A Model Enhancement Approach for Optimizing the Integrated Shift Scheduling and Vehicle Routing Problem in Waste Collection

Philippe De Bruecker, Jeroen Beliën, Liesje De Boeck, Simon De Jaeger, Erik Demeulemeester

PII: S0377-2217(17)30790-7
DOI: 10.1016/j.ejor.2017.08.059
Reference: EOR 14678

To appear in: *European Journal of Operational Research*

Received date: 2 September 2016
Revised date: 29 August 2017
Accepted date: 31 August 2017

Please cite this article as: Philippe De Bruecker, Jeroen Beliën, Liesje De Boeck, Simon De Jaeger, Erik Demeulemeester, A Model Enhancement Approach for Optimizing the Integrated Shift Scheduling and Vehicle Routing Problem in Waste Collection, *European Journal of Operational Research* (2017), doi: 10.1016/j.ejor.2017.08.059

Highlights

- An integrated shift scheduling and waste collection routing is studied.
- A model enhancement approach accurately estimates the required collection times.
- The solutions are compared with a practical lower bound based on flexible routes.

A Model Enhancement Approach for Optimizing the Integrated Shift Scheduling and Vehicle Routing Problem in Waste Collection

Philippe De Bruecker

KU Leuven, Research Center for Operations Management, Faculty of Economics and Business (FEB), Naamsestraat 69, 3000, Leuven (Belgium)
KU Leuven, Research Center for Economics and Corporate Sustainability, Faculty of Economics and Business (FEB), Warmoesberg 26, 1000, Brussels (Belgium)
Odisee University College, Warmoesberg 26, 1000, Brussels (Belgium)

Jeroen Beliën*

KU Leuven, Research Center for Information Management, Modeling and Simulation (CIMS), Faculty of Economics and Business (FEB), Warmoesberg 26, 1000, Brussels (Belgium)
KU Leuven, Research Center for Operations Management, Faculty of Economics and Business (FEB), Naamsestraat 69, 3000, Leuven (Belgium)

Liesje De Boeck

KU Leuven, Research Center for Information Management, Modeling and Simulation (CIMS), Faculty of Economics and Business (FEB), Warmoesberg 26, 1000, Brussels (Belgium)
KU Leuven, Research Center for Operations Management, Faculty of Economics and Business (FEB), Naamsestraat 69, 3000, Leuven (Belgium)

Simon De Jaeger

KU Leuven, Research Center for Economics and Corporate Sustainability, Faculty of Economics and Business (FEB), Warmoesberg 26, 1000, Brussels (Belgium)

Erik Demeulemeester

KU Leuven, Research Center for Operations Management, Faculty of Economics and Business (FEB), Naamsestraat 69, 3000, Leuven (Belgium)

---

*Corresponding author
Email addresses: philippe.debruecker@kuleuven.be (Philippe De Bruecker), jeroen.belien@kuleuven.be (Jeroen Beliën), liesje.deboeck@kuleuven.be (Liesje De Boeck), simon.dejaeger@kuleuven.be (Simon De Jaeger), erik.demeulemeester@kuleuven.be (Erik Demeulemeester)

Abstract

This paper presents a model enhancement approach for the integrated problem of developing shift schedules and waste collection routes. Given a variable amount of waste to be collected the objective is to find fixed, minimal cost shift schedules and collection routes under a service level constraint. While regular shifts during traffic peak hours are cheaper in terms of labour costs, the collection speed is on average lower than during expensive, non-regular shifts. Our findings can be summarized as follows. (1) Solutions can be found within reasonable computation time for real-life instances. (2) The model enhancement approach accurately estimates the required collection times and therefore consistently finds a feasible solution. (3) The solutions not only result in considerable savings, but are also proven to be (near)optimal by comparison with a practical lower bound based on flexible routes.

Keywords: Routing; model enhancement, waste collection, shift scheduling

1. Introduction

The growing tendency towards waste separation at the source (i.e., the separation of waste into different flows at household or firm level) stresses the need for an effective and efficient organization of the collection process.

This study was inspired by a research question we received from the company Fost Plus concerning the optimization of the collection process of glass. Fost Plus is a private not-for-profit company that promotes, coordinates and finances the selective collection, sorting and recycling of household packaging waste in Belgium.

The model developed in this paper is, however, more generic as it can also be applied to other waste or material flows. For instance, the recent shift from door-to-door collection towards centralised (underground) drop-off containers in densely populated areas also shows the need for combined scheduling and routing models. Moreover, even with door-to-door collection the model can be used on a more tactical level by considering waste generation on neighbourhood levels instead of on household levels.

In practice, the glass collection is not performed by Fost Plus, but is decentralized to different intermunicipal authorities (IAs), which can in turn decide to outsource this to another party. A typical IA has its own fixed periodical collection scheme that defines the work schedule (comprising the work days and the days off) for each truck driver as well as the collection routes for each driver on each day. In order to optimize the current collection process, we will consider a second shift type (N shifts) on top of the single current shift type (P shifts) which contains the peak traffic hours on the road. The current P shifts (containing the peak traffic hours) are cheaper than the N shifts (not containing the peak traffic hours) because the P shifts cover the normal daytime working hours (i.e., 9 AM to 5 PM) while the working hours of the N shifts can lie (partially) outside this interval. Prior to any negotiations concerning the definition of the N shifts, we are primarily interested in the potential benefits of these N shifts. While the P shifts are cheaper than the N shifts, the driving times during the P shifts are on average higher than those during the N shifts. This difference creates a trade-off between higher costs and faster driving times which possibly results in a better workforce schedule with lower weekly labor costs.

As the amount of glass put in the glass containers differs from day to day, the time required to collect this glass also differs from day to day. Glass containers are only emptied if they reached a certain fill level. If on a particular day more glass containers reached this fill level, the collection trucks, which have a limited capacity, need to return more often to the collection point. This has again consequences on the fill levels and the collection times of the next day. For this reason, a static model that accurately calculates the collection time for a given truck on a given day is virtually impossible. Therefore, we introduce a dynamic optimization model that uses as input the variable fill rates of each glass container on every day of the year.

The collection scheme will be optimized using a model enhancement (ME) technique (Bachelet and Yon (2007)) that accurately estimates the collection time on every particular day of the considered time horizon. In order to construct a mathematical optimization model for solving a real-life problem, often several modeling simplifications are needed (Bachelet and Yon (2007)). In most cases, the resulting model therefore fails to give a correct representation of reality. In the ME framework, however, simulation is used to find better estimators for the model's parameters and as such 'enhances' the mathematical model increasing the realism and applicability of the solution. While most optimization-simulation couplings focus on improving the objective function evaluated from simulation (like the simulation optimization approach), ME still focuses on optimizing the combinatorial optimization problem. As the problem under study involves solving a complex integrated shift and tour scheduling problem, ME is particularly effective in this case. We illustrate the performance of the ME approach using several test cases based on real-life data. Finally, the model is applied on the real-life data of a single IA.

The remainder of this paper is organized as follows. First, Section 2 reviews the literature related to this study. Next, Section 3 gives a detailed problem description as well as a problem formulation. Section 4 describes the model enhancement solution approach, while Section 5 presents the results of the computational experiments. Finally, Section 6 concludes this paper and discusses some avenues for future research.

2. Literature review

Constructing a workforce schedule for glass collection is a complicated task. As in all industries, workforce schedules should be constructed according to certain legal constraints. Each schedule is for example constrained by a maximum time limit and should include a break of a certain duration. However, designing a workforce schedule for glass collection also requires a routing decision. This means that we have to decide on the composition of the collection routes (the routing decision) and the personnel and shift schedules (the scheduling decision) simultaneously, because the feasibility of a shift schedule cannot be evaluated without solving the routing problems. Assume it is decided to work according to a shift schedule P-P-P-P-P. The only way to know whether these shifts are sufficient is by constructing the collection routes for every shift and verifying whether the glass can be collected in this shift schedule. The collection routing is thus necessary to evaluate the shift schedule. Solving both problems independently cannot guarantee a feasible solution. Unfortunately, the integration of the routing decision and the scheduling decision is not straightforward and makes these types of problems very challenging.

The routing decision is an important complicating factor when solving the glass collection problem. For a general review on municipal solid waste collection problems we refer to Beliën et al. (2014). The routing problem considered here belongs to the broad class of Vehicle Routing Problems (VRP) (Mes, 2012). In the VRP, a given set of vehicles must deliver goods to a given set of customers such that the overall transportation costs are minimized. Hence, the goal is to construct a set of optimal routes in order to reduce the total travelled distance and possibly the required number of vehicles. Translating the VRP to our case can be done by assuming that the glass containers represent the customers and the goods to be delivered is empty space. This implies that within the VRP collecting glass can be seen as filling the containers with air. For an overview of the solution techniques designed for the VRP we refer to Carić and Gold (2008).

In this paper, the goal is to find a fixed weekly schedule that is repeated each week during the considered time horizon (e.g., one year). This problem is related to the periodic vehicle routing problem (PVRP) where customers require service on multiple days during a given planning horizon, while the VRP is only concerned with one period. Two decisions have to be made using an integrated or a two-stage approach. First, the weekly service frequency (i.e., how often each customer is served) and service pattern (i.e., which customers will be served on which day of the week) must be determined. Second, a VRP is solved for each day based on the selected customers for that day according to the VRP rules.

Francis et al. (2008) present a literature review on the PVRP and its extensions, showing that most of the PVRP research assumes a predetermined service frequency. Only a few researchers incorporate the service frequency as a decision variable in the optimization model. While we also assume a predetermined service frequency (i.e., each container should be visited at least once a week), the service pattern decision is integrated with the routing decision.

Our model has three special features which increases the complexity compared to the standard PVRP. First, we incorporate a shift scheduling decision, which is barely investigated in the existing literature in combination with the PVRP. In their literature survey, Ghiani et al. (2014) state that a large percentage of total waste management cost related to waste collection is due to the equipment and the workforce (about 75% according to Shamshiry et al. (2011)). Optimizing the workforce scheduling process can therefore result in significant savings. However, these aspects have not been given much attention in the literature (Ghiani et al., 2014). This is confirmed by Ernst et al. (2004) in their literature review on staff scheduling and rostering where the authors point out the lack of contributions related to personnel and vehicle shift scheduling in the waste management literature. In the literature review of Francis et al. (2008) on the (P)VRP, shift scheduling is not even mentioned. The papers that do consider a combination of staff scheduling and the vehicle routing problem propose a multi-staged approach instead of an integrated approach, or fail to incorporate important routing constraints such as truck capacity constraints (Baudach et al., 2009; Ghiani et al., 2013; Hansmann and Zimmermann, 2009; List et al., 2006).

Second, while the standard PVRP only links the different days in the planning horizon in the objective function, seeking the overall minimal transportation costs over all days, we also link the days in the constraints. Like Coene et al. (2010), we consider the scenario where the load of a vehicle at the end of a day needs to be equal to the load of that vehicle at the start of the following day. Furthermore, Francis et al. (2008) state that in the PVRP literature it is assumed that a fraction $\frac{1}{f_i}$ of the total demand has to be delivered to customer i on each visit, with f_i the number of visits required for customer i during the planning horizon. Hence, at each visit, a demand of $w_i = \frac{W_i}{f_i}$ is delivered, with W_i the total demand of customer i. This can be a good approach when each visit also involves a delivery and when the daily demand can be assumed to be constant. However, in our problem, we assume that each visit does not necessarily involve emptying the container. Furthermore, we show that strong seasonality effects exist in our data which implies that we cannot assume a constant daily fill rate of glass over the considered time horizon. Hence, our procedure will link all days in the considered time horizon by taking into account the effect of the visits and/or emptying on each day on all succeeding days in the considered time horizon.

Third, our problem features intermediate facilities where vehicles can unload (or reload) and thus renew capacity during a route. The PVRP with intermediate facilities is described by Angelelli and Speranza (2002), Kim et al. (2006), Alonso et al. (2008) and Coene et al. (2010). In order to deal with the increased complexity in the PVRP caused by these three elements, we propose a model enhancement heuristic that iteratively combines simulation and optimization.

3. Problem definition

3.1. Glass collection procedure

This section first describes the glass collection procedure as it is currently performed by the IA under consideration in our paper. Note that both the practical organization of the collection round as the features of the glass containers might differ somewhat between IAs.

In the IA a certain number of trucks is available each day for glass collection. The IA employs a certain number of truck drivers that cannot work in the weekend. Each glass container in the IA is located on a site. Each site can hold one or more glass containers. There are two different types of glass containers: duo containers and mono containers. Duo containers are divided in two equal compartments; one compartment for white glass and one compartment for colored glass. Mono containers have only one compartment and can be used for either white glass or colored glass. We make a difference between these two types of containers because of the differences in capacity and the time required to empty the container and collect the glass. Duo containers are overground containers that are smaller compared to the mono containers. Therefore, it takes less time to empty duo containers compared to mono containers that are placed underground.

For each truck, the collection route starts at the depot of the IA. Each truck carries one large container with two compartments, one for colored glass and one for white glass. Leaving the depot, the truck will visit the glass containers as specified by the route in the workforce schedule. While all containers specified in the route must be visited, they will only be emptied when one of the compartments is filled for at least a certain percentage. This percentage is referred to as the collection threshold and is further discussed in Section 5. The truck continues to check and empty glass containers until one of its compartments is getting full. At this time, the truck has to make a trip to the drop-off site of the IA. At the drop-off site, the full container is unloaded from the truck and is replaced with an empty container. Of course, this unloading and loading takes a certain amount of time. When all containers in the route are visited, the truck returns to the depot location.

Apart from the above description we make following assumptions:

1) The truck drivers are paid on a daily basis instead of on an hourly basis. This implies that on each week day, each truck driver is paid for 8 hours or has a day off. When a driver has a day off, he is also not paid for that day. We realize that, in reality, truck drivers often receive a monthly salary independent of the working days. We have opted for this objective function in order to reach a solution in which a driver either has a highly occupied working day or a day without glass collection routing. This has several advantages. In contrast with half days work, complete days-off (without any collection routing at all) lead to more flexibility in planning as drivers do not have to come to work and can have a vacation day. Moreover, a day without collection routes planned can also be used for training or other tasks that have to be done by the IA. Often, IAs offer different community serving tasks and truck drivers regularly rotate to other jobs. In order to be able to value a day without planned collection routing, our model uses the shift costs (as some kind of opportunity cost).

2) To minimize the glass placed next to the containers when the container is full (i.e., to minimize overflow), we assume that each glass container is visited at least once a week.

3) Because a truck is only emptied when one of its compartments is getting full, its final fill level at the end of the day equals the fill level of that truck in the beginning of the next day. We assume that a trip to the drop-off site at the end of the day is not allowed.

3.2. Fill rate of glass containers

The fill level of each compartment in each container on each day depends on the fill rate. The fill rate is the amount of glass that is added to a certain container on a specific day. Hence, accurate data regarding the fill rate is very important to make a realistic model. We calculated the daily fill rates based on daily glass collection data for a 1-year time horizon. Note that real daily fill rates are not constant but might change from day to day. Because we only have data on the amounts collected on different days per container and thus not on the daily amounts disposed in the containers, we are confident that a constant daily fill rate between two consecutive collections is the most acceptable assumption in this case. As an example of our calculations, suppose that our data shows that a container was emptied on days 2, 7 and 9. If 7500 dm^3 and 2000 dm^3 of white glass were collected on day 7 and on day 9, respectively, the daily fill rate is assumed to be 1500 dm^3 for days 3 until 7 and 1000 dm^3 for days 8 and 9.

3.3. Shift scheduling

As we consider a combination of different shift types (i.e., P shifts and N shifts), we propose a general shift scheduling model to optimize the glass collection process. The goal of this general model is to analyze different scenarios regarding shift costs and driving times.

We first list the sets, along with their associated indices:

$d \in D$:	days in the week. With $D = \{1, 2, ..., 5\}$
$w \in W$:	available truck drivers = daily available trucks
$i \in I$:	set of glass containers
$r \in R$:	set of feasible routes
$t \in T$:	set of different shift types

The coefficients and right hand side constants are presented below:

$C_{t,d,w}$:	cost of scheduling a shift of type t on day d for truck w
$V_{i,r}$:	= 1 if container i is visited in route r; = 0 otherwise
Θ^{Max}:	maximum daily average working time (in hours)

The decision variables are:

$x_{t,d,w} \in \{0, 1\}$:	= 1 if a shift of type t is scheduled on day d for truck w; = 0 otherwise
$\lambda_{r,d,w} \in \{0, 1\}$:	= 1 if route r is used on day d for truck w; = 0 otherwise

We define the following auxiliary variables which completely depend on the former two decision variables:

$\tau^{route}_{t,r,d,w}$:	average time required to perform route r on day d with truck w with a shift of type t (in hours)

Although Model 1 presented hereafter does not explicitly model the routing decision, our solution approach does (heuristically) solve the full integrated shift scheduling and routing problem. The set R contains all feasible routes r and hence the variable $\lambda_{r,d,w}$ implicitly represents all feasible routes r on day d for truck w. The routes will be constructed dynamically using a cheapest insertion heuristic as explained in Section 4.2.

Model 1: Shift scheduling model

$$\text{Minimize: } \sum_{t \in T} \sum_{d \in D} \sum_{w \in W} C_{t,d,w} x_{t,d,w} \tag{1}$$

Subject to:

$$\sum_{t \in T} x_{t,d,w} \leq 1, \quad \forall d \in D, \forall w \in W \tag{2}$$

$$\sum_{r \in R} \lambda_{r,d,w} - \sum_{t \in T} x_{t,d,w} = 0, \quad \forall d \in D, \forall w \in W \tag{3}$$

$$\sum_{t' \in T \setminus t} x_{t',d+1,w} \leq 1 - x_{t,d,w}, \quad \forall t \in T, \forall w \in W, \quad \forall d \in \{1, ..., 4\} \tag{4}$$

$$\sum_{d \in D} \sum_{w \in W} \sum_{r \in R} V_{i,r} \lambda_{r,d,w} \geq 1, \quad \forall i \in I \tag{5}$$

$$\sum_{t \in T} \sum_{r \in R} \tau^{route}_{t,r,d,w} \lambda_{r,d,w} x_{t,d,w} \leq \Theta^{Max}, \quad \forall d \in D, \forall w \in W \tag{6}$$

$$\tau^{route}_{t,r,d,w} = f \begin{pmatrix} \{\lambda_{r',d',w'} : r' \in R, d' \in D, w' \in W\}, \\ \{x_{t',d',w'} : t' \in T, d' \in D, w' \in W\} \end{pmatrix}, \quad \forall t \in T, \forall r \in R, \quad \forall d \in D, \forall w \in W \tag{7}$$

In the objective function (1) the weekly labor costs are minimized. The total number of shifts required (i.e., $\sum_{t \in T} \sum_{d \in D} \sum_{w \in W} x_{t,d,w}$) is also referred to as the total number of truck days.

Expressions (2) to (7) represent the constraints in the shift scheduling problem. Constraint (2) ensures that there will be at most one shift scheduled on each day for each driver. Constraint (3) shows that each shift should be associated with exactly one collection route $r \in R$. The set of feasible routes R contains all collection routes that meet certain conditions. First, each route $r \in R$ is a tour that begins and ends at the depot location of the IA. Second, a feasible collection route consists of at least one glass container and at most 60 glass containers. According to Fost Plus, this maximum number of containers keeps the schedule manageable and allows the truck drivers to become familiar with the collection routes.

According to labor legislation, there should be at least a certain amount of time between two consecutive shifts. Because two different shift types (e.g., an N shift and a P shift) cover different working hours, they cannot succeed each other. For example, an N shift cannot be followed by a P shift or vice versa. This is ensured in our model by Constraint (4) which represents the shift succession constraint. Because none of the workers can work in the weekend, the shift succession constraint is only concerned with the week days.

The requirement that each glass container should be visited at least once a week is ensured by Constraint (5).

Finally, the labor legislation also states that a worker can work (on average) for at most 8 hours in a shift including a 30 minute break. With the average working time, we mean the average working time for that day and truck over all weeks in the considered time horizon. This requirement is represented by Constraint (6) in which $\Theta^{Max} = 7.5$. Since both $\lambda_{r,d,w}$ and $x_{t,d,w}$ are binary variables, $\tau^{route}_{t,r,d,w}$ must be smaller than 7.5.

Note that, for ease of exposition and because we will not solve Model 1 using a mathematical programming approach, Constraint (6) is stated in a non-linear form. This constraint could easily be linearized by introducing a new binary decision variable that reflects whether or not truck w

rides collection route r on day d in shift t and adding constraints that ensure that this new variable is 1 if both $\lambda_{r,d,w}$ and $x_{t,d,w}$ are 1; and 0 otherwise.

Constraint (7) shows that $\tau^{route}_{t,r,d,w}$ is a function of all routing variables $\lambda_{r',d',w'}$ with $r' \in R$, $d' \in D$, $w' \in W$ and all shift scheduling variables $x_{t',d',w'}$ with $t' \in T$, $d' \in D$ and $w' \in W$. Recall that $\tau^{route}_{t,r,d,w}$ represents the **average** working time of truck w on day d riding route r during shift t. This means that this working time could be longer than $\tau^{route}_{t,r,d,w}$ in some weeks (this will be the case in weeks where there are relatively fewer drop-offs thanks to low fill levels of the containers and truck at the start of the day), but this must be compensated by higher working times (for the same route and shift) in other weeks, in order to reach an average working time equal to $\tau^{route}_{t,r,d,w}$. Unfortunately, it is very hard to calculate $\tau^{route}_{t,r,d,w}$ exactly using a closed-form expression. Therefore, we will approximate $\tau^{route}_{t,r,d,w}$ using simulation as explained in Section 4.2. However, some components of $\tau^{route}_{t,r,d,w}$ do not depend on the other routing and shift scheduling decisions and therefore can easily be calculated exactly for a certain route r during shift type t. To see this, $\tau^{route}_{t,r,d,w}$ can be written as the sum of three separate times, as follows:

$$\tau^{route}_{t,r,d,w} = \Theta^{driving}_{t,r} + \tau^{collection}_{r,d} + \tau^{drop\text{-}off}_{t,r,d,w} \tag{8}$$

According to Equation (8), the total average working time ($\tau^{route}_{t,r,d,w}$) consists of three parts, namely the driving time ($\Theta^{driving}_{t,r}$), the collection time ($\tau^{collection}_{r,d}$) and the drop-off time ($\tau^{drop\text{-}off}_{t,r,d,w}$). The first part ($\Theta^{driving}_{t,r}$) only represents the driving time from the depot location to the first container in route r, the driving time between all consecutive containers in route r and the driving time from the last container in route r back to the depot location. Hence, $\Theta^{driving}_{t,r}$ only depends on the sequence of glass containers in route r and is independent of the fill level of the containers and the fill level of the truck. This means that $\Theta^{driving}_{t,r}$ is independent from the other routing and shift scheduling decisions, but only depends on the current route r and the scheduled shift type t. Recall that these driving times depend on the shift type, however they are assumed to be deterministic in the considered time horizon.

The second part of the total average working time is the collection time $\tau^{collection}_{r,d}$. Note that this time is independent of the scheduled shift type t, because it does not contain any driving time. The collection time only consists of the *average* collection time for all containers in route r. Hence, it is the time required to empty containers when one of its compartments is filled for at least the collection threshold on day d. Therefore, the collection time $\tau^{collection}_{r,d}$ not only depends on the routing decision for truck w on day d but also on the routing decisions on the other days and for the other trucks. Moreover, whereas the driving time $\Theta^{driving}_{t,r}$ is independent of the day, the collection time $\tau^{collection}_{r,d}$ does depend on the day during which the route is executed because the fill level of each container can be different on each day. In our model $\tau^{collection}_{r,d}$ represents an average over all weeks in the considered time horizon while we assumed $\Theta^{driving}_{t,r}$ to be constant over all weeks.

The drop-off time $\tau^{drop\text{-}off}_{t,r,d,w}$ consists of two parts: the average time required to interrupt the route when the truck is getting full and the average time required to unload the truck at the drop-off location. Just as $\tau^{collection}_{r,d}$, the drop-off time $\tau^{drop\text{-}off}_{t,r,d,w}$ also depends on all other routing decisions (for other trucks on other days), because the position of the different drop-offs in the route (which determines the total driving time to and from the drop-off location) and the number of required drop-offs (which determines the total unloading time), not only depend on the fill level of the containers on day d, but also on the initial fill level of truck w at the beginning of that day. Just as $\Theta_{t,r}^{driving}$, the drop-off time $\tau_{t,r,d,w}^{drop\text{-}off}$ contains driving times (during the trips to and from the drop-off) and thus depends on the scheduled shift type t. Finally, just as $\tau_{r,d}^{collection}$, $\tau_{t,r,d,w}^{drop\text{-}off}$ represents an average over all weeks in the considered time horizon.

Note that, based on the former definition of $\Theta_{t,r}^{driving}$, the sum of the three terms in Equation (8) would account for more time than is actually required. Indeed, when a drop-off is required, the truck immediately goes from container K to the drop-off location and returns to the next container $K+1$ in the route (with K the value of the index of a container in the route). Hence, the trip from container K to $K+1$ (trip $K \to K+1$), which is included in $\Theta_{t,r}^{driving}$, gets replaced by trip $K \to$ drop-off $\to K+1$, which is included in the drop-off time $\tau_{t,r,d,w}^{drop\text{-}off}$. To make sure that we do not account for more driving time than is actually required, these excess driving times (from K to $K+1$) should be subtracted. The substraction of this excess driving time is accounted for in $\tau_{r,d}^{collection}$ and $\tau_{t,r,d,w}^{drop\text{-}off}$. This is very important in order for the proposed solution technique to perform well and is further explained in Section 4.4.

Recall that $\tau_{r,d}^{collection}$ and $\tau_{t,r,d,w}^{drop\text{-}off}$ not only depend on the current routing decision but also depend on routing decisions on other days for other trucks, while $\Theta_{t,r}^{driving}$ only depends on the current route r and current shift type t. Therefore, both $\tau_{r,d}^{collection}$ and $\tau_{t,r,d,w}^{drop\text{-}off}$ are a function of the set of all routing variables $\lambda_{r',d',w'}$ and shift scheduling variables $x_{t',d',w'}$ with $t' \in T$, $d' \in D$ and $w' \in W$:

$$\tau_{r,d}^{collection} = f'\begin{pmatrix}\{\lambda_{r',d',w'} : r' \in R, d' \in D, w' \in W\}, \\ \{x_{t',d',w'} : t' \in T, d' \in D, w' \in W\}\end{pmatrix}, \quad \forall r \in R, \forall d \in D$$

$$\tau_{t,r,d,w}^{drop\text{-}off} = f''\begin{pmatrix}\{\lambda_{r',d',w'} : r' \in R, d' \in D, w' \in W\}, \\ \{x_{t',d',w'} : t' \in T, d' \in D, w' \in W\}\end{pmatrix}, \quad \forall t \in T, \forall r \in R, \forall d \in D, \forall w \in W$$

As our problem contains the vehicle routing problem (VRP), our problem is NP-hard. This makes it very difficult to solve to optimality in a reasonable amount of time for realistic sized instances. But even without the difficulty added by the VRP, solving Model 1 is not straightforward. The difficulty of solving Model 1 clearly lies in the complex calculation of $\tau_{t,r,d,w}^{route}$ and in particular of $\tau_{r,d}^{collection}$ and $\tau_{t,r,d,w}^{drop\text{-}off}$. An explicit definition of $\tau_{r,d}^{collection}$ and $\tau_{t,r,d,w}^{drop\text{-}off}$ implies an explicit formulation of the functions $f'()$ and $f''()$. This would require a complete mathematical description of the entire collection process in each week of the considered time horizon linking the fill level of each container and the route decision for each truck driver on each day with each other. Instead of such a complex explicit mathematical formulation, simulation is much better suited for these cases. We evaluate a certain workforce schedule with a simulation model resulting in a value for $\tau_{r,d}^{collection}$ and $\tau_{t,r,d,w}^{drop\text{-}off}$ without the requirement for an explicit mathematical formulation of $f'()$ and $f''()$ in the optimization model. Since $\tau_{r,d}^{collection}$ and $\tau_{t,r,d,w}^{drop\text{-}off}$ are averages on day d over all weeks in the considered time horizon, simulation also removes the need to model each single week explicitly in the optimization model.

4. Methodology

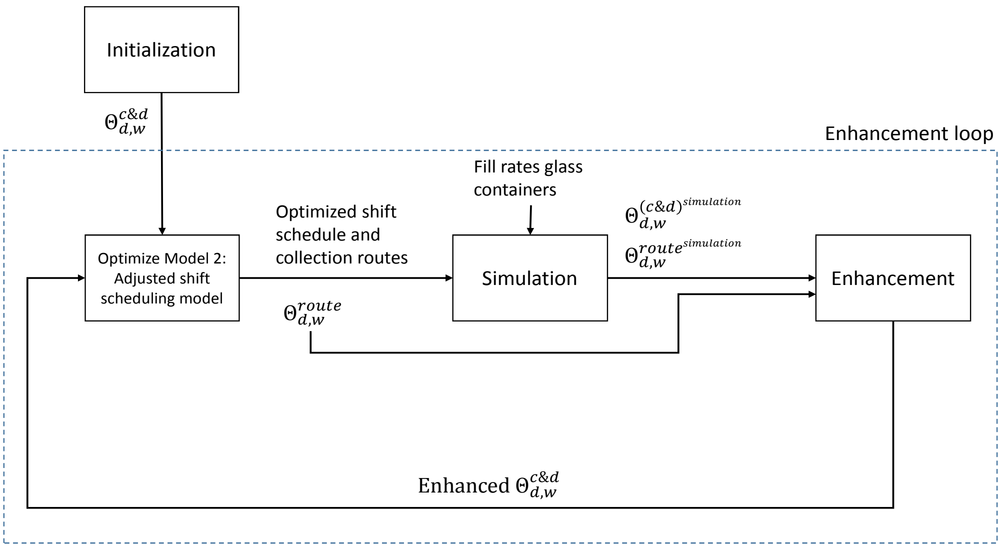
4.1. Model Enhancement

One way to solve Model 1 presented above is to estimate $\tau_{r,d}^{collection}$ and $\tau_{t,r,d,w}^{drop\text{-}off}$ for each day, truck, route and shift type and to use this estimate in the optimization model. This way, variables $\tau_{r,d}^{collection}$ and $\tau_{t,r,d,w}^{drop\text{-}off}$ are transformed into parameters $\Theta_{r,d}^{collection}$ and $\Theta_{t,r,d,w}^{drop\text{-}off}$, removing the need for Constraint (7) in Model 1. Hence, $\Theta_{r,d}^{collection}$ and $\Theta_{t,r,d,w}^{drop\text{-}off}$ are independent of the shift and route decisions in the optimization model. This is of course a simplification that allows us to approximate $\tau_{r,d}^{collection}$ and $\tau_{t,r,d,w}^{drop\text{-}off}$ without explicitly modeling them in the optimization model. However, we do not know whether we will obtain a good or even feasible solution this way. Because of its simplicity, this approach is called straightforward optimization by Bachelet and Yon (2007).

A better way to approximate $\tau_{r,d}^{collection}$ and $\tau_{t,r,d,w}^{drop\text{-}off}$ is to use ME which allows to iteratively improve the initial estimate of $\tau_{r,d}^{collection}$ and $\tau_{t,r,d,w}^{drop\text{-}off}$ with the help of simulation. In an ME model, optimization and simulation are used in an iterative procedure to enhance the optimization model. Hence, the goal is to exploit the benefits of simulation which allows us to solve the problem without an explicit formulation of $f'()$ and $f''()$. Just as with straightforward optimization, ME allows us to replace the variables $\tau_{r,d}^{collection}$ and $\tau_{t,r,d,w}^{drop\text{-}off}$ by parameters. However, in contrast to straightforward optimization, the estimate of the parameter values is enhanced during each ME iteration based on a simulation run.

The three phases of the ME procedure are shown in Figure 1 and are discussed below.

Figure 1: Model enhancement algorithm



4.2. Phase I: Optimization

In order to apply ME to solve Model 1, variables $\tau_{r,d}^{collection}$ and $\tau_{t,r,d,w}^{drop\text{-}off}$ are transformed into parameters. Therefore, $\tau_{r,d}^{collection}$ and $\tau_{t,r,d,w}^{drop\text{-}off}$ are modeled to be independent of the routing and shift scheduling decisions during the intermediate optimizations. This means that we will estimate the collection time and the drop-off time during a certain shift avoiding the need to calculate these times based on the start information (container and truck fill levels) and collection routes. We simply start with an estimate and update this estimate during the ME phase III based on the information received from the simulation phase II. If the simulation results show that our estimate was too low for the collection route during a particular shift, the parameter estimate will be increased for the next optimization phase using ME in such a way that the estimate will converge to the correct value.

To translate this strategy to our model, the route index r in the subscripts of $\tau_{r,d}^{collection}$ and $\tau_{t,r,d,w}^{drop\text{-}off}$ should be removed (since the model decides on the route). Since there can only be one route for each day and truck (see Constraint (2)), the route index r can be replaced by the truck index w. Second, making $\tau_{r,d}^{collection}$ and $\tau_{t,r,d,w}^{drop\text{-}off}$ independent of the decisions made by the optimization model means that also the shift type index t can be removed (since the model decides on the scheduled shift types).

Hence, both variables are transformed into parameters as follows:

$$\begin{array}{lcl} \tau_{r,d}^{collection} & \rightarrow & \Theta_{d,w}^{collection} \\ \tau_{t,r,d,w}^{drop\text{-}off} & \rightarrow & \Theta_{d,w}^{drop\text{-}off} \end{array}$$

Because both $\Theta_{d,w}^{collection}$ and $\Theta_{d,w}^{drop\text{-}off}$ will now be parameters in the optimization model with the same indices d and w, we can add them together as $\Theta_{d,w}^{c\&d}$:

$$\Theta_{d,w}^{c\&d} = \Theta_{d,w}^{collection} + \Theta_{d,w}^{drop\text{-}off}, \qquad \forall d \in D, \forall w \in W$$

We can now formulate Model 2, the adjusted shift scheduling model, as an approximation of Model 1. Model 2 only differs from Model 1 regarding Constraint (6) and Constraint (7). These two constraints are replaced by Constraint (9) as follows:

Model 2: Adjusted shift scheduling model

$$\text{Minimize: } \sum_{t \in T} \sum_{d \in D} \sum_{w \in W} x_{t,d,w} C_{t,d,w}$$

Subject to:

Constraints (2) to (5)

$$\sum_{t \in T} \sum_{r \in R} \Theta_{t,r}^{driving} \lambda_{r,d,w} x_{t,d,w} + \sum_{r \in R} \Theta_{d,w}^{c\&d} \lambda_{r,d,w} \leq \Theta^{Max}, \qquad \forall d \in D, \forall w \in W \quad (9)$$

At the start of the ME algorithm the parameter $\Theta_{d,w}^{c\&d}$ is initialized to an initial estimate for each day $d \in D$ and each truck $w \in W$. The estimates for $\Theta_{d,w}^{c\&d}$ are subsequently enhanced during the enhancement phases (phase III) of the ME algorithm.

For real-life dimensions, Model 2 cannot be solved to optimality in a reasonable time limit. The real-life problem under study consists of 300 glass containers that have to be visited each week by a truck. For each of these containers, we have to decide on which day during which shift and in which position in the route they will be visited. Moreover, we have to decide on the number and the types of shifts in which the type of shift has an impact on the collection speed. This type of integrated vehicle routing - shift scheduling problem is a complex problem that with the current state of knowledge cannot be solved efficiently using a mathematical programming approach. Moreover, Model 2 needs to be solved in each iteration of the ME algorithm, after which simulation is used to verify the estimates used. Obviously, we want a quality solution to Model 2 in each iteration of ME, but optimality is not strictly required as the best solution found is saved and updated each time a better solution is found. For all of these reasons a metaheuristic, that combines Tabu Search (TS) (Glover and Laguna, 1997) for the high-level shift scheduling problem and cheapest insertion for the lower-level routing problem, is used to solve Model 2.

The TS algorithm swaps the shift type of a scheduled shift. The idea behind swapping P by N shifts is to reduce the number of truck days (which is the total number of required shifts). Depending on the cost of an N shift, this swap move could decrease the objective value (the total weekly labor costs). However, the capability of TS to escape from local optima is particularly suitable here because swapping a P shift for an N shift will in most cases not immediately decrease the objective value. The idea behind swapping N shifts by P shifts is to decrease the total weekly costs while maintaining the same number of truck days.

In each optimization phase, the TS algorithm is applied to the shift schedule obtained during the previous optimization phase. For the first iteration, a start shift schedule is constructed using a greedy heuristic that adds P shifts until all containers can be included in a collection route.

In order to evaluate each swap move, a collection route is constructed for each scheduled shift in the adjusted shift schedule until all containers are included in a collection route. The collection routes are constructed using a cheapest insertion heuristic aiming at small total driving times. When not all shifts are needed to include all containers in the collection routes, the unnecessary shifts are removed. Conversely, when the scheduled capacity (in terms of shifts) is insufficient to construct collection routes such that all containers can be included, an extra P shift is added to the end of the shift schedule. The constructed collection routes are first assigned to the schedule of the first truck and only then to the second truck.

Note that compressing the collection routes in view of reducing the required number of shifts means that the total driving time of the obtained solution does not necessarily decrease during the enhancement iterations. Therefore, the best shift schedule with the lowest total driving time is saved during the enhancement procedure.

When the collection routes are constructed, the succession constraints (4) are checked and the shift schedule is adjusted if necessary. When the succession constraints (4) are violated because of the swap move, the necessary days off are inserted (if possible) to render the shift schedule feasible again. This step also allows to remove unnecessary days off from the shift schedule resulting from the swap move.

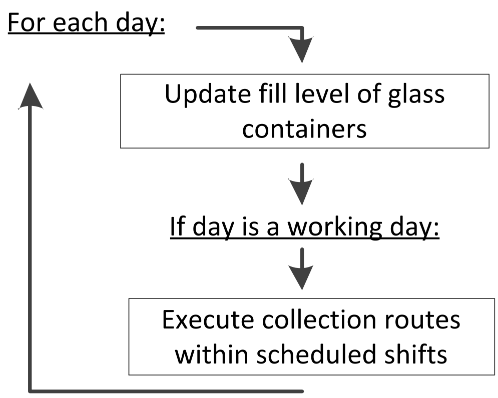
After building and optimizing the collection routes and adding or removing shifts from the adjusted shift schedule, the cost of the shift schedule is calculated according to objective function (1) in order to numerically evaluate each move. Note that it is only during the construction of the collection routes that Constraint (9) is checked to ensure a feasible shift schedule.

During each optimization phase, 100 tabu search iterations are performed. The optimization phase will always result in a feasible result with respect to Constraint (9). While the objective value of the obtained result is not necessarily lower than the one during the previous enhancement iteration, the assumptions made in the model (i.e., the approximation of the real average collection and drop-off times by $\Theta_{d,w}^{c\&d}$) are getting more realistic. Eventually, this will result in good feasible solutions with respect to Constraints (6) and (7) in model 1.

4.3. Phase II: Simulation

During phase II a simulation model is ran in order to evaluate the solution obtained in phase I. Figure 2 shows a schematic overview of the steps in the simulation process.

Figure 2: Schematic overview of the simulation process



As Figure 2 shows, the fill level of all glass containers is only updated at the beginning of each day based on the fill rate (see Section 3.2). This means that the simulation model has a precision of one day. Hence, we assume that the containers are filled at the beginning of each day with the total amount of glass that was dropped in the container during the previous day. During the rest of the day, no glass is added to the container. When the current day in the simulation is a working day (i.e., not a weekend day), the scheduled collection routes are executed within the scheduled shifts. The execution of the collection routes is simulated by letting a truck with a certain capacity follow the route within the scheduled shift. Recall that the initial fill level of the truck depends on the final fill level during the previous shift of that truck. The truck visits each container according to the collection route and collects the glass of the visited container if one of its compartments is filled for at least the collection threshold. When the truck is full, the collection route is interrupted by a trip to the drop-off location.

The goal of the simulation is to evaluate the solution obtained during the optimization phase with respect to the total average working time on each day d for each truck w. Hence, the simulation gives us the real (under the assumptions of the simulation) value of the Left-Hand Side (LHS) of Constraint (6) in model 1. Since Constraint (9) in model 2 is only an approximation of Constraint (6) in Model 1, Constraint (6) may or may not be satisfied according to the simulation results. To make sure that Constraint (9) is a good approximation of Constraint (6), causing both Constraint (9) and Constraint (6) to be satisfied, the simulation information is used to enhance the approximation. This is done during the enhancement phase.

4.4. Phase III: Enhancement

During the enhancement phase, the estimate of $\Theta_{d,w}^{c\&d}$ in Model 2 is enhanced based on the simulation results during phase II. The following notations are used to formulate the enhancement function:

$\Theta_{d,w}^{route^{Simulation}}$: average time required according to the simulation to perform the route scheduled on day d with truck w with the scheduled shift type on day d for truck w (in hours). Recall that we define the total route time as the sum of the driving, collection and drop-off time.

$\Theta_{d,w}^{(c\&d)^{Simulation}}$: average time required according to the simulation to empty glass containers and to perform the required drop-offs in the route scheduled on day d with truck w with the scheduled shift type on day d for truck w (in hours).

Next, we define δ as the index of the enhancement iterations, with $\delta = 1$ the first enhancement iteration. Using δ, all notations in Model 2 can be indexed for each enhancement iteration. This way, we can define:

$\Theta_{d,w}^{route^{\delta}}$: total estimated average time (resulting from the optimization of Model 2) required to perform the route scheduled on day d with truck w with the scheduled shift type on day d for truck w during enhancement iteration δ (in hours). Recall that we define the total route time as the sum of the driving, collection and drop-off time. Hence, this equals the value of the LHS of Constraint (9) in the optimal solution for Model 2 during enhancement iteration δ.

$\Theta_{d,w}^{(c\&d)^{\delta}}$: estimate during enhancement iteration δ of the average time required to empty glass containers and to perform the required drop-offs in the route scheduled on day d with truck w with the scheduled shift type on day d for truck w (in hours).

Based on the former definitions, we can now state the enhancement function to enhance the previous value of $\Theta_{d,w}^{c\&d}$ as follows:

$$\text{If} \quad \left(\Theta_{d,w}^{route^{Simulation}} \leq \Theta^{Max}\right):$$

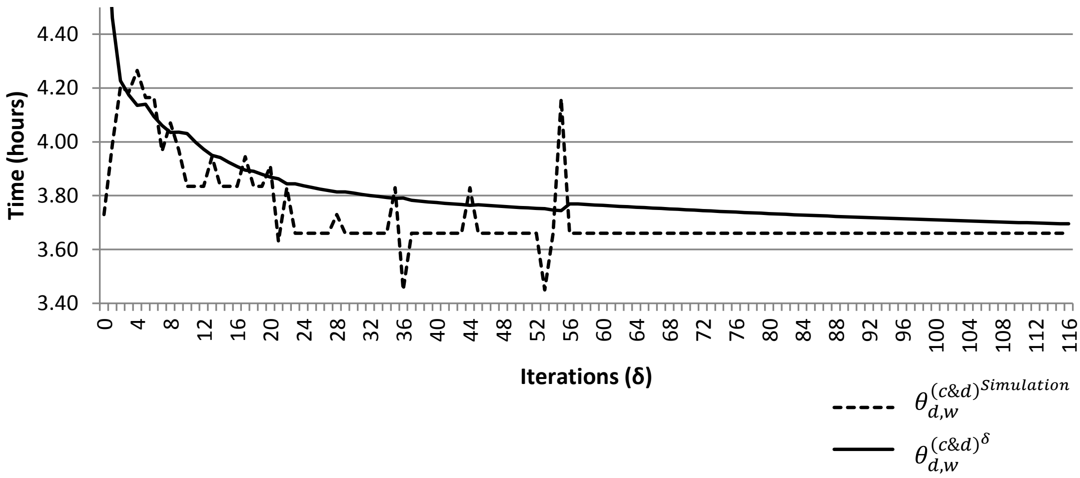
$$\Theta_{d,w}^{(c\&d)^{\delta+1}} = \frac{\Theta_{d,w}^{(c\&d)^{\delta}} \cdot \delta}{\delta+1} + \frac{\Theta_{d,w}^{(c\&d)^{Simulation}}}{\delta+1}$$

Else:

$$\Theta_{d,w}^{(c\&d)^{\delta+1}} = \Theta_{d,w}^{(c\&d)^{\delta}} + \Theta^{Max} - \Theta_{d,w}^{route^{\delta}} + 0.01 \qquad (10)$$

In enhancement function (10), $\Theta_{d,w}^{(c\&d)^{\delta+1}}$ is the estimate during the next enhancement iteration of the average time required to empty glass containers and to perform the required drop-offs in the route scheduled on day d with truck w with the scheduled shift type on day d for truck w. If $\Theta_{d,w}^{route^{Simulation}} \leq \Theta^{Max}$, a moving average is calculated causing the impact of the simulation to diminish over time. This way, we seek after the convergence of $\Theta_{d,w}^{c\&d}$. As $\Theta_{d,w}^{c\&d}$ converges and stabilizes, $\Theta_{d,w}^{(c\&d)^{Simulation}}$ can also converge and stabilize. In most cases, $\Theta_{d,w}^{c\&d}$ will therefore converge to $\Theta_{d,w}^{(c\&d)^{Simulation}}$ just as in Figure 3.

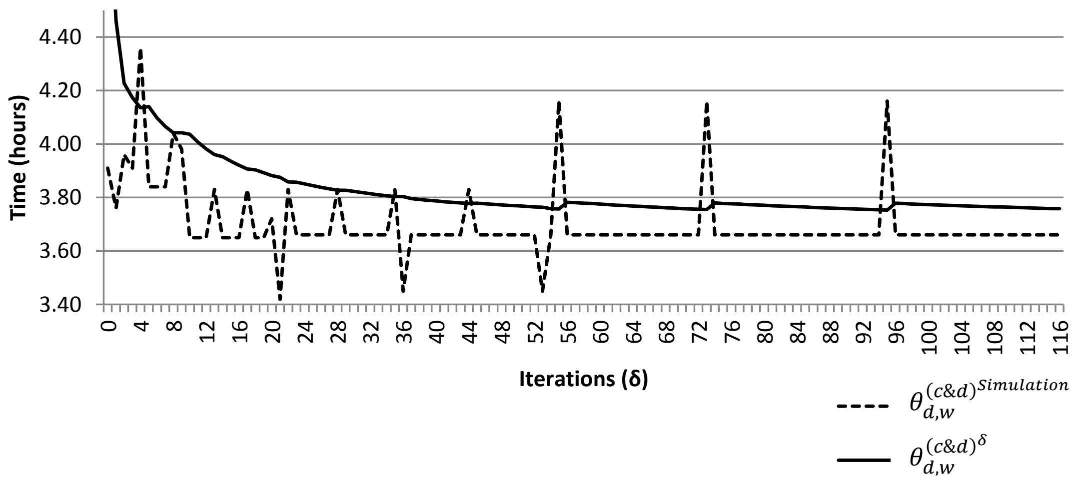
Figure 3: Example of the convergence of $\Theta_{d,w}^{c\&d}$ to $\Theta_{d,w}^{(c\&d)^{Simulation}}$



However, it is possible that $\Theta_{d,w}^{c\&d}$ will not converge to $\Theta_{d,w}^{(c\&d)^{Simulation}}$ as is shown in Figure 4. Figure 4 shows an example of the progress of $\Theta_{d,w}^{c\&d}$ and $\Theta_{d,w}^{(c\&d)^{Simulation}}$ over the course of 116 enhancement iterations for a certain day and truck. As the graph in Figure 4 shows, $\Theta_{d,w}^{c\&d}$ descends towards $\Theta_{d,w}^{(c\&d)^{Simulation}}$ during the first 54 iterations. However, during iteration 55, $\Theta_{d,w}^{(c\&d)^{Simulation}}$ suddenly peaks over $\Theta_{d,w}^{c\&d}$. It is at this point that $\Theta_{d,w}^{c\&d}$ is small enough to add one extra glass container in the route of this truck according to Model 2. Recall, however, that Model 2 does not immediately take into account the possible extra collection and drop-off time that is required to add this extra glass container. In order for Model 2 to take this extra time into account, we have to wait for the feedback from the simulation evaluation. As the peaks during iterations 55, 73 and 95 show, it appears to be impossible to add an extra container to the route when the extra collection and drop-off time is accounted for. In other words, the total average working time is greater than Θ^{Max} during these peaks. Hence, $\Theta_{d,w}^{c\&d}$ can never be as low as $\Theta_{d,w}^{(c\&d)^{Simulation}}$ in this case since we do not immediately take into account the extra required collection and drop-off time.

When $\Theta_{d,w}^{route^{Simulation}} > \Theta^{Max}$, we want to escape as quickly as possible from this infeasible situation. Therefore, the second part (the Else case) of the enhancement function (10) is applied. In order to avoid spending too much time in the infeasible situation waiting for $\Theta_{d,w}^{(c\&d)^{\delta}}$ to increase with the help of the moving average, $\Theta_{d,w}^{(c\&d)^{\delta}}$ is immediately increased by the spare time during iteration δ ($\Theta^{Max} - \Theta_{d,w}^{route^{\delta}}$). To ensure that the extra container cannot remain in the route, an extra 0.01 hours is added. This makes sure that the container is removed from the route during iteration $\delta + 1$. This explains why $\Theta_{d,w}^{(c\&d)^{Simulation}}$ peaks at iterations 55, 73 and 95, and drops immediately at the next iteration. This procedure renders the solution feasible more quickly and assures more stability during the next iterations which allows to find better solutions more quickly.

Figure 4: Example of the convergence of $\Theta_{d,w}^{c\&d}$



To determine the value of $\Theta_{d,w}^{(c\&d)^{Simulation}}$ during the enhancement procedure, we do not directly use the collection and drop-off time supplied by the simulation. In Section 3.3 we argued that the drop-off time, as it is defined in Section 3.3, should be reduced by some driving time in order for Equation (8) to be exact as $\Theta_{t,r}^{driving}$ contains some unnecessary container-to-container driving times when one or more drop-offs are required. To ensure that we only account for the necessary driving time, $\Theta_{d,w}^{(c\&d)^{Simulation}}$ should be reduced by these excess driving times. Therefore, we use Equation (11) to determine the value of $\Theta_{d,w}^{(c\&d)^{Simulation}}$ based on $\Theta_{d,w}^{route^{Simulation}}$ and the driving times resulting from the optimization phase. $\Theta_{d,w}^{route^{Simulation}}$ contains the driving times for a trip to and from the drop-off ($K \rightarrow$ *drop-off* $\rightarrow K+1$), but not the driving time for the unnecessary trip $K \rightarrow K+1$, while $\sum_{t\in T}\sum_{r\in R}\Theta_{t,r}^{driving}\lambda_{r,d,w}x_{t,d,w}$ does contain the driving time for the unnecessary trip $K \rightarrow K+1$. Hence, enhancing $\Theta_{d,w}^{(c\&d)^{\delta}}$ based on $\Theta_{d,w}^{(c\&d)^{Simulation}}$ and using it in Constraint (9) ensures that we only account for the necessary driving time:

$$\Theta_{d,w}^{(c\&d)^{Simulation}} = \Theta_{d,w}^{route^{Simulation}} - \sum_{t\in T}\sum_{r\in R}\Theta_{t,r}^{driving}\lambda_{r,d,w}x_{t,d,w} \tag{11}$$

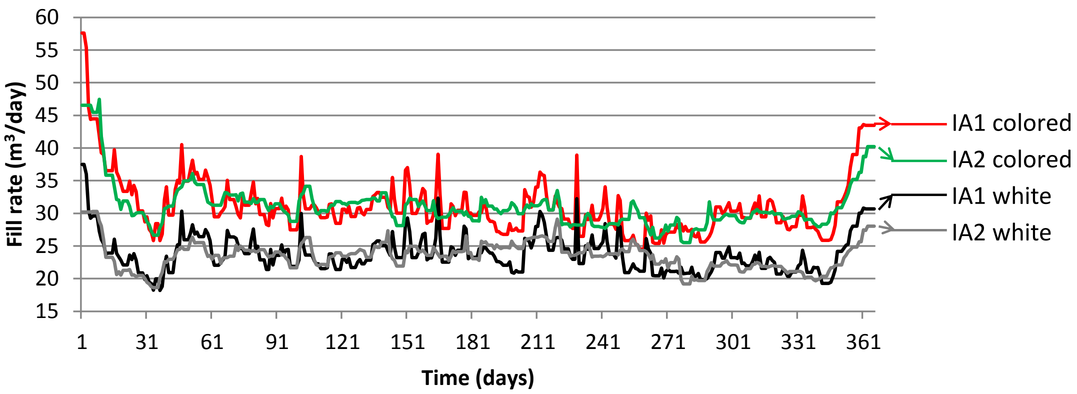
5. Results and discussion

The proposed ME procedure (developed in C++) allows to solve Model 1 in order to analyze the possible advantages of introducing a second shift type. We focus on one specific IA. This IA is selected based on the availability of data, the reliability of the available data and the geographic location of the IA (a fairly urbanized and busy area). Because of confidentiality reasons, we cannot give the name of the IA under study, but we can present some of its key properties. In the IA under study, two trucks are available each day for glass collection. Each truck has 2 compartments - one for white and one for colored glass. Although in practice both compartments can hold about 50% of the total volume, we will assume the more efficient proportion of 13 m^3 for white glass and 17 m^3 for colored glass (see De Bruecker et al. (2015) for a more detailed discussion). Furthermore, two truck drivers are employed that cannot work in the weekend. In total, there are more than 300 containers in the IA, located on more than 200 different sites. Most of the containers are duo containers, while only a small fraction consists of standard containers. We assume that duo containers take 6 minutes to empty and can hold 1.675 m^3 glass in each of its compartments, while standard containers take 12 minutes and can hold 4 m^3 glass. At the drop-off site, loading and unloading is assumed to take 20 minutes. Finally, we assume a collection threshold of 40%, meaning that visited containers are only emptied when one of its compartments is filled for at least 40%. This percentage is based on a trade-off between overtime and glass overflow volume and is discussed in more detail in De Bruecker et al. (2015).

The driving times were obtained automatically through the Google Maps API and hence take into account speed limits, congestion, traffic lights and even the driving direction (A to B is different from B to A).

Based on real-life collection data of one year, the daily fill rate of each compartment of each container is calculated according to the procedure described in Section 3.2. Figure 5 shows a graphical representation of the aggregated daily fill rate (in m^3) for white and colored glass for two IAs, where IA1 is the IA under study. The fill rate shows a similar trend for both IAs and shows large peaks during the New Year period. The ratio between white and colored glass is also very similar in both IAs.

Figure 5: Aggregated daily fill rate during one year



5.1. Theoretical results

Before we apply the ME model to the real-life setting, we first analyze the performance of the model regarding feasibility and solution quality. To get a good view on the performance of the proposed solution technique, we create a set of test cases that are based on the first 4 weeks of the year. Recall that this considered time frame falls within the peak period for glass collection. Therefore, we can assume that the fill rate during the rest of the year will not be higher than during these four weeks. Hence, finding a good feasible schedule for this period is more challenging which makes the considered time frame very interesting.

To allow for a thorough analysis, five different scenarios are constructed regarding the average driving speed during an N shift compared to a P shift. For each of the different speed-up scenarios, six different scenarios are constructed regarding the cost premium for an N shift compared to a P shift. The results of the ME algorithm for these 30 different test cases are presented in Table 1 using the following definitions:

σ:	factor (≤ 1) that is used to multiply the driving times in a P shift to obtain the driving times in an N shift.
C_N:	cost of an N shift. The cost of a P shift (C_P) is always assumed to be 1.
$\theta_w^{estimate}$	$= Avg_{d \in D} \left\{ \Theta_{d,w}^{route} \right\}$ = estimate in Model 2 of the average working hours for truck w over all active truck days for truck w.
$\theta_w^{simulation}$	$= Avg_{d \in D} \left\{ \Theta_{d,w}^{route^{Simulation}} \right\}$ = average working hours for truck w over all active truck days for truck w according to the simulation.

We test the model for five different σ values ranging from 0.9 to 0.5 and six different C_N values ranging from 1.1 to 1.6. Columns 2 and 3 of Table 1 show the value of σ and C_N respectively. The index of each of the 30 test cases is shown in Column 1. The results presented in columns 4 to 9 are obtained by running the ME algorithm for 100 iterations. This takes on average 10 minutes for each test case. Columns 4 to 6 show the required number of truck days, the required number of P and N shifts and the resulting weekly costs of the shift schedule. Columns 8 to 9 show for each of the 2 trucks (indexed in column 7) the average estimated working hours and the average simulated working hours. At the bottom of Table 1, we show the average and the standard deviation of columns 8 and 9.

5.1.1. Feasibility

The first criterion for a good solution is of course the feasibility of the solution with respect to all the constraints in Model 1 (i.e., Constraints (2) to (7)). In this section we only focus on the feasibility with respect to Constraints (6) and (7) as these are the constraints that are approximated by constraint 9 in Model 2 with the aid of ME. All other constraints in Model 1 are also present in Model 2 and will therefore be satisfied by definition. Hence, we want the real (i.e., simulated over the four weeks in our considered time frame) total average working hours of the obtained solutions to be less than or equal to 7.5 hours (Θ^{Max}) on each day for each truck. The convergence of $\Theta_{d,w}^{c\&d}$ (possibly, but not necessarily to $\Theta_{d,w}^{(c\&d)^{Simulation}}$) which is aimed at during the enhancement phase in the ME procedure, should ensure that Constraints (6) and (7) in Model 1 are satisfied. When $\Theta^{c\&d}_{d,w}$ converges to $\Theta^{(c\&d)^{Simulation}}_{d,w}$, Constraint 9 is a good approximation of Constraints (6) and (7). Hence, when Constraint (9) is satisfied, Constraints (6) and (7) are also satisfied. As we have shown in Section 4.4, $\Theta^{c\&d}_{d,w}$ will not always converge to $\Theta^{(c\&d)^{Simulation}}_{d,w}$. If it does not converge, $\Theta^{c\&d}_{d,w}$ will be greater than $\Theta^{(c\&d)^{Simulation}}_{d,w}$. Therefore, Constraints (6) and (7) are satisfied when Constraint (9) is satisfied.

While the tabu search algorithm during the optimization phase in the ME procedure ensures that Constraint (9) in Model 2 is never violated, it is the enhancement phase that has to make sure that Constraints (6) and (7) are satisfied. We found that our ME procedure is able to find a feasible result for each test case (satisfying Constraints (6) and (7)). Column 9 of Table 1 then also shows that the real (simulated) average total working time (over all active truck days) $\theta^{simulation}_{w}$ is less than or equal to 7.5 hours for each test case. As can be observed in these two tables, $\theta^{estimate}_{w}$ and $\theta^{simulation}_{w}$ always lie fairly close to each other. Furthermore, there is no statistically significant difference between these two averages (two sided p value of 0.2994).

5.1.2. Solution quality

The second criterion of a good solution is the solution quality in terms of the obtained objective value (the weekly costs). The obtained objective value for each of the test cases can be found in column 6 of Table 1.

We compare the results of the ME procedure with the results of a flexible schedule (see De Bruecker et al. (2015)). Recall that in our fixed schedule, we assumed that each container must be visited at least once a week. However, visiting a container does not necessarily mean that it will also be emptied. A container is only emptied when one of its compartments is filled for at least 40%. Based on sensor information, it is possible to eliminate these useless trips. This means, however, that we have to abandon a fixed schedule and use a flexible schedule which can be different for each truck on each day in each week. A rolling horizon procedure is used by (De Bruecker et al., 2015) in order to construct this flexible schedule. Interested readers are referred to latter work for a detailed description of this approach.

It is very likely that a flexible schedule will result in fewer truck days since we only construct a collection route if necessary. However, the average weekly number of truck days of the flexible schedule cannot be seen as a theoretical lower bound (LB) since the rolling horizon approach does not take into account the long-term effects of the collection decisions (De Bruecker et al. (2015)). Hence, it cannot be proven that the flexible schedule will always perform better than the fixed schedule. However, we argue that the results of the flexible schedule can be seen as a practical lower bound for the minimal effort (in terms of truck days) that is required to make sure that the glass overflow (glass placed next to the containers) is minimal. Johansson (2006), for example, concludes that with relative large systems (more than 100 containers), dynamic scheduling (i.e., constructing a flexible schedule) performs best. Johansson (2006) further concludes that the highest savings of this dynamic policy are achieved in environments with high demand fluctuation. Also Mes (2012) states that with seasonal patterns and huge random variations from day to day, a flexible schedule outperforms a fixed schedule. Both authors compare their flexible scheduling results to a fixed schedule and conclude that a flexible schedule can save on average 10% in working time or costs. As we also face a very large system (over 300 containers) and an environment with seasonal patterns and high glass disposal fluctuations, similar savings are expected.

Table 2 shows a comparison of the ME results with the results of the flexible schedule (LB) in terms of the minimal average required number of truck days. Again, we focus on the same four weeks as previously to produce the results and we make this comparison for the same five σ cases. Columns 2 and 3 of Table 2 give the results for the scenario where we only consider N shifts. Columns 4 and 5 give the results for the scenario where we only consider P shifts. It is impossible to test the scenarios where we allow for a mix of P and N shifts since this is impossible within the framework of a flexible schedule. The rolling horizon procedure to obtain a flexible schedule (as outlined by (De Bruecker et al., 2015)) makes decisions on a daily basis and is therefore not designed to produce a good (or optimal) overall (over all days) mix of N and P shifts which satisfies the shift succession constraints. Therefore, only N or only P shifts are considered to analyze the LB.

As Table 2 shows, the LB is always smaller than the ME result. Note that the LB is an average calculated by dividing the total number of required truck days over the considered planning horizon by the number of weeks in the considered time horizon. Since each week can be different in a flexible schedule, the LB can therefore have a fractional value. This is of course impossible for the fixed schedule scenario. Hence, rounding the LB to the next integer also results in an even stronger (practical) lower bound for the fixed schedule scenario. Comparing the (rounded) LB and the ME results shows that the ME procedure produces the best possible solution for a fixed schedule, compared to a flexible schedule (at least for the cases where we consider only N or only P shifts). This strongly suggests that our ME method is capable of finding good (even possibly optimal) solutions for the fixed schedule scenario. In the research presented by (De Bruecker et al., 2015), the authors go even further and also analyze the quality of the obtained solutions based on the properties of an optimal solution. They prove that the proposed solution technique can produce results that meet certain optimality conditions. This does, however, still not prove the optimality of the individual solutions. It does, however, indicate that the proposed solution approach does not seem to arbitrarily perform better or worse for some problem instances as the full set of solutions resembles an optimal structure. Interested reader are referred to the latter research for more information.

Table 1: Theoretical results Fost Plus

Case	σ	C_N	Truck days	Shifts	Weekly costs	Truck w	$\theta_w^{estimate}$	$\theta_w^{simulation}$
1	0.9	1.1	8	8P + 0N	8.00	1	7.36	7.26
						2	6.94	6.94
2	0.9	1.2	8	8P + 0N	8.00	1	7.36	7.26
						2	6.94	6.94
3	0.9	1.3	8	8P + 0N	8.00	1	7.36	7.26
						2	6.94	6.94
4	0.9	1.4	8	8P + 0N	8.00	1	7.36	7.26
						2	6.94	6.94
5	0.9	1.5	8	8P + 0N	8.00	1	7.36	7.26
						2	6.94	6.94
6	0.9	1.6	8	8P + 0N	8.00	1	7.36	7.26
						2	6.94	6.94
7	0.8	1.1	7	0P + 7N	7.70	1	7.38	7.33
						2	6.54	6.39
8	0.8	1.2	8	8P + 0N	8.00	1	7.36	7.26
						2	6.94	6.94
9	0.8	1.3	8	8P + 0N	8.00	1	7.36	7.26
						2	6.94	6.94
10	0.8	1.4	8	8P + 0N	8.00	1	7.36	7.26
						2	6.94	6.94
11	0.8	1.5	8	8P + 0N	8.00	1	7.36	7.26
						2	6.94	6.94
12	0.8	1.6	8	8P + 0N	8.00	1	7.36	7.26
						2	6.94	6.94
13	0.7	1.1	7	5P + 2N	7.20	1	7.39	7.39
						2	7.40	7.38
14	0.7	1.2	7	5P + 2N	7.40	1	7.39	7.39
						2	7.40	7.38
15	0.7	1.3	7	5P + 2N	7.60	1	7.39	7.39
						2	7.40	7.38

Theoretical results Fost Plus Cont.

Case	σ	C_N	Truck days	Shifts	Weekly costs	Truck w	$\theta_w^{estimate}$	$\theta_w^{simulation}$
16	0.7	1.4	7	5P + 2N	7.80	1	7.39	7.39
						2	7.40	7.38
17	0.7	1.5	8	8P + 0N	8.00	1	7.36	7.26
						2	6.94	6.94
18	0.7	1.6	8	8P + 0N	8.00	1	7.36	7.26
						2	6.94	6.94
19	0.6	1.1	6	1P + 5N	6.50	1	7.34	7.33
						2	7.20	7.21
20	0.6	1.2	6	1P + 5N	7.00	1	7.34	7.33
						2	7.20	7.21
21	0.6	1.3	6	1P + 5N	7.50	1	7.34	7.33
						2	7.20	7.21
22	0.6	1.4	7	5P + 2N	7.80	1	7.33	7.33
						2	7.33	7.12
23	0.6	1.5	8	8P + 0N	8.00	1	7.36	7.26
						2	6.94	6.94
24	0.6	1.6	8	8P + 0N	8.00	1	7.36	7.26
						2	6.94	6.94
25	0.5	1.1	6	2P + 4N	6.40	1	7.36	7.36
						2	6.98	6.98
26	0.5	1.2	6	2P + 4N	6.80	1	7.36	7.36
						2	6.98	6.98
27	0.5	1.3	6	2P + 4N	7.20	1	7.36	7.36
						2	6.98	6.98
28	0.5	1.4	6	2P + 4N	7.60	1	7.36	7.36
						2	6.98	6.98
29	0.5	1.5	6	2P + 4N	8.00	1	7.36	7.36
						2	6.98	6.98
30	0.5	1.6	8	8P + 0N	8.00	1	7.36	7.26
						2	6.94	6.94
						Average:	7.20	7.16
						St.dev.:	0.22	0.20

Table 2: Comparison of the weekly average required number of truck days

	Only N shifts		Only P shifts	
Case	LB	ME	LB	ME
$\sigma = 0.9$	7.25	8.00	7.75	8.00
$\sigma = 0.8$	6.50	7.00	7.75	8.00
$\sigma = 0.7$	6.25	7.00	7.75	8.00
$\sigma = 0.6$	5.75	6.00	7.75	8.00
$\sigma = 0.5$	5.50	6.00	7.75	8.00

Note: LB (Lower Bound) refers to the average number of truck days resulting from the flexible schedule.
ME (Model Enhancement) refers to the average number of truck days resulting from the fixed schedule.

5.2. Application to a real-life problem

In this section we present the results of the ME procedure for the entire year based on real-life data for the IA under study. Furthermore, we also present the results of a flexible schedule for benchmarking purposes.

Table 3 presents the results of the ME procedure for the four most realistic σ scenarios with $C_P = 1$. Solving the ME procedure for one year instead of 4 weeks for 100 iterations increases the required computation time from on average 10 minutes to on average 70 minutes. The results show that we always find a solution where $\theta_w^{simulation}$ is less than or equal to 7.5 hours. Just as for the results in Section 5.1.1, we can again observe that $\theta_w^{estimate}$ and $\theta_w^{simulation}$ lie very close to each other.

As in Section 5.1.2, Table 4 shows the results of the flexible schedule (LB) compared to the results of the ME procedure. Note that the LB is now the average required number of truck days over the entire year. Comparing the (rounded) (practical) LB and the ME results shows that the ME procedure produces the best possible solution for a fixed schedule compared to a flexible schedule. Along with the results in Table 3, this again suggests that our ME method is capable of finding good (even possibly optimal) solutions for the fixed schedule scenario.

Regardless of the optimality of the obtained results, the improvement with respect to the current schedule in use at the IA under study is at least as important in order to evaluate the quality of the proposed solutions. At this time, the IA under study uses a fixed schedule with only P shifts employing two full time drivers. Since one collection route is assigned to each driver on each day, 10 truck days are required every week in the current schedule. Even without the inclusion of an N shift, Table 3 shows that our model already results in a saving of at least three truck days per week. Table 3 shows that even more savings are possible when N shifts are used in combination with P shifts depending on the premium of an N shift and the value of σ. These results allow Fost Plus to evaluate different cost possibilities under different σ assumptions.

Appendix 6 shows the Graphical User Interface (GUI) developed for this application. Besides visualizing the collection routes, the GUI also allows a non-expert user to analyze a fixed or flexible schedule under different parameter settings such as driving time (e.g., highways or no highways), overtime, and drop-off rules. For instance, the user can analyze the possible effects of allowing a truck to go to the drop-off site at the end of the day without it being completely full.

Table 3: Real case results

Case	σ	C_N	Truck days	Shifts	Weekly costs	Truck w	$\theta_w^{estimate}$	$\theta_w^{simulation}$
1 - 6	0.9	1.1 - 1.6	7	7P + 0N	7.00	1	7.418	7.418
						2	6.895	6.895
7 - 12	0.8	1.1 - 1.6	7	7P + 0N	7.00	1	7.418	7.418
						2	6.895	6.895
13	0.75	1.1	6	1P + 5N	6.50	1	7.295	7.295
						2	7.125	7.125
14	0.75	1.2	6	1P + 5N	7.00	1	7.295	7.295
						2	7.125	7.125
15 - 18	0.75	1.3 - 1.6	7	7P + 0N	7.00	1	7.418	7.418
						2	6.895	6.895
19	0.7	1.1	6	2P + 4N	6.40	1	7.375	7.375
						2	7.045	7.020
20	0.7	1.2	6	2P + 4N	6.80	1	7.375	7.375
						2	7.045	7.020
21 - 24	0.7	1.3 - 1.6	7	7P + 0N	7.00	1	7.418	7.418
						2	6.895	6.895
						Average:	7.165	7.164
						St.dev.:	0.245	0.246

Table 4: Comparison of the minimal average required number of truck days

	Only N shifts		Only P shifts	
Case	LB	ME	LB	ME
$\sigma = 0.9$	6.37	7.00	6.40	7.00
$\sigma = 0.8$	6.10	7.00	6.40	7.00
$\sigma = 0.75$	5.70	6.00	6.40	7.00
$\sigma = 0.70$	5.34	6.00	6.40	7.00

Note: LB (Lower Bound) refers to the average number of truck days resulting from the flexible schedule. ME (Model Enhancement) refers to the average number of truck days resulting from the fixed schedule.

6. Conclusion and future research

In this paper we successfully showed how an ME approach can be used to integrate a routing problem with a personnel planning problem in a waste collection context. We apply our solution approach to several test cases and to the real-life data from a particular IA. In order to evaluate the performance of the ME model, both the feasibility and the solution quality of the obtained results are analyzed.

First, the feasibility of the results is an important performance indicator of the ME approach as it shows how good the simplified model approximates the real model. The results show that each obtained solution (for all test cases as well as the real-life case) is feasible in both the simplified and the real model.

Second, the quality of the ME results is evaluated based on a practical lower bound (LB). This lower bound is calculated based on the results obtained for a flexible schedule (see De Bruecker et al. (2015)). In the flexible scheduling model, useless trips are eliminated since only the most urgent containers are visited. As the ME results are equal to the rounded LB results for the tested scenarios, this strongly suggests that the proposed ME method is capable of finding good (even possibly optimal) solutions.

Regardless of the optimality of the obtained results for the test cases, the improvement with respect to the schedule used in reality is at least as important in order to evaluate the quality of the proposed techniques. We show that even without the inclusion of an N shift, the ME model results in significant savings. Even more savings are possible when N shifts are used in combination with P shifts depending on the additional cost for an N shift. Furthermore, the results presented in this paper also allow Fost Plus to evaluate the benefits of installing sensors in each container. This analysis goes, however, beyond the scope of this paper.

Finally, we propose some interesting topics for future research. In this paper we assume to know the exact fill level of the containers based on historical fill rate data. However, some stochasticity can be expected in the fill rate. Hence, incorporating a stochastic fill rate can contribute to the construction of a more realistic and applicable model. Furthermore, stochasticity can also be introduced in the driving times, collection times, loading and unloading times, etc. However, while stochasticity is an interesting additional element, we rather prefer to emphasize the lack of research related to the combination of personnel and vehicle shift scheduling in the waste management literature. This lack was already pointed out by Ernst et al. (2004) and still exists today according to the literature review of Ghiani et al. (2014). Another interesting avenue for future research is developing a decomposition approach, e.g., column generation, for solving Model 1 and examining its performance as compared to the heuristic neighbourhood search proposed in this paper.

Acknowledgments

This research was funded by FWO Flanders under contract number G050311N. We would like to thank Ivan Vaesen (Fost Plus) and 2 anonymous referees for their valuable comments and suggestions. All remaining errors remain off course ours.

7. References

References

Alonso, F., Alvarez, M. J., Beasley, J. E., 2008. A tabu search algorithm for the periodic vehicle routing problem with vehicle trips and accessibility restrictions. Journal of the Operational Research Society 59, 963–976.

Angelelli, E., Speranza, M. G., 2002. The periodic vehicle routing problem with intermediate facilities. European Journal of Operational Research 137 (2), 233–247.

Bachelet, B., Yon, L., 2007. Model enhancement: Improving theoretical optimization with simulation. Simulation Modelling Practice and Theory 15 (6), 703 – 715.

Baudach, J., Chmielewski, A., Clausen, U., 2009. Integrated vehicle routing and crew scheduling in waste management (part II). In: Barnhart, C., Clausen, U., Lauther, U., Möhring, R. H. (Eds.), Models and Algorithms for Optimization in Logistics. No. 09261 in Dagstuhl Seminar Proceedings. Schloss Dagstuhl - Leibniz-Zentrum fuer Informatik, Germany, Dagstuhl, Germany.

Beliën, J., De Boeck, L., Van Ackere, J., 2014. Municipal solid waste collection and management problems: A literature review. Transportation Science 48 (1), 78–102.

Carić, T., Gold, H., 2008. Enhancing solution similarity in multi-objective vehicle routing problems with different demand periods. In: Murata, T., Itai, R. (Eds.), Vehicle Routing Problem. In-Teh Publishers, Ch. 7.

Coene, S., Arnout, A., Spieksma, F. C. R., 2010. The periodic vehicle routing problem: A case study. Journal of the Operational Research Society, 1–10.

De Bruecker, P., De Jaeger, S., Beliën, J., Demeulemeester, E., De Boeck, L., 2015. Optimizing the workforce schedule and collection routes for glass containers. FEB Research Report KBI1527, 53 pp.

Ernst, A. T., Jiang, H., Krishnamoorthy, M., Sier, D., 2004. Staff scheduling and rostering: A review of applications, methods and models. European Journal of Operational Research 153, 3–27.

Francis, P., Smilowitz, K., Tzur, M., 2008. The period vehicle routing problem and its extensions. In: Golden, B., Raghavan, S., Wasil, E. (Eds.), The Vehicle Routing Problem: Latest Advances and New Challenges. Vol. 43 of Operations Research/Computer Science Interfaces. Springer US, pp. 73–102.

Ghiani, G., Guerriero, E., Manni, A., Manni, E., Potenza, A., 2013. Simultaneous personnel and vehicle shift scheduling in the waste management sector. Waste Management 33 (7), 1589–1594.

Ghiani, G., Laganá, D., Manni, E., Musmanno, R., Vigo, D., 2014. Operations research in solid waste management: A survey of strategic and tactical issues. Computers & Operations Research 44, 22–32.

Glover, F., Laguna, M., 1997. Tabu Search. Kluwer Academic Publishers, Boston.

Hansmann, R., Zimmermann, U., 2009. Integrated vehicle routing and crew scheduling in waste management (part i). In: Barnhart, C., Clausen, U., Lauther, U., Mohring, R. H. (Eds.), Models and Algorithms for Optimization in Logistics. Number 09261 in Dagstuhl Seminar Proceedings.

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

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

List, G. F., Wood, B., Turnquist, M. A., Nozick, L. K., Jones, D. A., Lawton, C. R., 2006. Logistics planning under uncertainty for disposition of radioactive wastes. Computers & Operations Research 33 (3), 701–723.

Mes, M., 2012. Using simulation to assess the opportunities of dynamic waste collection. In: Bangsow, S. (Ed.), Use Cases of Discrete Event Simulation. Springer Berlin Heidelberg, pp. 277–307.

Shamshiry, E., Nadi, B., Mahmud, A. R., 2011. Optimization of municipal solid waste management. In: Proceedings of the 2010 international conference on biology, environment and chemistry 1, 19–21.

8. Appendix

Figure 6: Graphical User Interface