be 2 weeks in which the company overestimates the deposit volumes and 2 weeks in which it underestimates these volumes. To simulate the random fluctuations, we further multiply the mean deposit volumes with a factor uniformly drawn from $[1-FR,1+FR]$ with $FR\leq 1$. To mimic the current situation, we use $FA=0.05$ and $FR=0.7$.

As default value for the maximum number of jobs per day (L), we use 22% of the number of containers. For our reference point, this gives $L=0.22*378=83$. The final setting is related to the time we use between updating the smoothed ratio (see Section 5.2). For this we use a week. So, at the end of each week, we compute the average emptying ratio's (required additional travel time to empty this container divided by the volume of waste in this container) for each container and smooth these values, using α=0.05, with the smoothed historical average.

6.3 Experimental factors

To see how a planning methodology performs, we will test its behaviour under varying circumstances. We chose the following factors for our simulation experiments:

- Number of containers (N): 378 and 700. At our reference point, 378 where in use. We extend this number to 700 by randomly selecting new container locations from the current locations.
- Planning methodologies (Policies): Static, MustGo, Dynamic. The MustGo policy is a dynamic planning methodology in which we only empty the MustGo's.
- Fill-level sensors: with and without. Without fill-level sensors, we estimate the fill levels by multiplying the number of lid openings with the expected mean deposit volume. With fill-level sensors, we have a perfect estimate of the actual fill level. We denote the use of fill-level sensors in combination with the three previously mentioned policies by StaticS, MustGoS, and DynamicS.
- Factor amplitude in sinus fluctuations (FA): [0, 0.5].
- Factor mean deposit volumes (FM): [0.5, 1.5]. Here, we multiple the mean deposit volumes every day with a factor FM.
- Factor expected deposit volumes (FE): [0.75, 1.25]. Here, we multiply the expected deposit volumes with FE. The expected deposit volumes are used to estimate the fill-level of the containers (and hence the days left) based on the number of lid openings. A value of 1 means that our expectation is accurate. However, the actual deposit volumes might still fluctuate due to the random fluctuations (FR) and the seasonal fluctuations (FA).
- Factor maximum number of emptying's (FL): here we multiple the maximum number of emptying's L with a factor FL.

6.4 Performance indicators

With our simulation model, we evaluate the performance of the dynamic planning methodology and benchmark it against the current way of working. As key performance indictor in this analysis, we use a weighted combination of transportation costs, handling costs, and penalty costs for emptying too late. As weights, we use c^t for the travel costs per time unit, c^h for the handling costs per time unit, and c^p for the penalty costs per volume overflow. The key performance indicator CL gives the total costs per litre:

$$CL = \frac{c^t(travel\ time) + c^h(handling\ time) + c^p(volume\ overflow)}{volume\ collected},$$

where time and volume are measured over the whole simulation run.

With this objective function, we aim to minimize the travelling costs, while at the same time ensuring the service level by penalizing when a container is emptied too late. In agreement with the company, we set the parameters as follows: $c^t = 1$, $c^h = 0.5$, and $c^p = 0.7$. Here, the travel costs are considered to be the most influential with respect to the overall performance; one time unit of travelling costs twice as much as spending one time unit on loading\unloading. The penalty factor is also relatively large to maintain customer satisfaction.

As secondary performance indicators we consider:

- CT = average travel time per day (hours)
- CH = average handling time per day (hours)
- CP = average volume of overflow per day (m^3)
- VC = average volume of collected waste per day (m^3)

6.5 REPLICATION/DELETION APPROACH

Given we are facing a non-terminating simulation, we use the replication/deletion approach (see Law, 2007). This involves a number of replications each having a certain warm-up period. The warm-up period indicates after which time the system comes into a steady state. In our case, the warm-up period is necessary for (i) learning the smoothed ratios used for adding MayGo's and (ii) to create realistic fill levels in the underground containers. We initialize the simulation by filling the containers uniformly between 0 and 80% of the container capacity. For calculating the warm-up period, we use Welch's graphical procedure as described in Law (2007). The use of 10 replications and a window of 40 days, results in a warm-up period of around 8 weeks. Given the warm-up period of 8 weeks, we use a run length of 24 weeks (excluding the warm-up). Next, we calculate the number of runs using the sequential procedure (Law, 2007). With a confidence level $\alpha=0.05$ and relative error $\gamma=0.05$, the required number of runs for different experimental settings fluctuates around five replications. To avoid inaccuracies, we use 10 replications for all our experiments.

6.6 MODEL VERIFICATION AND VALIDATION

To verify our model, we tested each module separately. In addition, we kept the management of the company in the process to establish credibility. After completing the simulation model, we validated our model to see whether the reality was approached accurately enough. Validation is done using data from the actual operations and it is intended to prove that the assumptions incorporated in the model were well chosen. For the case of the Twente Milieu, the validation process is relatively difficult to execute, since the current collection process involves human decision making which we had to approximate with our static planning model (Section 0). We distinguish the following validation and verification criteria:

- From the interviews conducted with the planning department, it became clear that, on average, each working day 22% of the containers are emptied. Upon the chosen reference point in time, the total number of containers is 378 which results in 83 emptying's per day. The emptying's are done by two trucks, one of them being utilized for 50%. This corresponds with the average workload of 55 containers which we found during our data analysis using observations from half a year around the reference point. This data analysis also revealed an average of 412 emptying's per week which confirms the results from our interviews (5*83=415 emptying's).

- From the interviews conducted with the planning department, it became clear that, on average, the amount of garbage that is collected from a container is 2500 litres. Our data analysis revealed that the daily deposal volume is 148.070 litres and 415 emptying's take place weekly. This translates to an average of 7*148.070/415=2498 litre per emptying which confirms the expectations of the planning department.

- Criteria such as deposit and emptying frequencies cannot be used to validate our simulation model since we use them as input. A useful validation criterion we can use here is the time required for the collection process, which depends on the travel times, handling times, and the routing efficiency. From the interviews conducted with the truck drivers, it became clear that, under normal circumstances, emptying 55 containers can be seen as the maximum workload for one truck on one day. Under ideal circumstances (no traffic delays and many containers to empty close to each other), a maximum workload of around 70 emptying's can be achieved. To validate our simulation model, we used (i) the static planning methodology without the fixed maximum of 83 emptying's per day and (ii) the dynamic planning methodology without a maximum and using D^m=1 and D^n=5. The results of these experiments can be found in Table 1. Here, we use as maximum in our simulation experiments the 97.5 percentile. Clearly, the static planning approach provides a perfect match with respect to the normal maximum amount of daily emptying's. This amount of emptying's is higher in case of dynamic planning due to the insertion of MayGo's which are normally chosen such that they require limited additional travel time. With respect to the maximum number of emptying's that can be achieved under ideal circumstances, we see a perfect match with the dynamic planning approach. In reality, this maximum is only achieved with human intervention where one deviates from the original static plan, thereby including additional containers that are closely located to the current routes. This is exactly the reason that the static planning approach yields a lower maximum in our simulation.

	Reality	Static	Dynamic
Normal	55	55.4	61.7
Maximum	70	61.8	69.7

Table 1 - Validation results

The verification and validation steps described above convince us that our simulation model provides an accurate representation of the real system. The numerical results from this simulation model are presented in the next section.

7 RESULTS

In this section we present the results of our simulation study. First, the results for the sensitivity analysis are shown (Section 7.1) and then the results for expected network growth (Section 7.2). We end with a benchmark of the current way of working, thereby providing an indication of the savings that can be achieved by Twente Milieu when switching to a dynamic planning methodology (Section 7.3).

7.1 SENSITIVITY ANALYSIS

In our sensitivity analysis, we vary the following things: the mean deposit volumes, the maximum number of emptying's per day, the deviation of the expectation, and the amplitude of the sinus pattern of daily deposit frequencies. The results can be found in Figure 7.

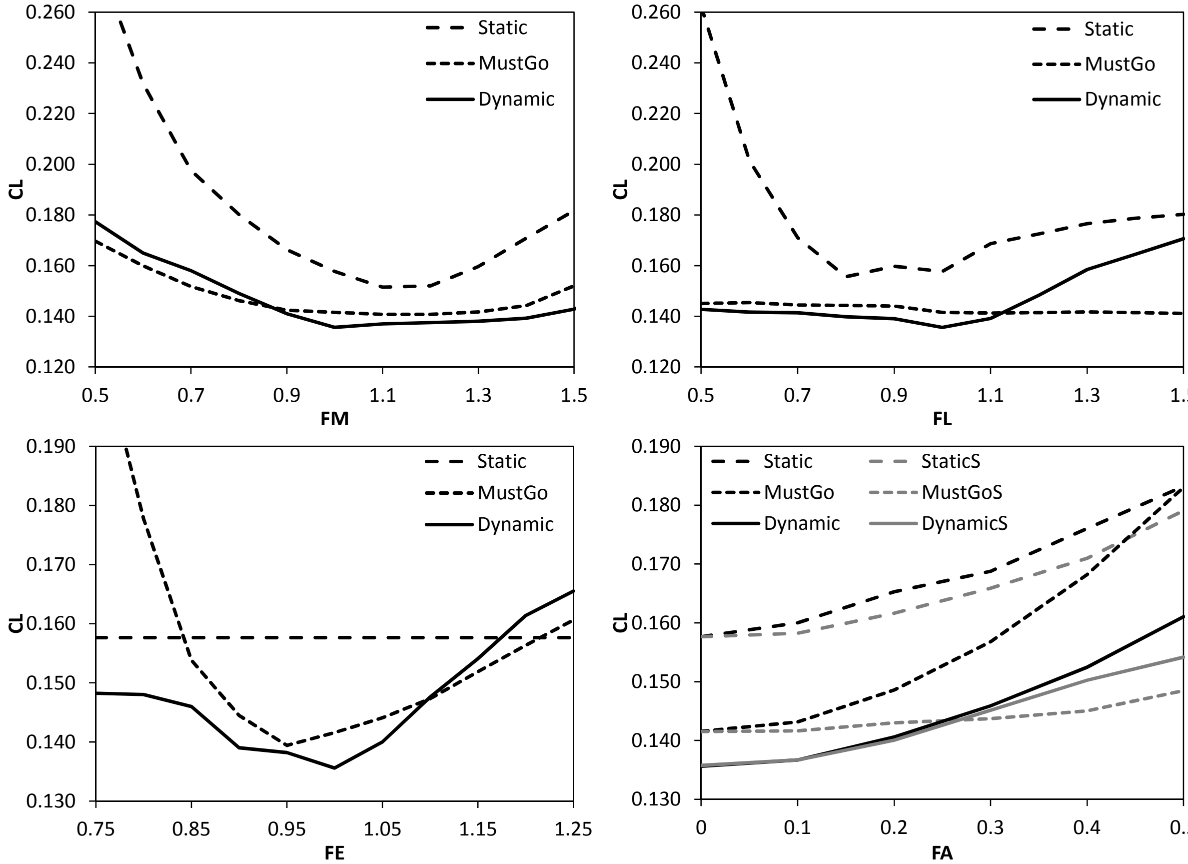

Figure 7 - Results sensitivity analysis

We draw the following conclusions. First, with a varying factor *FM* for the mean deposit volumes, the different policies have their lowest costs *CL* around 1.1. Obviously, an increase in deposit volumes will result in higher costs. However, the costs per litre initially decrease. With further increase in deposit volumes, the penalty costs will raise. We also observe that with relative low deposit volumes, Dynamic will be outperformed by MustGo. The reason for this is that the policy Dynamic is bounded with the maximum of 83 emptying's (0.22*378) per day. With low deposit volumes, this bound is too low. The consequence of this is that Dynamic is simply doing too many MayGo's which results in relative high costs per litre collected.

If we look at varying factor *FL* for the maximum number of jobs, we see the following. First, the policy MustGo is not sensitive to this maximum. We also see that for a low maximum, the difference between the performance of MustGo and Dynamic becomes smaller, since the ability of adding MayGo's decreases. With increasing maximum, we see that MustGo outperforms Dynamic. Again, the explanation is that Dynamic is using too many MayGo's. Finally, we observe that the minimum of Static is attained in the area 0.8-1, which provides an indication that the choice of emptying 22% of the total container population daily, seems to be a good choice in combination with the weights of the three costs factors (travel time, handling time and overflow). The number of emptying's is a bit on the save side, which indicates that in reality the company puts even more weight on the penalty costs and hence on customer satisfaction.

If we look at varying factor *FE* for the expected mean disposal volume, we observe the following. First, Static is not sensitive to this value since it does not estimate the average fill levels (although it does require to determine the time between emptying's which we assume to be known in this study). Obviously, the dynamic policies are influenced by this. If we underestimate the deposit volumes, we will incur more penalty costs. If we overestimate the deposit volumes, we are doing more emptying's then necessary. Overestimation will be worst for dynamic since it uses too many MayGo's.

Finally, we consider the factor *FA* for the amplitude in sinus pattern of deposit frequencies. Obviously, for all policies, the costs increase with increasing amplitude. This is because there will be periods of heavy over estimation as well as under estimation. However, with increasing amplitude, the added value of using fill level sensors increases. Particularly for the policy MustGo since this policy only empties the containers that are expected to be almost full. MustGo without sensors will eventually be outperformed by Static. Remarkable here is that MustGo with sensors will eventually outperform Dynamic with sensors. The explanation for this is that, if we perfectly know the fill levels, the value of adding MayGo's decreases. Finally, the policy Dynamic heavily depends on the choice of parameter levels D^n and D^m. With increasing amplitude, these parameters will be too low in some periods and too high in other periods.

7.2 Analysis of network growth

We now compare the original network with 378 containers with an increased network consisting of 700 containers. The results can be found in Table 2. It appears that the costs for the three policies practically remain the same. Note that these are the costs per litre. Since more litres are collected with 700 containers, the total costs will obviously be higher. Further, if we look at the individual costs components, we see that all costs are higher with 700 containers, especially the penalty costs. The reason for this is that we still use the same amount of trucks (2 trucks).

N	Policy	CL	CT	CH	CP	VC
378	Static	0.1576	5.53	6.33	2.05	207.54
378	MustGo	0.1416	5.18	4.92	2.66	207.47
378	Dynamic	0.1356	4.53	6.29	0.73	207.57
700	Static	0.1587	6.23	8.42	33.22	383.37
700	MustGo	0.1384	6.27	8.42	21.90	383.23
700	Dynamic	0.1352	6.67	8.14	18.84	383.35

Table 2 - results of growth in number of containers

Next, we vary the mean deposit volumes. The results can be found in Figure 8. Here we clearly see that two trucks are sufficient to cope with an increase in deposit volumes whereas this is no longer the case with 700 containers. With 378 containers, increasing volumes will reduce the costs per litre since there is a situation of overcapacity. In case of 700 containers, an increase in mean deposit volume will results in an increase in penalty costs.

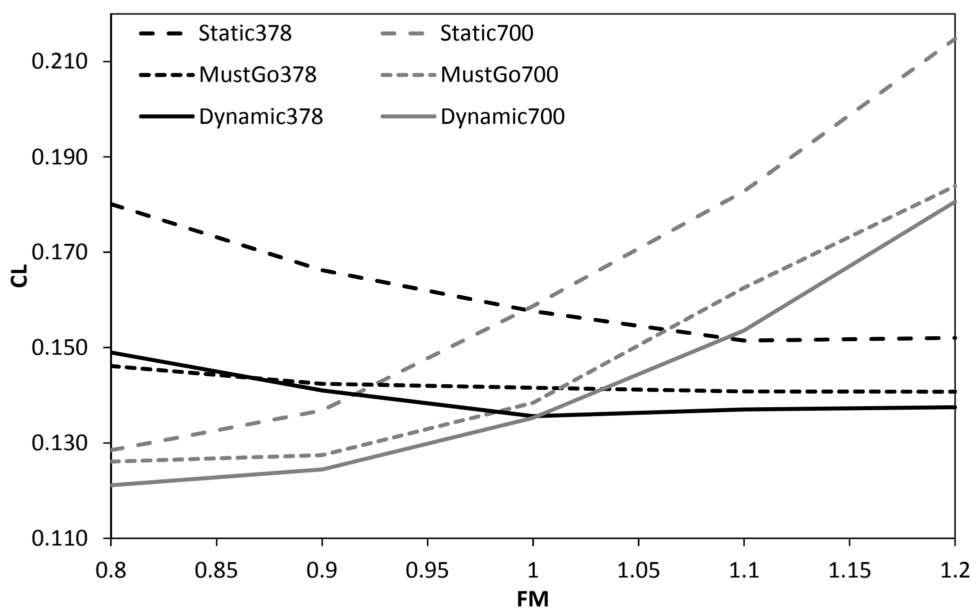

Figure 8 - Varying mean deposit volumes for 378 and 700 containers

7.3 Benchmarking

In the last experiment, we compare the performance of the dynamic planning methodology with the static planning methodology as currently used by the company. For this we use the settings with both periodic and random fluctuations. The results can be found in Table 3.

Policy	CL	CT	CH	CP
Static	0.1687	5.70	6.40	4.42
StaticS	0.1656	5.57	6.33	4.37
Dynamic	0.1468	4.73	6.24	3.29
DynamicS	0.1434	5.02	5.85	1.78

Table 3- Benchmarking results

We clearly see that the travel costs as well as the penalty costs can be decreased significantly. To make it more clearly, we also present the savings of all policies compared to the static planning methodology. These results can be found in Table 4.

Policy	CL	CT	CH	CP
StaticS	1.81%	2.31%	1.09%	1.08%
Dynamic	12.96%	17.07%	2.42%	25.63%
DynamicS	14.95%	11.94%	8.61%	59.74%

Table 4 - Relative savings

The total savings of switching to a dynamic planning methodology would be almost 13%. When we also switch to the more reliable fill level sensors, the savings increase to almost 15%.

The savings obviously depend on the truck capacities. In the current situation, Twente Milieu uses two trucks to empty the 378 containers. This is a situation of overcapacity. We have seen earlier (Section 7.1) that the dynamic planning methodologies will require less capacity and therefore still perform well with increasing network size. To study this effect, we vary the maximum number of emptying's per day. The relative savings compared to the static policy are displayed in Figure 9.

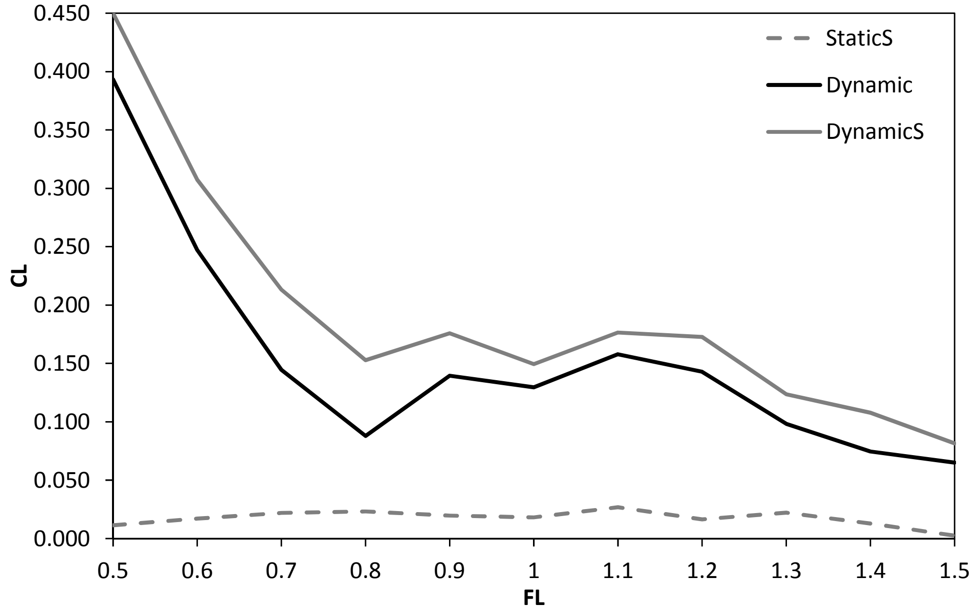

Figure 9 - Varying maximum workload

We clearly see that savings increase with decreasing capacity. For example, if trucks are allowed to do only 50% of their regular workload (resembling the case with 50% less tucks or 50% shorter working days), the relative savings of the dynamic planning methodology are close to 40%. Again, additional savings can be achieved by using fill level sensors, which yields savings of up to 45% savings.

Even though the performance of the dynamic policy seems promising, there is still room for improvement. One specific weakness of the dynamic policy is its strong sensitivity to used parameter settings, i.e., the values of D^m, D^n, and L. As a result, we need to tune these parameters first. This also means that with changing deposit patterns (such as the simulated seasonal and random fluctuations in deposit volumes), we continuously need to adapt our parameters. This also explains our earlier observations that in some cases Dynamic is outperformed by MustGo (situations in which Dynamic is doing too many MayGo's). We also observed (results not shown here) that the right choice of parameter values also heavily depends on the day of the week. As a result, we need to tune (D_t^m, D_t^n, L_t) for *t=1,..,5*, with *t* being the day of the week. Moreover, there are also several dependencies between these parameters, e.g., a high value for D_t^m or a low value for L_t, reduces the impact of D_t^n. In principle, we could optimize over these parameters, in this case over a 25 dimensional function which we measure using simulation. This simulation optimization approach is part of our future research.

8 CONCLUSIONS AND RECOMMENDATIONS

In this paper, we analysed the options to use a dynamic planning methodology to increase efficiency in the emptying process of underground containers in terms of logistical costs, customer satisfaction, and CO_2 emissions. We proposed a dynamic planning methodology that relies on the common distinction between MustGo's and MayGo's. The MustGo's are those containers that have to be emptied. The MayGo's are those that might be emptied depending on how efficient they can be incorporated in the current routes. From the set of MustGo's, seed customers are selected to (i) spread the trucks across the area, (ii) realize insertion of collection jobs from containers close as well as far from the depot, and (iii) balance the workload per route to anticipate the insertion of MayGo's. The algorithm then schedules all remaining MustGo's using the cheapest insertion heuristic. Then the MayGo's are scheduled as long as there is capacity left. We proposed a new criterion for the MayGo's depending on the relative improvement over an historical smoothed average ratio of the additional travel time required to empty a specific container and its volume. The algorithm is used in the morning to plan all emptying's for that day. During the day replanning takes place to cope with inaccurate estimates of the fill levels.

We evaluated the performance of our dynamic policy using simulation. We conclude that, for our reference point in time, the benefit for Twente Milieu of switching to a dynamic waste collection policy is a cost reduction of 13%, which consists of a reduction in travel costs of 17% and a reduction in penalty costs of 26%. We further conclude that with increasing deposit volumes or decreasing truck capacities, these savings increase. In other words, by switching to a dynamic collection policy, investments in additional trucks can be postponed. We showed that the savings per litre remain almost the same with an expanded network of 700 containers. This means that the absolute savings increase drastically with increasing network size. We also analysed the added value of investing in fill-level sensors. Obviously, the higher the (unforeseen) fluctuations in deposit volumes, the higher the potential benefits of using fill-level sensors. For our reference point in time, the dynamic policy with fill-level sensors result in cost savings of 15%, which consist of a reduction in travel costs of 12% and a reduction in penalty costs of 60%.

We end with suggestions for further research. We made several simplifying assumptions which have an impact on the reliability of our simulation model (and to some extend the usability of our planning methodology). First, we assumed deterministic travelling times. Of course, in reality, the time to travel from one container to another is stochastic. Although we can use a deterministic algorithm to make decisions in a stochastic environment, it would be nice to study the impact of stochastic travel- and handling times in our simulation model as it will definitely impact the need for rescheduling. Next, we looked at each container individually. However, at many locations there are multiple underground containers placed. It is arguable to look at all containers at the same location together. Only when all containers of the group are almost full, the group is eligible for emptying. The final direction for further research is the simulation optimization approach as mentioned at the end of Section 7. The methodology we have in mind for this is based on the hierarchical knowledge gradient policy as described by Mes et al. (2011).

9 REFERENCES

Andersson, H., Hoff, A., Christiansen, M., Hasle, G., and Løkketangen, A. (2010) Industrial aspects and literature survey: Combined inventory management and routing, *Computers & Operations Research* **37**(9): pp. 1515-1536.

Angelelli, E., Bianchessi, N., Mansini, R., and Speranza, M.G. (2009). Short term strategies for a dynamic multi-period routing problem, *Transportation Research Part C* **17**(2): pp. 106–119.

Engelelli, E., Speranza, M.G., and Savelsbergh, M.W.P. (2007). Competitive analysis for dynamic multi-period uncapacitated routing problems, *Networks* **49**(4): pp. 308–317.

Beltrami, E. J., and Bodin, L. D. (1974). Networks and Vehicle Routing for Municipal Waste Collection. *Networks* **4**: pp. 9-32.

Berbeglia, G., Cordeau, J.F., and Laporte, G. (2010). Dynamic pickup and delivery problems, *European Journal of Operational Research* **202**(1): pp. 8–15.

Campbell, A., Clarke, L., Kleywegt, A., and Savelsbergh, M. (1998). Inventory routing. T. Crainic, G. Laporte, eds. *Fleet Management and Logistics*. Kluwer Academic Publishers, Boston, MA.

Campbell, A.M., and Savelsbergh, M. (2004). Efficient insertion heuristics for vehicle routing and scheduling problems, *Transportation Science* **38**: pp. 369–378.

Chalkias, C., and Lasaridi, K. (2009). A GIS based model for the optimisation of municipal solid waste collection: the case study of Nikea, Athens, Greece, *WSEAS Transactions on Environment and development* 10(5): pp. 640–650.

Chang, N.B., and Wei, Y. (2002). Comparative study between the heuristic algorithm and the optimization technique for vehicle routing and scheduling in a solid waste collection system. *Civil Engineering and Environmental Systems* **19**(10): pp. 41-65.

Chao, I.M., Golden, B., and Wasil, E. (1995). An improved heuristic for the period vehicle routing problem, *Networks* **26**: pp. 25–44.

Cordeau, J.F., Gendreau, M., and Laporte, G. (1997). A tabu search heuristic for periodic and multi-depot vehicle routing problems, *Networks* **30**(2): 105–119.

Dantzig, G.B., and Ramser, J.H. (1959). The Truck Dispatching Problem. *Management Science* **6**(1): pp. 80–91.

Francis, P.M., Smilowitz, K.R., and Tzur, M. (2006). The Period Vehicle Routing Problem with Service Choice, *Transportation Science* **40**(4), pp. 439–454.

Francis, P.M., Smilowitz, K.R., and Tzur, M. (2008). The period vehicle routing problem and its extensions. In: B.L. Golden, S. Raghavan and E.A. Wasil, Editors, *The Vehicle Routing Problem: Latest Advances and New Challenges*, Springer, New York, pp. 73–102.

Golden, B., Assad, A., and Dahl, R. (1984). Analysis of a large scale vehicle routing problem with an inventory component, *Large Scale Systems* **7**(2-3), pp. 181-190.

Golden, B., Raghavan, S., and Wasil, E. (2008). *The Vehicle Routing Problem: Latest Advances and New Challenges*, Springer, New York, NY.

Jaillet, P., Huang, L., Bard, J.F., and Dror, M. (1997). *A rolling horizon framework for the inventory routing problem*. Working paper, University of Texas, Austin, TX.

Johansson, O.M. (2006). The effect of dynamic scheduling and routing in a solid waste management system, *Waste Management* **26**(8): pp. 875-885.

Jozefowiez, N., Semet, F., and Talbi, E.G. (2008). Multi-objective vehicle routing problems, *European Journal of Operational Research* **189**(2): 293–309.

Karadimas, N. V., Papatzelou, K., and Loumos, V. G. (2007). Optimal solid waste collection routes identified by the ant colony system algorithm. *Waste Management & Research* **25**(2): pp. 139-147.

Kim, B.I., Kim, S., and Sahoo, S. (2006). Waste collection vehicle routing problem with time windows. *Computers and Operations Research* **33**(12): pp. 3624-3642.

Lacomme, P., Prins, C., and Sevaux, M. (2006). A genetic algorithm for a bi-objective capacitated arc routing problem, *Computers & Operations Research* **33**(12): pp. 3473–3493.

Larsen, A., Madsen, O.B.G., and Solomon, M.M. (2008). Recent developments in dynamic vehicle routing systems. In: B.L. Golden, S. Raghavan and E.A. Wasil, Editors, *The vehicle routing problem: latest advances and new challenges*, Springer, New York, pp. 199–218.

Law, A. (2007). *Simulation Modeling and Analysis*, 4th Edition, McGraw-Hill, New York, NY.

McLeod, F., and Cherrett, T. (2008). Quantifying the transport impacts of domestic waste collection strategies, *Waste Management* **28**(11), pp. 2271-2278.

Mes, M.R.K., Powell, W.B., and Frazier, P.I. (2011). Hierarchical Knowledge Gradient for Sequential Sampling. *Journal of Machine Learning Research* **12**, pp. 2931-2974.

Mourgaya, M., and Vanderbeck, F. (2007). Column generation based heuristic for tactical planning in multi-period vehicle routing, *European Journal of Operational Research* **183**(3): pp. 1028–1041.

Newman, A. M., Yano, C. A., and Kaminsky, P. M. (2005). Third party logistics planning with routing and inventory costs. In J. Geunes and P. M. Pardalos, editors, *Supply Chain Optimization*. Springer, New York, NY.

Nuortio, T., Kytöjoki, J., Niska, H., and Bräysy, O. (2006). Improved route planning and scheduling of waste collection and transport. *Expert Systems with Applications* **30**(2): pp. 223-232.

Pacheco, J., and Martí, R. (2007). Tabu search for a multi-objective routing problem, *Journal of the Operational Research Society* **57**(1): pp. 29–37.

Plant Simulation (2011). http://www.plm.automation.siemens.com/.

Russell, R. A., and Igo, W. (1979). An Assignment Routing Problem. *Networks* **9**: pp. 1-17.

Tan, K.C., Chew, Y.H., and Lee, L.H. (2006). A hybrid multi-objective evolutionary algorithm for solving truck and trailer vehicle routing problems, *European Journal of Operational Research* **172**(3): pp. 855–885.

Toth, P., and Vigo, D. (2001). *The Vehicle Routing Problem*, SIAM, Philadelphia, PA.

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