Vehicle Routing and Demand Forecasting in a Generalized Waste Collection Problem

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Ecological waste management

*ecopoint in Rue de Neuchâtel, Geneva; photo source: self*
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In more details...

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- Level data is used for container selection and vehicle routing, with tours often planned several days in advance.
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- 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.
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- Multiple depots, containers, and dumps (recycling plants) with TW
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- practiced in sparsely populated rural areas
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- **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

c = container
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

\[ O' = \text{set of origins} \quad O'' = \text{set of destinations} \]
\[ D = \text{set of dumps} \]
\[ N = O' \cup O'' \cup D \cup P \]
\[ K = \text{set of vehicles} \]

Parameters

\[ \pi_{ij} = \text{length of edge } (i, j) \]
\[ \alpha_{ijk} = 1 \text{ if edge } (i, j) \text{ is accessible for vehicle } k, 0 \text{ otherwise} \]
\[ \tau_{ijk} = \text{travel time of vehicle } k \text{ on edge } (i, j) \]
\[ \epsilon_i = \text{service duration at point } i \]
\[ [\lambda_i, \mu_i] = \text{time window lower and upper bound at point } i \]
\[ H = \text{maximum tour duration} \]
\[ \eta = \text{maximum continuous work limit after which a break is due} \]
\[ \delta = \text{break duration} \]
\[ \rho_i^v, \rho_i^w = \text{volume and weight pickup quantity at point } i \]
\[ \Omega_k^v, \Omega_k^w = \text{volume and weight capacity of vehicle } k \]
\[ \phi_k = \text{fixed cost of vehicle } k \]
\[ \beta_k = \text{unit-distance running cost of vehicle } k \]
\[ \theta_k = \text{unit-time wage rate of vehicle } k \]
\[ \Psi = \text{weight of relocation cost term} \]
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

\[ S_{ik} = \text{start-of-service time of vehicle } k \text{ at point } i \]

\[ Q_{ik}^{v} = \text{cumulative volume on vehicle } k \text{ at point } i \]

\[ Q_{ik}^{w} = \text{cumulative weight on vehicle } k \text{ at point } i \]
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

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

$$+ \psi \sum_{k \in K} \sum_{i \in O'_{k}} \sum_{j \in O'_{k}''} \left( \beta_k \pi_{ji} + \theta_k \tau_{jik} \right) z_{ijk}$$ (1)
Formulation

\[
\begin{align*}
\min \quad & f = \sum_{k \in K} \left( \phi_k y_k + \beta_k \sum_{i \in N} \sum_{j \in N} \pi_{ij} x_{ijk} + \theta_k \left( \sum_{j \in O_k''} S_{jk} - \sum_{i \in O_k'} S_{ik} \right) \right) \\
& \quad + \psi \sum_{k \in K} \sum_{i \in O_k'} \sum_{j \in O_k''} \left( \beta_k \pi_{ji} + \theta_j \tau_{jik} \right) z_{ijk} \\
\text{s.t.} \quad & \sum_{k \in K} \sum_{j \in DUP} x_{ijk} = 1, \quad \forall i \in P
\end{align*}
\]
Formulation

\[
\min f = \sum_{k \in K} \left( \phi_k y_k + \beta_k \sum_{i \in N} \sum_{j \in N} \pi_{ij} x_{ijk} + \theta_k \left( \sum_{j \in O_k''} S_{jk} - \sum_{i \in O_k'} S_{ik} \right) \right) \\
+ \psi \sum_{k \in K} \sum_{i \in O_k'} \sum_{j \in O_k''} \left( \beta_k \pi_{ji} + \theta_k \tau_{jik} \right) z_{ijk}
\]

s.t. \[
\sum_{k \in K} \sum_{j \in D \cup P} x_{ijk} = 1, \quad \forall i \in P
\]
\[
\sum_{i \in O_k'} \sum_{j \in N} x_{ijk} = y_k, \quad \forall k \in K
\]
\[
\sum_{i \in D} \sum_{j \in O_k''} x_{ijk} = y_k, \quad \forall k \in K
\]
Formulation

\[
\min f = \sum_{k \in K} \left( \phi_k y_k + \beta_k \sum_{i \in N} \sum_{j \in N} \pi_{ij} x_{ijk} + \theta_k \left( \sum_{j \in O_k'} S_{jk} - \sum_{i \in O_k'} S_{ik} \right) \right) \\
+ \psi \sum_{k \in K} \sum_{i \in O_k'} \sum_{j \in O_k''} \left( \beta_k \pi_{ji} + \theta_k \tau_{jik} \right) z_{ijk}
\]

\[\text{s.t.} \sum_{k \in K} \sum_{j \in D \cup P} x_{ijk} = 1, \quad \forall i \in P \]  

\[\sum_{i \in O_k'} \sum_{j \in N} x_{ijk} = y_k, \quad \forall k \in K \]  

\[\sum_{i \in D} \sum_{j \in O_k''} x_{ijk} = y_k, \quad \forall k \in K \]  

\[\sum_{i \in N} x_{ijk} = 0, \quad \forall k \in K, j \in O' \cup (O'' \setminus O_k'') \]  

\[\sum_{j \in N} x_{ijk} = 0, \quad \forall k \in K, i \in O'' \cup (O' \setminus O_k') \]
Formulation

\[
\begin{align*}
\min \quad & f = \sum_{k \in K} \left( \phi_k y_k + \beta_k \sum_{i \in N} \sum_{j \in N} \pi_{ij} x_{ijk} + \theta_k \left( \sum_{j \in O_k'} S_{jk} - \sum_{i \in O_k'} S_{ik} \right) \right) \\
& + \psi \sum_{k \in K} \sum_{i \in O_k'} \sum_{j \in O_k''} (\beta_k \pi_{ji} + \theta_k \tau_{jik}) z_{ijk} \\
\text{s.t.} \quad & \sum_{k \in K} \sum_{j \in D \cup P} x_{ijk} = 1, \quad \forall i \in P \tag{2} \\
& \sum_{i \in O_k'} \sum_{j \in N} x_{ijk} = y_k, \quad \forall k \in K \tag{3} \\
& \sum_{i \in D} \sum_{j \in O_k''} x_{ijk} = y_k, \quad \forall k \in K \tag{4} \\
& \sum_{i \in N} x_{ijk} = 0, \quad \forall k \in K, j \in O' \cup (O'' \setminus O_k'') \tag{5} \\
& \sum_{j \in N} x_{ijk} = 0, \quad \forall k \in K, i \in O'' \cup (O' \setminus O_k') \tag{6} \\
& \sum_{i \in N: i \neq j} x_{ijk} = \sum_{i \in N: i \neq j} x_{jik}, \quad \forall k \in K, j \in D \cup P \tag{7}
\end{align*}
\]
s.t. \[ \sum_{m \in P} x_{imk} + \sum_{m \in D} x_{mjk} - 1 \leq z_{ijk}, \quad \forall k \in K, i \in O_k', j \in O_k'' \] (8)
Formulation

\[ \sum_{m \in P} x_{imk} + \sum_{m \in D} x_{mjk} - 1 \leq z_{ijk}, \quad \forall k \in K, i \in O'_k, j \in O''_k \]  

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\[ x_{ijk} \leq \alpha_{ijk}, \quad \forall k \in K, i \in O'_k \cup P \cup D, j \in P \cup D \cup O''_k \]  

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\[ \rho_i^v \leq Q_{ik}^v \leq \Omega_k^v, \quad \forall k \in K, i \in P \]  (10)

\[ \rho_i^w \leq Q_{ik}^w \leq \Omega_k^w, \quad \forall k \in K, i \in P \]  (11)

\[ Q_{ik}^v = 0, \quad \forall k \in K, i \in N \setminus P \]  (12)

\[ Q_{ik}^w = 0, \quad \forall k \in K, i \in N \setminus P \]  (13)

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

\[ Q_{ik}^w + \rho_j^w \leq Q_{jk}^w + \Omega_k^w \left( 1 - x_{ijk} \right), \quad \forall k \in K, i \in O'_k \cup P \cup D, j \in P \]  (15)
Vehicle Routing

Formulation

\[
\text{s.t. } \sum_{m \in P} x_{imk} + \sum_{m \in D} x_{mjk} - 1 \leq z_{ijk}, \quad \forall k \in K, i \in O'_k, j \in O''_k
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\[
Q_{ik}^w + \rho_j^w \leq Q_{jk}^w + \Omega_k^w (1 - x_{ijk}), \quad \forall k \in K, i \in O'_k \cup P \cup D, j \in P
\] (15)

\[
S_{ik} + \varepsilon_i + \delta b_{ijk} \leq S_{jk} + M(1 - x_{ijk}), \quad \forall k \in K, i \in O'_k \cup P \cup D, j \in P \cup D \cup O''_k
\] (16)

\[
\lambda_i \sum_{j \in N} x_{ijk} \leq S_{ik}, \quad \forall k \in K, i \in O'_k \cup P \cup D
\] (17)

\[
S_{jk} \leq \mu_j \sum_{i \in N} x_{ijk}, \quad \forall k \in K, j \in P \cup D \cup O''_k
\] (18)

\[
0 \leq \sum_{j \in O''_k} S_{jk} - \sum_{i \in O'_k} S_{ik} \leq H, \quad \forall k \in K
\] (19)
Formulation

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

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

\[
b_{ijk} \leq x_{ijk}, \quad \forall k \in K, i, j \in N
\]

\[
\left( \sum_{j \in O''_k} S_{jk} - \sum_{i \in O'_k} S_{ik} \right) - \eta \leq (H - \eta) \sum_{i \in N} \sum_{j \in N} b_{ijk}, \quad \forall k \in K
\]
Formulation

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

\[
\eta - \left( S_{jk} - \sum_{m \in O_k'} S_{mk} \right) \leq M \left( 1 - b_{ijk} \right), \quad \forall k \in K, i \in O_k' \cup P \cup D, j \in P \cup D \cup O_k'' \quad (21)
\]

\[b_{ijk} \leq x_{ijk}, \quad \forall k \in K, i, j \in N \quad (22)\]

\[
\left( \sum_{j \in O_k''} S_{jk} - \sum_{i \in O_k'} S_{ik} \right) - \eta \leq (H - \eta) \sum_{i \in N} \sum_{j \in N} b_{ijk}, \quad \forall k \in K \quad (23)
\]

\[x_{ijk}, b_{ijk}, y_k \in \{0, 1\}, \quad \forall k \in K, i, j \in N \quad (24)\]

\[z_{ijk} \in \{0, 1\}, \quad \forall k \in K, i \in O', j \in O'' \quad (25)\]

\[Q_{ik}^x, Q_{ik}^w, S_{ik} \geq 0, \quad \forall k \in K, i \in N \quad (26)\]
Solution methodology: Exact approach

- We strengthen the formulation with variable fixing and valid inequalities

  Impossible traversals:
  \[ x_{iik} = 0, \quad \forall k \in K, \, i \in N \]  
  \[ x_{ijk} = 0, \quad \forall k \in K, \, i \in O', \, j \in D \cup O'' \]  
  \[ x_{ijk} = 0, \quad \forall k \in K, \, i \in P, \, j \in O'' \]  
  \[ x_{ijk} = 0, \quad \forall k \in K, \, i \in D, \, j \in D: \, i \neq j \]  

  Time-window infeasible traversals:
  \[ x_{ijk} = 0, \quad \forall k \in K, \, i \in O'_k \cup P \cup D, \, j \in P \cup D \cup O''_k: \, \lambda_i + \varepsilon_i + \tau_{ijk} > \mu_j \]  

  Lower bound on total time:
  \[ \sum_{j \in O''_k} S_{jk} - \sum_{i \in O'_k} S_{ik} \geq \sum_{i \in N} \sum_{j \in N} x_{ijk}(\varepsilon_i + \tau_{ijk}), \quad \forall k \in K \]
Solution methodology: Exact approach

- Symmetry breaking for subsets $K'$ of identical vehicles:

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

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

$$
\sum_{j \in P} x_{ji}^g k \leq \sum_{j \in P} x_{ji}^g_{g+1} k, \quad \forall k \in K, g \in 1, \ldots, (|D'| - 1) \quad (34)
$$

- Bounds on dump visits:

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

$$
\sum_{i \in D} \sum_{j \in P} x_{ijk} \leq \min (|D| - 1, |P|), \quad \forall k \in K \quad (36)
$$
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
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- 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 $K'' \in K$

```plaintext
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
    end
    changeNeighborhood(); resetCurrentNeighbor();
    if reached maxNonImpIter then
        break;
    end
end
```

I. Markov (TRANSP-OR, EPFL)
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

<table>
<thead>
<tr>
<th>Instance</th>
<th># of tours</th>
<th>Heuristic</th>
<th>Solver</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Objective</td>
<td>MIP gap(%)</td>
</tr>
<tr>
<td>i1</td>
<td>1</td>
<td>214.85</td>
<td>0.00</td>
</tr>
<tr>
<td>i1_wtw</td>
<td>1</td>
<td>252.83</td>
<td>0.00</td>
</tr>
<tr>
<td>i1_ntw</td>
<td>2</td>
<td>394.82</td>
<td>0.00</td>
</tr>
<tr>
<td>i2</td>
<td>1</td>
<td>249.32</td>
<td>0.00</td>
</tr>
<tr>
<td>i2_wtw</td>
<td>1</td>
<td>257.58</td>
<td>0.00</td>
</tr>
<tr>
<td>i2_ntw</td>
<td>2</td>
<td>439.77</td>
<td>0.00</td>
</tr>
<tr>
<td>i3</td>
<td>1</td>
<td>240.13</td>
<td>0.00</td>
</tr>
<tr>
<td>i3_wtw</td>
<td>1</td>
<td>245.46</td>
<td>0.00</td>
</tr>
<tr>
<td>i3_ntw</td>
<td>2</td>
<td>444.59</td>
<td>0.00</td>
</tr>
<tr>
<td>i4</td>
<td>1</td>
<td>138.64</td>
<td>0.00</td>
</tr>
<tr>
<td>i4_wtw</td>
<td>1</td>
<td>140.20</td>
<td>0.00</td>
</tr>
<tr>
<td>i4_ntw</td>
<td>1</td>
<td>179.54</td>
<td>0.00</td>
</tr>
<tr>
<td>i5</td>
<td>1</td>
<td>220.77</td>
<td>0.00</td>
</tr>
<tr>
<td>i5_wtw</td>
<td>1</td>
<td>233.21</td>
<td>0.00</td>
</tr>
<tr>
<td>i5_ntw</td>
<td>2</td>
<td>405.62</td>
<td>0.00</td>
</tr>
</tbody>
</table>
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

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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)
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

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  - 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)
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  - 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:

\[
Q_{i,t}^* = \sum_{k=1}^{K} n_{i,t,k} q_k
\]  

(37)

Let \( n_{i,t,k} \overset{iid}{\longrightarrow} \mathcal{P}(\lambda_{i,t,k}) \) with probability \( \pi_{i,t,k} \). Then we obtain:

\[
\mathbb{E}(Q_{i,t}^*) = \sum_{k=1}^{K} q_k \lambda_{i,t,k} \pi_{i,t,k}
\]  

(38)

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

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

(39)

assuming strict exogeneity
Methodology

- Given vectors of covariates $x_{i,t}$ and $z_{i,t}$ and vectors of parameters $\beta_k$ and $\gamma_k$, we define Poisson rates and logit-type probabilities:

$$
\lambda_{i,t,k}(\theta) = \exp\left(x_{i,t}^T \beta_k\right) \quad (40)
$$

$$
\pi_{i,t,k}(\theta) = \frac{\exp\left(z_{i,t}^T \gamma_k\right)}{\sum_{j=1}^{K} \exp\left(z_{i,t}^T \gamma_j\right)} \quad (41)
$$

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

$$
\min_{\theta \in \Theta} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Q_{i,t} - \sum_{k=1}^{K} \frac{\exp\left(x_{i,t}^T \beta_k + z_{i,t}^T \gamma_k + \ln(q_k)\right)}{\sum_{j=1}^{K} \exp\left(z_{i,t}^T \gamma_j\right)}\right)^2 \quad (42)
$$

- $\Theta := (\beta_k, \gamma_k : \forall k)$, and $\gamma_{k^*} = 0$ for one arbitrarily chosen $k^*$

- 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:

\[
\min_{\theta \in \Theta} \sum_{i=1}^{N} \sum_{t=1}^{T} \left( Q_{i,t} - \exp \left( x_{i,t}^T \beta + \ln(q) \right) \right)^2 \tag{43}
\]

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

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

$$\dot{Q}_{i,t} = \sum_{k=1}^{K} \frac{\exp (\dot{x}_{i,t}^T \hat{\beta}_k + \dot{z}_{i,t}^T \hat{\gamma}_k + \ln (q_k))}{\sum_{j=1}^{K} \exp (\dot{z}_{i,t}^T \hat{\gamma}_j)}$$  \hspace{1cm} (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
Demand Forecasting

Covariates

- Based on the above observations, we use the following covariates
- They are all used both for $x_{i,t}$ (rates) and $z_{i,t}$ (probabilities)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Container fixed effect</td>
<td>dummy</td>
</tr>
<tr>
<td>Day of the week</td>
<td>dummy</td>
</tr>
<tr>
<td>Month</td>
<td>dummy</td>
</tr>
<tr>
<td>Minimum temperature in Celsius</td>
<td>continuous</td>
</tr>
<tr>
<td>Precipitation in mm</td>
<td>continuous</td>
</tr>
<tr>
<td>Pressure in hPa</td>
<td>continuous</td>
</tr>
<tr>
<td>Wind speed in kmph</td>
<td>continuous</td>
</tr>
</tbody>
</table>

Table 2: Table of covariates
Evaluating the fits

- Coefficient of determination
  \[ R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \]  
  with higher values for a better model

- Akaike information criterion (AIC):
  \[ AIC = \left( \frac{SS_{res}}{N} \right) \exp(2K/N) \]  
  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

<table>
<thead>
<tr>
<th></th>
<th>$\hat{\beta}_1$ (5L)***</th>
<th>$\hat{\beta}_2$ (15L)***</th>
<th>$\hat{\gamma}_2$***</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum temperature in Celsius</td>
<td>1461.356</td>
<td>0.022</td>
<td>-0.037</td>
</tr>
<tr>
<td>Precipitation in mm</td>
<td>-0.821</td>
<td>-0.009</td>
<td>0.018</td>
</tr>
<tr>
<td>Pressure in hPa</td>
<td>-13.724</td>
<td>-0.001</td>
<td>0.010</td>
</tr>
<tr>
<td>Wind speed in kmph</td>
<td>7.580</td>
<td>-0.004</td>
<td>0.020</td>
</tr>
<tr>
<td>Monday</td>
<td>402.235</td>
<td>2.166</td>
<td>-9.693</td>
</tr>
<tr>
<td>Tuesday</td>
<td>1908.233</td>
<td>2.293</td>
<td>-9.977</td>
</tr>
<tr>
<td>Wednesday</td>
<td>-844.662</td>
<td>1.432</td>
<td>0.202</td>
</tr>
<tr>
<td>Thursday</td>
<td>1937.385</td>
<td>1.198</td>
<td>1.453</td>
</tr>
<tr>
<td>Friday</td>
<td>1876.162</td>
<td>1.239</td>
<td>4.419</td>
</tr>
<tr>
<td>Saturday</td>
<td>-6981.339</td>
<td>1.358</td>
<td>4.723</td>
</tr>
<tr>
<td>Sunday</td>
<td>1831.715</td>
<td>1.905</td>
<td>2.832</td>
</tr>
<tr>
<td>March</td>
<td>-27.136</td>
<td>2.955</td>
<td>-1.453</td>
</tr>
<tr>
<td>April</td>
<td>1071.406</td>
<td>2.746</td>
<td>-1.532</td>
</tr>
<tr>
<td>May</td>
<td>1689.979</td>
<td>2.988</td>
<td>-1.603</td>
</tr>
<tr>
<td>June</td>
<td>-2604.520</td>
<td>2.901</td>
<td>-1.452</td>
</tr>
</tbody>
</table>
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>
<thead>
<tr>
<th>Table 4: Mean $R^2$ for estimation and validation sets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimation</td>
</tr>
<tr>
<td>Validation</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>
Validation

Figure 5: Histograms for estimation and validation samples
Contents

1 Introduction
2 Vehicle Routing
3 Demand Forecasting
4 Conclusion
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- 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.
Conclusion

Thank you.

Questions?


