Vehicle Routing and Demand Forecasting in a Generalized Waste Collection Problem

Iliya Markov[1,2], Matthieu de Lapparent[1], Sacha Varone[2], Michel Bierlaire[1]

[1]Transport and Mobility Laboratory
School of Architecture, Civil and Environmental Engineering
École Polytechnique Fédérale de Lausanne

[2]Haute École de Gestion de Genève
University of Applied Sciences Western Switzerland (HES-SO)

VeRoLog 2015 / Vienna, June 8–10, 2015

Contents

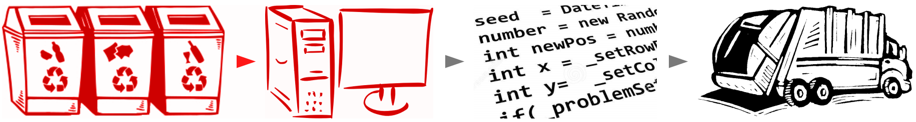
Contents

Ecological waste management

*ecopoint in Rue de Neuchâtel, Geneva; photo source: self

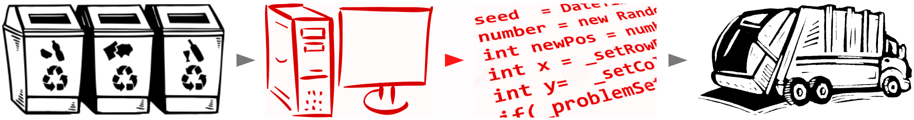
In more details...

- Sensorized containers periodically send waste level data to a centralized database



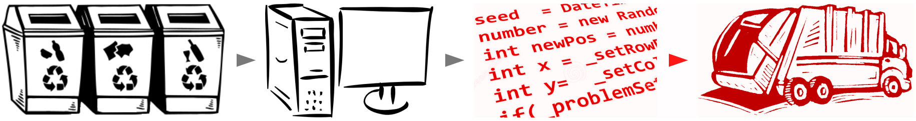
In more details...

- Sensorized containers periodically send waste level data to a centralized database
- Level data is used for container selection and vehicle routing, with tours *often planned several days in advance*



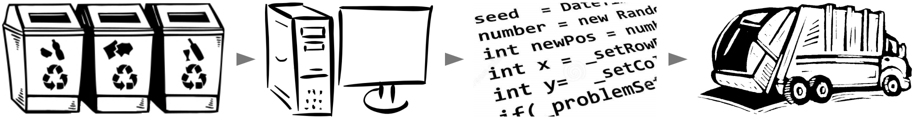
In more details...

- Sensorized containers periodically send waste level data to a centralized database
- Level data is used for container selection and vehicle routing, with tours *often planned several days in advance*
- Vehicles are dispatched to carry out the daily schedules produced by the routing algorithm



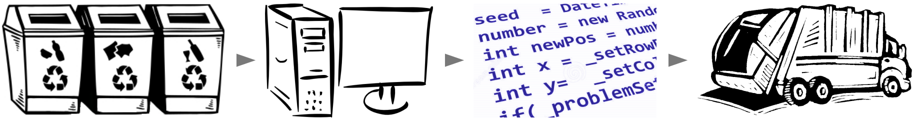
In more details...

- Sensorized containers periodically send waste level data to a centralized database
- Level data is used for container selection and vehicle routing, with tours *often planned several days in advance*
- Vehicles are dispatched to carry out the daily schedules produced by the routing algorithm
- Efficient waste collection thus depends on the ability to:
  - make **good forecasts** of the container levels at the time of collection
  - and **optimally route** the vehicles to service the selected containers



In more details...

- Sensorized containers periodically send waste level data to a centralized database
- Level data is used for container selection and vehicle routing, with tours *often planned several days in advance*
- Vehicles are dispatched to carry out the daily schedules produced by the routing algorithm
- Efficient waste collection thus depends on the ability to:
  - make **good forecasts** of the container levels at the time of collection
  - and **optimally route** the vehicles to service the selected containers



Contents

Problem description

- Multiple depots, containers, and dumps (recycling plants) with TW

Problem description

- Multiple depots, containers, and dumps (recycling plants) with TW
- Maximum tour duration, interrupted by a break

Problem description

- Multiple depots, containers, and dumps (recycling plants) with TW
- Maximum tour duration, interrupted by a break
- Site dependencies (accessibility restrictions)

Problem description

- Multiple depots, containers, and dumps (recycling plants) with TW
- Maximum tour duration, interrupted by a break
- Site dependencies (accessibility restrictions)
- Tours are sequences of collections and disposals at the available dumps, with a mandatory disposal before the end

Problem description

- Multiple depots, containers, and dumps (recycling plants) with TW
- Maximum tour duration, interrupted by a break
- Site dependencies (accessibility restrictions)
- Tours are sequences of collections and disposals at the available dumps, with a mandatory disposal before the end

- **Tours need not finish at the depot they started from**
    - flexible assignment of destination depots
    - practiced in sparsely populated rural areas

Problem description

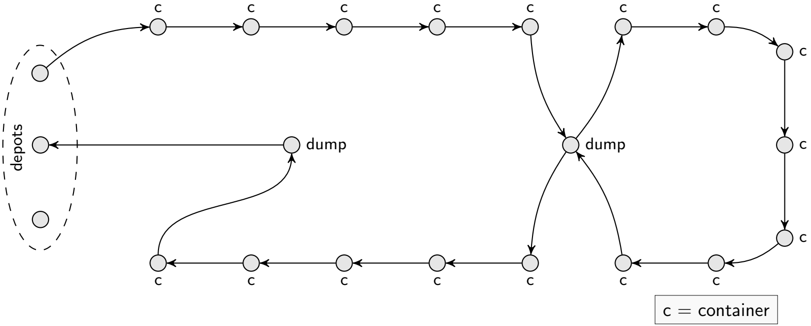
- Multiple depots, containers, and dumps (recycling plants) with TW
- Maximum tour duration, interrupted by a break
- Site dependencies (accessibility restrictions)
- Tours are sequences of collections and disposals at the available dumps, with a mandatory disposal before the end

- **Tours need not finish at the depot they started from**
  - flexible assignment of destination depots
  - practiced in sparsely populated rural areas

- **There is a heterogeneous fixed fleet**
  - different volume and weight capacities, speeds, costs, etc...

Problem description

Figure 1: Tour illustration



State of the art (VRP-IF)

- VRP with satellite facilities (Bard et al., 1998)
  - no time windows, no driver break, homogeneous fleet
  - branch-and-cut
- Waste collection VRP (Kim et al., 2006)
  - time windows, driver break, homogeneous fleet
  - simulated annealing
- MDVRPI (Crevier et al., 2007)
  - no time windows, no driver break, homogeneous fleet at single depot
  - SP on a pool of single-depot, multi-depot and inter-depot routes

State of the art (Electric VRP)

- Recharging VRP (Conrad and Figliozzi, 2011)
  - recharging at customer sites with time windows, homogeneous fleet
  - mathematical model, derived solution bounds
- Green VRP (Erdoğan and Miller-Hooks, 2012)
  - maximum tour duration, no time windows, homogeneous fleet
  - two construction heuristics and an improvement procedure
- E-VRPTW with recharging stations (Schneider et al., 2014a)
  - hierarchical objective, variable recharging times, TW, homog. fleet
  - hybrid VNS/TS
- VRP with intermediate stops (Schneider et al., 2014b)
  - combination of recharging and reloading decisions
  - weighted objective, max tour duration, no time windows, homog. fleet
  - ALNS

State of the art (Other)

- Heterogeneous fixed fleet VRP (HFFVRP)
  - proposed by Taillard (1996)
  - best exact solutions by Baldacci and Mingozzi (2009)
  - best heuristic solutions by Subramanian et al. (2012) and Penna et al. (2013)

- Flexible assignment of depots
  - Kek et al. (2008): a case study in Singapore finds significant benefits

Contributions

- Integration of dynamic destination depot assignment into the VRP-IF
  - consideration of relocation costs
- Integration of heterogeneous fixed fleet into the VRP-IF
  - challenges posed by intermediate facility visits
- Benchmarking to several classes of simpler problems from the literature and state of practice
  - *E-VRPTW (modified from Schneider et al., 2014a)*
  - MDVRPI (Crevier et al., 2007)
  - optimal solutions, state of practice, etc...

Formulation

Sets

O'	= set of origins	O''	= set of destinations
D	= set of dumps	P	= set of containers
N	$= O' \cup O'' \cup D \cup P$	K	= set of vehicles

Parameters

π_{ij}	= length of edge (i, j)
α_{ijk}	= 1 if edge (i, j) is accessible for vehicle k, 0 otherwise
τ_{ijk}	= travel time of vehicle k on edge (i, j)
ϵ_i	= service duration at point i
$[\lambda_i, \mu_i]$	= time window lower and upper bound at point i
H	= maximum tour duration
η	= maximum continuous work limit after which a break is due
δ	= break duration
ρ_i^v, ρ_i^w	= volume and weight pickup quantity at point i
Ω_k^v, Ω_k^w	= volume and weight capacity of vehicle k
ϕ_k	= fixed cost of vehicle k
β_k	= unit-distance running cost of vehicle k
θ_k	= unit-time wage rate of vehicle k
Ψ	= weight of relocation cost term

Formulation

Decision variables: binary

$$x_{ijk} = \begin{cases} 1 & \text{if vehicle } k \text{ traverses edge } (i,j) \\ 0 & \text{otherwise} \end{cases}$$

$$z_{ijk} = \begin{cases} 1 & \text{if } i \text{ and } j \text{ are, respectively, the origin and destination of vehicle } k \\ 0 & \text{otherwise} \end{cases}$$

$$b_{ijk} = \begin{cases} 1 & \text{if vehicle } k \text{ takes a break on edge } (i,j) \\ 0 & \text{otherwise} \end{cases}$$

$$y_k = \begin{cases} 1 & \text{if vehicle } k \text{ is used} \\ 0 & \text{otherwise} \end{cases}$$

Decision variables: continuous

S_{ik} = start-of-service time of vehicle k at point i

Q^v_{ik} = cumulative volume on vehicle k at point i

Q^w_{ik} = cumulative weight on vehicle k at point i

Formulation

- The sets of origins O' and destinations O'' may be restricted for each individual vehicle k
- The set O'_k:
  - degenerates to one point - the current depot of vehicle k
  - or coincides with O' if we want to optimize the home depot of vehicle k
- The set O''_k:
  - degenerates to one point if vehicle k is required to return to its home depot
  - or coincides with O'' for the purpose of dynamic destination depot assignment

Formulation

$$\min \quad f = \sum_{k \in K} \left(\phi_k y_k + \beta_k \sum_{i \in N} \sum_{j \in N} \pi_{ij} x_{ijk} + \theta_k \left(\sum_{j \in O''_k} S_{jk} - \sum_{i \in O'_k} S_{ik} \right) \right) + \Psi \sum_{k \in K} \sum_{i \in O'_k} \sum_{j \in O''_k} \left(\beta_k \pi_{ji} + \theta_k \tau_{jik} \right) z_{ijk} \tag{1}$$

Formulation

$$\min \quad f = \sum_{k \in K} \left(\phi_k y_k + \beta_k \sum_{i \in N} \sum_{j \in N} \pi_{ij} x_{ijk} + \theta_k \left(\sum_{j \in O''_k} S_{jk} - \sum_{i \in O'_k} S_{ik} \right) \right) + \Psi \sum_{k \in K} \sum_{i \in O'_k} \sum_{j \in O''_k} \left(\beta_k \pi_{ji} + \theta_k \tau_{jik} \right) z_{ijk} \qquad (1)$$

$$\text{s.t.} \quad \sum_{k \in K} \sum_{j \in D \cup P} x_{ijk} = 1, \qquad \forall i \in P \qquad (2)$$

Formulation

$$\min \quad f = \sum_{k \in K} \left(\phi_k y_k + \beta_k \sum_{i \in N} \sum_{j \in N} \pi_{ij} x_{ijk} + \theta_k \left(\sum_{j \in O''_k} S_{jk} - \sum_{i \in O'_k} S_{ik} \right) \right) + \Psi \sum_{k \in K} \sum_{i \in O'_k} \sum_{j \in O''_k} \left(\beta_k \pi_{ji} + \theta_k \tau_{jik} \right) z_{ijk} \qquad (1)$$

$$\text{s.t.} \quad \sum_{k \in K} \sum_{j \in D \cup P} x_{ijk} = 1, \qquad \forall i \in P \qquad (2)$$

$$\sum_{i \in O'_k} \sum_{j \in N} x_{ijk} = y_k, \qquad \forall k \in K \qquad (3)$$

$$\sum_{i \in D} \sum_{j \in O''_k} x_{ijk} = y_k, \qquad \forall k \in K \qquad (4)$$

Formulation

$$\min \quad f = \sum_{k \in K} \left(\phi_k y_k + \beta_k \sum_{i \in N} \sum_{j \in N} \pi_{ij} x_{ijk} + \theta_k \left(\sum_{j \in O''_k} S_{jk} - \sum_{i \in O'_k} S_{ik} \right) \right) + \Psi \sum_{k \in K} \sum_{i \in O'_k} \sum_{j \in O''_k} \left(\beta_k \pi_{ji} + \theta_k \tau_{jik} \right) z_{ijk} \tag{1}$$

$$\text{s.t.} \quad \sum_{k \in K} \sum_{j \in D \cup P} x_{ijk} = 1, \qquad \forall i \in P \tag{2}$$

$$\sum_{i \in O'_k} \sum_{j \in N} x_{ijk} = y_k, \qquad \forall k \in K \tag{3}$$

$$\sum_{i \in D} \sum_{j \in O''_k} x_{ijk} = y_k, \qquad \forall k \in K \tag{4}$$

$$\sum_{i \in N} x_{ijk} = 0, \qquad \forall k \in K, j \in O' \cup (O'' \setminus O''_k) \tag{5}$$

$$\sum_{j \in N} x_{ijk} = 0, \qquad \forall k \in K, i \in O'' \cup (O' \setminus O'_k) \tag{6}$$

Formulation

$$\min \quad f = \sum_{k \in K} \left(\phi_k y_k + \beta_k \sum_{i \in N} \sum_{j \in N} \pi_{ij} x_{ijk} + \theta_k \left(\sum_{j \in O_k''} S_{jk} - \sum_{i \in O_k'} S_{ik} \right) \right) \tag{1}$$

$$+ \Psi \sum_{k \in K} \sum_{i \in O_k'} \sum_{j \in O_k''} \left(\beta_k \pi_{ji} + \theta_k \tau_{jik} \right) z_{ijk}$$

$$\text{s.t.} \quad \sum_{k \in K} \sum_{j \in D \cup P} x_{ijk} = 1, \qquad \forall i \in P \tag{2}$$

$$\sum_{i \in O_k'} \sum_{j \in N} x_{ijk} = y_k, \qquad \forall k \in K \tag{3}$$

$$\sum_{i \in D} \sum_{j \in O_k''} x_{ijk} = y_k, \qquad \forall k \in K \tag{4}$$

$$\sum_{i \in N} x_{ijk} = 0, \qquad \forall k \in K, j \in O' \cup (O'' \setminus O_k'') \tag{5}$$

$$\sum_{j \in N} x_{ijk} = 0, \qquad \forall k \in K, i \in O'' \cup (O' \setminus O_k') \tag{6}$$

$$\sum_{i \in N:\, i \neq j} x_{ijk} = \sum_{i \in N:\, i \neq j} x_{jik}, \qquad \forall k \in K, j \in D \cup P \tag{7}$$

Formulation

$$\text{s.t.} \quad \sum_{m \in P} x_{imk} + \sum_{m \in D} x_{mjk} - 1 \leqslant z_{ijk}, \qquad \forall k \in K, i \in O'_k, j \in O''_k \tag{8}$$

Formulation

$$\text{s.t.} \quad \sum_{m \in P} x_{imk} + \sum_{m \in D} x_{mjk} - 1 \leqslant z_{ijk}, \qquad \forall k \in K, i \in O'_k, j \in O''_k \qquad (8)$$

$$x_{ijk} \leqslant \alpha_{ijk}, \qquad \forall k \in K, i \in O'_k \cup P \cup D, j \in P \cup D \cup O''_k \qquad (9)$$

Formulation

$$\text{s.t.} \quad \sum_{m \in P} x_{imk} + \sum_{m \in D} x_{mjk} - 1 \leqslant z_{ijk}, \qquad \forall k \in K, i \in O'_k, j \in O''_k \quad (8)$$

$$x_{ijk} \leqslant \alpha_{ijk}, \qquad \forall k \in K, i \in O'_k \cup P \cup D, j \in P \cup D \cup O''_k \quad (9)$$

$$\rho^v_i \leqslant Q^v_{ik} \leqslant \Omega^v_k, \qquad \forall k \in K, i \in P \quad (10)$$

$$\rho^w_i \leqslant Q^w_{ik} \leqslant \Omega^w_k, \qquad \forall k \in K, i \in P \quad (11)$$

$$Q^v_{ik} = 0, \qquad \forall k \in K, i \in N \setminus P \quad (12)$$

$$Q^w_{ik} = 0, \qquad \forall k \in K, i \in N \setminus P \quad (13)$$

$$Q^v_{ik} + \rho^v_j \leqslant Q^v_{jk} + \Omega^v_k \left(1 - x_{ijk}\right), \qquad \forall k \in K, i \in O'_k \cup P \cup D, j \in P \quad (14)$$

$$Q^w_{ik} + \rho^w_j \leqslant Q^w_{jk} + \Omega^w_k \left(1 - x_{ijk}\right), \qquad \forall k \in K, i \in O'_k \cup P \cup D, j \in P \quad (15)$$

Formulation

$$\text{s.t.} \quad \sum_{m \in P} x_{imk} + \sum_{m \in D} x_{mjk} - 1 \leqslant z_{ijk}, \qquad \forall k \in K, i \in O'_k, j \in O''_k \tag{8}$$

$$x_{ijk} \leqslant \alpha_{ijk}, \qquad \forall k \in K, i \in O'_k \cup P \cup D, j \in P \cup D \cup O''_k \tag{9}$$

$$\rho_i^v \leqslant Q_{ik}^v \leqslant \Omega_k^v, \qquad \forall k \in K, i \in P \tag{10}$$

$$\rho_i^w \leqslant Q_{ik}^w \leqslant \Omega_k^w, \qquad \forall k \in K, i \in P \tag{11}$$

$$Q_{ik}^v = 0, \qquad \forall k \in K, i \in N \setminus P \tag{12}$$

$$Q_{ik}^w = 0, \qquad \forall k \in K, i \in N \setminus P \tag{13}$$

$$Q_{ik}^v + \rho_j^v \leqslant Q_{jk}^v + \Omega_k^v \left(1 - x_{ijk}\right), \qquad \forall k \in K, i \in O'_k \cup P \cup D, j \in P \tag{14}$$

$$Q_{ik}^w + \rho_j^w \leqslant Q_{jk}^w + \Omega_k^w \left(1 - x_{ijk}\right), \qquad \forall k \in K, i \in O'_k \cup P \cup D, j \in P \tag{15}$$

$$S_{ik} + \varepsilon_i + \delta b_{ijk} + \tau_{ijk} \leqslant S_{jk} + M \left(1 - x_{ijk}\right), \qquad \forall k \in K, i \in O'_k \cup P \cup D, j \in P \cup D \cup O''_k \tag{16}$$

$$\lambda_i \sum_{j \in N} x_{ijk} \leqslant S_{ik}, \qquad \forall k \in K, i \in O'_k \cup P \cup D \tag{17}$$

$$S_{jk} \leqslant \mu_j \sum_{i \in N} x_{ijk}, \qquad \forall k \in K, j \in P \cup D \cup O''_k \tag{18}$$

$$0 \leqslant \sum_{j \in O''_k} S_{jk} - \sum_{i \in O'_k} S_{ik} \leqslant \mathrm{H}, \qquad \forall k \in K \tag{19}$$

Formulation

$$\text{s.t.} \left(S_{ik} - \sum_{m \in O'_k} S_{mk} \right) + \varepsilon_i - \eta \leqslant M \left(1 - b_{ijk} \right), \quad \forall k \in K, i \in O'_k \cup P \cup D, j \in P \cup D \cup O''_k \quad (20)$$

$$\eta - \left(S_{jk} - \sum_{m \in O'_k} S_{mk} \right) \leqslant M \left(1 - b_{ijk} \right), \quad \forall k \in K, i \in O'_k \cup P \cup D, j \in P \cup D \cup O''_k \quad (21)$$

$$b_{ijk} \leqslant x_{ijk}, \quad \forall k \in K, i, j \in N \quad (22)$$

$$\left(\sum_{j \in O''_k} S_{jk} - \sum_{i \in O'_k} S_{ik} \right) - \eta \leqslant (\mathrm{H} - \eta) \sum_{i \in N} \sum_{j \in N} b_{ijk}, \quad \forall k \in K \quad (23)$$

Formulation

$$\text{s.t.} \left(S_{ik} - \sum_{m \in O'_k} S_{mk} \right) + \varepsilon_i - \eta \leqslant M\left(1 - b_{ijk}\right), \quad \forall k \in K, i \in O'_k \cup P \cup D, j \in P \cup D \cup O''_k \tag{20}$$

$$\eta - \left(S_{jk} - \sum_{m \in O'_k} S_{mk} \right) \leqslant M\left(1 - b_{ijk}\right), \quad \forall k \in K, i \in O'_k \cup P \cup D, j \in P \cup D \cup O''_k \tag{21}$$

$$b_{ijk} \leqslant x_{ijk}, \quad \forall k \in K, i, j \in N \tag{22}$$

$$\left(\sum_{j \in O''_k} S_{jk} - \sum_{i \in O'_k} S_{ik} \right) - \eta \leqslant (\mathrm{H} - \eta) \sum_{i \in N} \sum_{j \in N} b_{ijk}, \quad \forall k \in K \tag{23}$$

$$x_{ijk}, b_{ijk}, y_k \in \{0, 1\}, \quad \forall k \in K, i, j \in N \tag{24}$$

$$z_{ijk} \in \{0, 1\}, \quad \forall k \in K, i \in O', j \in O'' \tag{25}$$

$$Q^v_{ik}, Q^w_{ik}, S_{ik} \geqslant 0, \quad \forall k \in K, i \in N \tag{26}$$

Solution methodology: Exact approach

- We strengthen the formulation with variable fixing and valid inequalities
- Impossible traversals:

$$x_{iik} = 0, \qquad \forall k \in K, i \in N \tag{27}$$

$$x_{ijk} = 0, \qquad \forall k \in K, i \in O', j \in D \cup O'' \tag{28}$$

$$x_{ijk} = 0, \qquad \forall k \in K, i \in P, j \in O'' \tag{29}$$

$$x_{ijk} = 0, \qquad \forall k \in K, i \in D, j \in D \colon i \neq j \tag{30}$$

- Time-window infeasible traversals:

$$x_{ijk} = 0, \qquad \forall k \in K, i \in O'_k \cup P \cup D, j \in P \cup D \cup O''_k \colon \lambda_i + \varepsilon_i + \tau_{ijk} > \mu_j \tag{31}$$

- Lower bound on total time:

$$\sum_{j \in O''_k} S_{jk} - \sum_{i \in O'_k} S_{ik} \geqslant \sum_{i \in N} \sum_{j \in N} x_{ijk}(\varepsilon_i + \tau_{ijk}), \qquad \forall k \in K \tag{32}$$

Solution methodology: Exact approach

- Symmetry breaking for subsets K' of identical vehicles:

$$\sum_{i \in P} \sum_{j \in P \cup D} \rho_i^v x_{ijk'_g} \geqslant \sum_{i \in P} \sum_{j \in P \cup D} \rho_i^v x_{ijk'_{g+1}}, \qquad \forall g \in 1, \ldots, (|K'| - 1) \qquad (33)$$

- Symmetry breaking for replications of the same dump D':

$$\sum_{j \in P} j x_{ji'_g k} \leqslant \sum_{j \in P} j x_{ji'_{g+1} k}, \qquad \forall k \in K, g \in 1, \ldots, (|D'| - 1) \qquad (34)$$

- Bounds on dump visits:

$$\sum_{i \in P} x_{ijk} \leqslant 1, \qquad \forall k \in K, j \in D \qquad (35)$$

$$\sum_{i \in D} \sum_{j \in P} x_{ijk} \leqslant \min\left(|D| - 1, |P|\right), \qquad \forall k \in K \qquad (36)$$

Solution methodology: Heuristic approach

- To solve instances of realistic size, we developed a heuristic algorithm
- It constructs a feasible initial solution using an insertion procedure
- It improves the initial solution through local search admitting intermediate infeasibility with a dynamically evolving penalty

Solution methodology: Heuristic approach

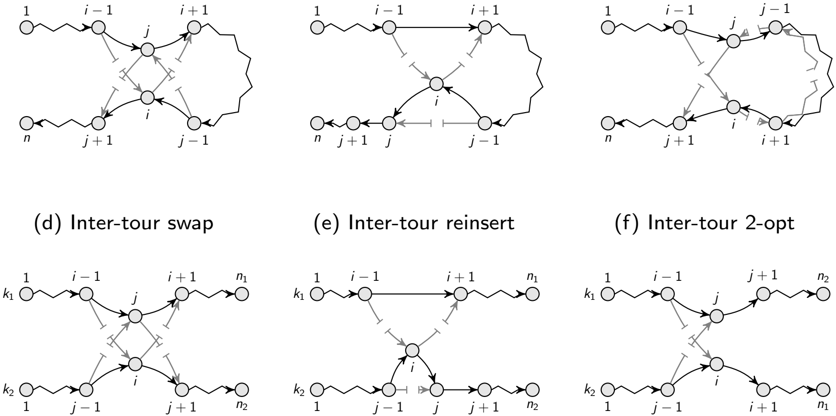
- To solve instances of realistic size, we developed a heuristic algorithm
- It constructs a feasible initial solution using an insertion procedure
- It improves the initial solution through local search admitting intermediate infeasibility with a dynamically evolving penalty
- Periodically, we recover the best feasible solution because feasibility may be hard to restore

Solution methodology: Heuristic approach

- To solve instances of realistic size, we developed a heuristic algorithm
- It constructs a feasible initial solution using an insertion procedure
- It improves the initial solution through local search admitting intermediate infeasibility with a dynamically evolving penalty
- Periodically, we recover the best feasible solution because feasibility may be hard to restore
- Periodically, we also reassign dump visits and evaluate vehicle reassignments because the fleet is heterogeneous and fixed

Solution methodology: Heuristic approach

Figure 2: Neighborhood operators



(a) Single-tour swap (b) Single-tour reinsert (c) Single-tour 2-opt

(d) Inter-tour swap (e) Inter-tour reinsert (f) Inter-tour 2-opt

Solution methodology: Heuristic approach

Define: K is the set of all available vehicles
Data: set of constructed tours $K' \in K$
Result: set of improved tours $K'' \in K$

```
setBanList();
setNeighborhood(); resetCurrentNeighbor();
for maxIter do
    for maxOpIter do
        N = generateNeighborSample();
        currentNeighbor = min(n){cost(n) | ∀n ∈ N: cost(n) ∉ banList};
        updateBanList();
        if reached recoverFreq then
            reassignVehiclesRecoverCapacity();
            improveIndividually();
            updateBanList();
        end
        if reached maxOpNonImpIter then
            changeNeighborhood(); resetCurrentNeighbor();
            break;
        end
        changeNeighborhood(); resetCurrentNeighbor();
    end
    if reached maxNonImpIter then
        break;
    end
end
```

Results

- We test the heuristic against the mathematical model on synthetic instances based on real underlying data
  - We are currently adapting the Schneider et al. (2014a) instances by adding site dependencies, a break period and a heterogeneous fixed fleet for the purpose of running additional tests
- Additionally, we test the heuristic on:
  - the Crevier et al. (2007) instances for the purpose of evaluating the benefit of flexible depot assignment,
  - and on state-of-practice data
- For each instance, the heuristic is run 10 times

Results: Synthetic instances (preliminary results)

Table 1: Synthetic instances

Instance	# of tours	Heuristic Objective avg	Heuristic Runtime avg(s.)	Solver Objective	Solver MIP gap(%)	Solver Relaxation	Solver Runtime avg(s.)	Opt gap(%)
i1	1	214.85	0.25	214.85	0.00	11.25	688.69	0.00
i1_wtw	1	252.83	0.19	252.83	0.00	95.63	1.97	0.00
i1_ntw	2	394.82	0.44	394.82	0.00	169.30	0.59	0.00
i2	1	249.32	0.21	249.32	0.00	58.79	778.58	0.00
i2_wtw	1	257.58	0.17	257.58	0.00	119.75	2.01	0.00
i2_ntw	2	439.77	0.65	439.77	0.00	217.32	2.01	0.00
i3	1	240.13	0.21	240.13	0.00	14.93	1724.26	0.00
i3_wtw	1	245.46	0.17	245.46	0.00	45.63	2.28	0.00
i3_ntw	2	444.59	0.59	444.59	0.00	76.17	1.22	0.00
i4	1	138.64	0.16	138.64	0.00	4.08	2720.74	0.00
i4_wtw	1	140.20	0.20	140.20	0.00	4.08	5.73	0.00
i4_ntw	1	179.54	0.21	179.54	0.00	19.99	1.79	0.00
i5	1	220.77	0.21	220.77	0.00	37.89	1404.74	0.00
i5_wtw	1	233.21	0.17	233.21	0.00	83.94	1.48	0.00
i5_ntw	2	405.62	0.57	405.62	0.00	105.23	1.83	0.00

Results: Crevier et al. (2007) instances

- 22 instances, with a limited homogeneous fleet stationed at one depot
- All depots can act as intermediate facilities
- BKS by Hemmelmayr et al. (2013)
- We applied the LS heuristic to evaluate the benefits from flexible destination depot assignments

Results: Crevier et al. (2007) instances

- 22 instances, with a limited homogeneous fleet stationed at one depot
- All depots can act as intermediate facilities
- BKS by Hemmelmayr et al. (2013)
- We applied the LS heuristic to evaluate the benefits from flexible destination depot assignments
- Keeping the home depot and optimizing the destination depot, we obtain:
  - **0.37%** average savings over 10 runs
  - **1.77%** savings in the best case

Results: Crevier et al. (2007) instances

- 22 instances, with a limited homogeneous fleet stationed at one depot
- All depots can act as intermediate facilities
- BKS by Hemmelmayr et al. (2013)
- We applied the LS heuristic to evaluate the benefits from flexible destination depot assignments

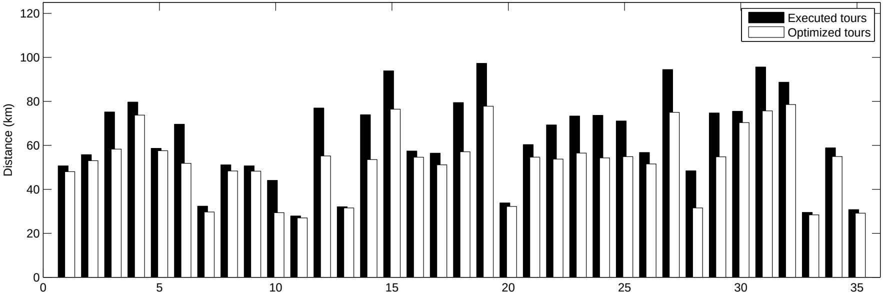
- Keeping the home depot and optimizing the destination depot, we obtain:
  - **0.37%** average savings over 10 runs
  - **1.77%** savings in the best case

- Optimizing the home depot and the destination depot, we obtain:
  - **1.37%** average savings over 10 runs
  - **2.54%** savings in the best case

Results: Comparison to the state of practice

- 35 tours planned by specialized software for the canton of Geneva
- 7 to 38 containers per tour, up to 4 dump visits per tour
- LS heuristic improves tours by **1.73%** to **34.91%**, on avg **14.75%**
- Extrapolating annually, cost reductions of at least **USD 300'000**

Figure 3: Comparison to the state of practice (average of 10 runs per tour)



Contents

State of the Art

- The literature on waste generation forecasting is abundant and varied (for a survey see Beigl et al., 2008)
- Much of it is focused on city and regional level

State of the Art

- The literature on waste generation forecasting is abundant and varied (for a survey see Beigl et al., 2008)
- Much of it is focused on city and regional level
- And a fairly small amount on the container (micro) level, e.g.:
  - Inventory levels in pharmacies (Nolz et al., 2011, 2014)
  - Recyclable materials from old cars (Krikke et al., 2008)
  - Charity donation banks (McLeod et al., 2013)
  - Waste container levels (Johansson, 2006; Faccio et al., 2011; Mes, 2012; Mes et al., 2014)

State of the Art

- The literature on waste generation forecasting is abundant and varied (for a survey see Beigl et al., 2008)
- Much of it is focused on city and regional level
- And a fairly small amount on the container (micro) level, e.g.:
  - Inventory levels in pharmacies (Nolz et al., 2011, 2014)
  - Recyclable materials from old cars (Krikke et al., 2008)
  - Charity donation banks (McLeod et al., 2013)
  - Waste container levels (Johansson, 2006; Faccio et al., 2011; Mes, 2012; Mes et al., 2014)
- Contribution:
  - Operational level forecasting rather than critical levels
  - Estimated and validated on real data, compared to most of the literature which uses simulated data

Methodology

- Let $n_{i,t,k}$ denote the number of deposits in container i at date t of size q_k. We define the data generating process as follows:

$$Q^{\star}_{i,t} = \sum_{k=1}^{K} n_{i,t,k} q_k \tag{37}$$

- Let $n_{i,t,k} \xrightarrow{\text{iid}} \mathcal{P}\left(\lambda_{i,t,k}\right)$ with probability $\pi_{i,t,k}$. Then we obtain:

$$\mathbb{E}\left(Q^{\star}_{i,t}\right) = \sum_{k=1}^{K} q_k \lambda_{i,t,k} \pi_{i,t,k} \tag{38}$$

- We minimize the sum of squared differences between observed and expected over all containers and dates:

$$\min_{\boldsymbol{\lambda},\boldsymbol{\pi}} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Q_{i,t} - \sum_{k=1}^{K} q_k \lambda_{i,t,k} \pi_{i,t,k} \right)^2 \tag{39}$$

assuming strict exogeneity

Methodology

- Given vectors of covariates $\mathbf{x}_{i,t}$ and $\mathbf{z}_{i,t}$ and vectors of parameters $\boldsymbol{\beta}_k$ and $\boldsymbol{\gamma}_k$, we define Poisson rates and logit-type probabilities:

$$\lambda_{i,t,k}(\boldsymbol{\theta}) = \exp\left(\mathbf{x}_{i,t}^{\mathsf{T}}\boldsymbol{\beta}_k\right) \tag{40}$$

$$\pi_{i,t,k}(\boldsymbol{\theta}) = \frac{\exp\left(\mathbf{z}_{i,t}^{\mathsf{T}}\boldsymbol{\gamma}_k\right)}{\sum_{j=1}^{K}\exp\left(\mathbf{z}_{i,t}^{\mathsf{T}}\boldsymbol{\gamma}_j\right)} \tag{41}$$

- Then, in compact form, the minimization problem writes as:

$$\min_{\boldsymbol{\theta}\in\boldsymbol{\Theta}} \sum_{i=1}^{N}\sum_{t=1}^{T}\left(Q_{i,t} - \sum_{k=1}^{K}\frac{\exp\left(\mathbf{x}_{i,t}^{\mathsf{T}}\boldsymbol{\beta}_k + \mathbf{z}_{i,t}^{\mathsf{T}}\boldsymbol{\gamma}_k + \ln(q_k)\right)}{\sum_{j=1}^{K}\exp\left(\mathbf{z}_{i,t}^{\mathsf{T}}\boldsymbol{\gamma}_j\right)}\right)^2 \tag{42}$$

- $\boldsymbol{\Theta} := (\boldsymbol{\beta}_k, \boldsymbol{\gamma}_k : \forall k)$, and $\boldsymbol{\gamma}_{k^\star} = \mathbf{0}$ for one arbitrarily chosen $k^\star$
- We will refer to this minimization problem as the *mixture model*

Methodology

- In case of only one deposit quantity, it degenerates to a pseudo-count data process:

$$\min_{\boldsymbol{\theta}\in\boldsymbol{\Theta}} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Q_{i,t} - \exp\left(\mathbf{x}_{i,t}^{\mathsf{T}} \boldsymbol{\beta} + \ln(q) \right) \right)^2 \qquad (43)$$

- We will refer to this minimization problem as the *simple model*

Methodology

- Using new sets of covariates $\dot{\mathbf{x}}_{i,t}$ and $\dot{\mathbf{z}}_{i,t}$, and the estimates $\hat{\beta}_k$ and $\hat{\gamma}_k$, we can generate a forecast as follows:

$$\dot{Q}_{i,t} = \sum_{k=1}^{K} \frac{\exp\left(\dot{\mathbf{x}}_{i,t}^{\top}\hat{\beta}_k + \dot{\mathbf{z}}_{i,t}^{\top}\hat{\gamma}_k + \ln\left(q_k\right)\right)}{\sum_{j=1}^{K} \exp\left(\dot{\mathbf{z}}_{i,t}^{\top}\hat{\gamma}_j\right)} \tag{44}$$

- Given the operational nature of the problem, the covariates should be quick and easy to obtain
- Examples include days of the week, months, weather data, holidays, etc...

Data

- 36 containers for PET in the canton of Geneva with capacity of 3040 or 3100 liters
- Balanced panel covering March to June, 2014 (122 days), which brings the total number of observations to 4392

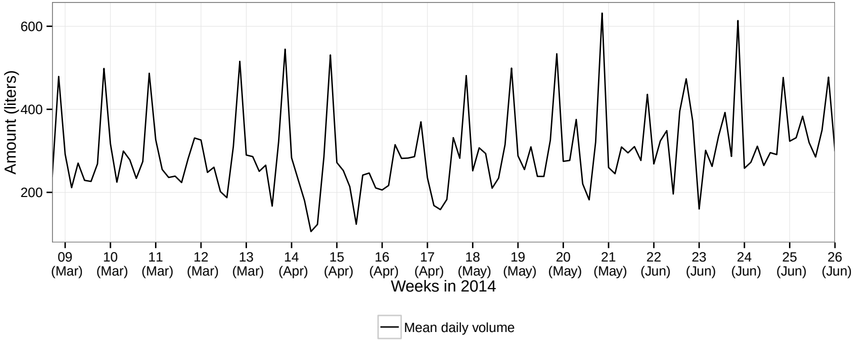
Data

- 36 containers for PET in the canton of Geneva with capacity of 3040 or 3100 liters
- Balanced panel covering March to June, 2014 (122 days), which brings the total number of observations to 4392
- The final sample excludes unreliable level data (removed after visual inspection)
- Missing data is linearly interpolated for the values of $Q_{i,t}$

Seasonality pattern

- Waste generation exhibits strong weekly seasonality
- Peaks are observed during the weekends
- There also appear to be longer-term effects for months

Figure 4: Mean daily volume deposited in the containers



Covariates

- Based on the above observations, we use the following covariates
- They are all used both for $\mathbf{x}_{i,t}$ (rates) and $\mathbf{z}_{i,t}$ (probabilities)

Table 2: Table of covariates

Variable	Type
Container fixed effect	dummy
Day of the week	dummy
Month	dummy
Minimum temperature in Celsius	continuous
Precipitation in mm	continuous
Pressure in hPa	continuous
Wind speed in kmph	continuous

Evaluating the fits

- Coefficient of determination

$$R^2 = 1 - \frac{SS_{\text{res}}}{SS_{\text{tot}}} \tag{45}$$

  with higher values for a better model
- Akaike information criterion (AIC):

$$\text{AIC} = \left(\frac{SS_{\text{res}}}{N}\right) \exp(2K/N) \tag{46}$$

  with lower values for a better model. The exponential penalizes model complexity
- SS_{res} is the residual sum of squares
- SS_{tot} is the total sum of squares
- K is the number of estimated parameters
- N is the number of observations

Estimation on full sample

- Mixture model: R^2 of **0.341** (AIC **52900**) with 5L and 15L
- Simple model: R^2 of **0.300** (AIC **53700**) with 10L

Table 3: Estimated coefficients of mixture model

	$\hat{\beta}_1$ (5L)***	$\hat{\beta}_2$ (15L)***	$\hat{\gamma}_2$***
Minimum temperature in Celsius	1461.356	0.022	-0.037
Precipitation in mm	-0.821	-0.009	0.018
Pressure in hPa	-13.724	-0.001	0.010
Wind speed in kmph	7.580	-0.004	0.020
Monday	402.235	2.166	-9.693
Tuesday	1908.233	2.293	-9.977
Wednesday	-844.662	1.432	0.202
Thursday	1937.385	1.198	1.453
Friday	1876.162	1.239	4.419
Saturday	-6981.339	1.358	4.723
Sunday	1831.715	1.905	2.832
March	-27.136	2.955	-1.453
April	1071.406	2.746	-1.532
May	1689.979	2.988	-1.603
June	-2604.520	2.901	-1.452

Validation

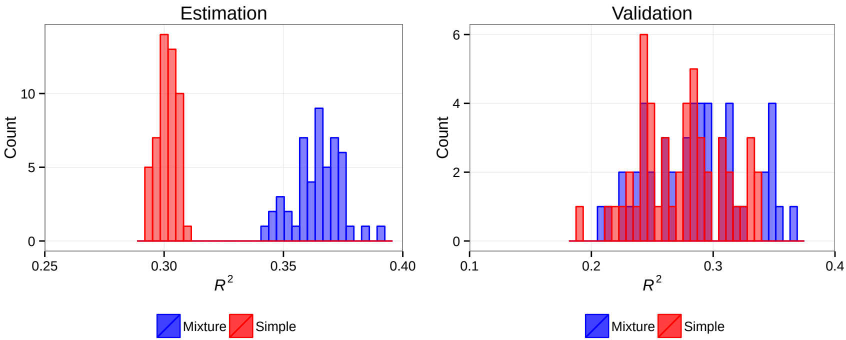
- 50 experiments
- The mixture and the simple model are estimated on a random sample of 90% of the panel
- They are validated on the remaining 10%

Table 4: Mean R^2 for estimation and validation sets

	Mixture model mean R^2	Simple model mean R^2
Estimation	0.364 (AIC 51400)	0.302 (AIC 53600)
Validation	0.286	0.274

Validation

Figure 5: Histograms for estimation and validation samples



Contents

Conclusion

- At the moment, the forecasting model can produce future levels, for which the routing problem is solved
- Future research will focus on:
  - more deposit sizes or a continuous deposit size distribution
  - integrating the forecasting model and the routing algorithm into an inventory routing problem (IRP)

Conclusion

- At the moment, the forecasting model can produce future levels, for which the routing problem is solved
- Future research will focus on:
  - more deposit sizes or a continuous deposit size distribution
  - integrating the forecasting model and the routing algorithm into an inventory routing problem (IRP)
- The IRP will solve simultaneously the container selection problem based on forecast levels and the routing problem in a periodic framework
- The increasing amount of available data will allow for more extensive testing and results

Thank you.
Questions?

Baldacci, R. and Mingozzi, A. (2009). A unified exact method for solving different classes of vehicle routing problems. *Mathematical Programming*, 120(2):347–380.

Bard, J. F., Huang, L., Dror, M., and Jaillet, P. (1998). A branch and cut algorithm for the VRP with satellite facilities. *IIE Transactions*, 30(9):821–834.

Beigl, P., Lebersorger, S., and Salhofer, S. (2008). Modelling municipal solid waste generation: A review. *Waste Management*, 28(1):200–214.

Conrad, R. G. and Figliozzi, M. A. (2011). The recharging vehicle routing problem. In Doolen, T. and Aken, E. V., editors, *Proceedings of the 2011 Industrial Engineering Research Conference*, Reno, NV, USA.

Crevier, B., Cordeau, J.-F., and Laporte, G. (2007). The multi-depot vehicle routing problem with inter-depot routes. *European Journal of Operational Research*, 176(2):756–773.

Erdoğan, S. and Miller-Hooks, E. (2012). A green vehicle routing problem. *Transportation Research Part E: Logistics and Transportation Review*, 48(1):100–114. Select Papers from the 19th International Symposium on Transportation and Traffic Theory.

Faccio, M., Persona, A., and Zanin, G. (2011). Waste collection multi objective model with real time traceability data. *Waste Management*, 31(12):2391 – 2405.

Hemmelmayr, V., Doerner, K. F., Hartl, R. F., and Rath, S. (2013). A heuristic solution method for node routing based solid waste collection problems. *Journal of Heuristics*, 19(2):129–156.

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

Kek, A. G., Cheu, R. L., and Meng, Q. (2008). Distance-constrained capacitated vehicle routing problems with flexible assignment of start and end depots. *Mathematical and Computer Modelling*, 47:140–152.

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

Krikke, H., le Blanc, I., van Krieken, M., and Fleuren, H. (2008). Low-frequency collection of materials disassembled from end-of-life vehicles: On the value of on-line monitoring in optimizing route planning. *International Journal of Production Economics*, 111(2):209 – 228. Special Section on Sustainable Supply Chain.

McLeod, F., Erdoğan, G., Cherrett, T., Bektaş, T., Davies, N., Speed, C., Dickinson, J., and Norgate, S. (2013). Dynamic collection scheduling using remote asset monitoring. *Transportation Research Record*, 2378:65–72.

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

Mes, M., Schutten, M., and Rivera, A. P. (2014). Inventory routing for dynamic waste collection. *Waste Management*, 34(9):1564–1576.

Nolz, P. C., Absi, N., and Feillet, D. (2011). Optimization of infectious medical waste collection using RFID. In Böse, J. W., Hu, H., Jahn, C., Shi, X., Stahlbock, R., and Voß, S., editors, *Computational Logistics*, volume 6971 of *Lecture Notes in Computer Science*, pages 86–100. Springer Berlin Heidelberg.

Nolz, P. C., Absi, N., and Feillet, D. (2014). A stochastic inventory routing problem for infectious medical waste collection. *Networks*, 63(1):82–95.

Penna, P. H. V., Subramanian, A., and Ochi, L. S. (2013). An iterated local search heuristic for the heterogeneous fleet vehicle routing problem. *Journal of Heuristics*, 19(2):201–232.

Schneider, M., Stenger, A., and Goeke, D. (2014a). The electric vehicle-routing problem with time windows and recharging stations. *Transportation Science*, 48(4):500–520.

Schneider, M., Stenger, A., and Hof, J. (2014b). An adaptive VNS algorithm for vehicle routing problems with intermediate stops. *OR Spectrum* (published online), pages 1–35.

Subramanian, A., Penna, P. H. V., Uchoa, E., and Ochi, L. S. (2012). A hybrid algorithm for the heterogeneous fleet vehicle routing problem. *European Journal of Operational Research*, 221(2):285–295.

Taillard, É. D. (1996). A heuristic column generation method for the heterogeneous fleet VRP. *Publication CRT-96-13*.