Waste collection inventory routing with non-stationary stochastic demands

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Outline

1. Introduction
2. Related Literature
3. Formulation
4. Methodology
5. Numerical Experiments
6. Conclusion
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Setup

- Sensorized containers for recyclables periodically send waste level data to a central database.
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Level data is used for container selection and route planning.
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Vehicles are dispatched to carry out the daily schedules produced by the routing algorithm.
Introduction

Setup

- Sensorized containers for recyclables periodically send waste level data to a central database.
- Level data is used for container selection and route planning.
- Vehicles are dispatched to carry out the daily schedules produced by the routing algorithm.
- Efficient waste collection thus depends on the ability to:
  - forecast container levels,
  - select the containers to collect each day,
  - and route the vehicles in an (near-)optimal way.
Problem Definition

The setup falls within the framework of the IRP with:

- stochastic demands,
- order-up-to level (OU) policy,
- no allowed expected overflows,
- single-day backorder limit (i.e. if a container overflows on a given day, it must be collected on that day).
Problem Definition

- The setup falls within the framework of the IRP with:
  - stochastic demands,
  - order-up-to level (OU) policy,
  - no allowed expected overflows,
  - single-day backorder limit (i.e. if a container overflows on a given day, it must be collected on that day).

- The routing component includes:
  - intermediate facility visits (recycling plants),
  - heterogeneous capacitated vehicles,
  - site dependencies,
  - vehicle-to-period availabilities,
  - time windows,
  - maximum tour duration.
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Related VRP Literature

- **VRP with intermediate facilities (VRP-IF):**
  - Bard et al. (1998a), Kim et al. (2006), Crevier et al. (2007).

- **Electric and alternative fuel VRP:**

- **Heterogeneous fixed fleet VRP:**
  - Taillard (1999), Baldacci and Mingozzi (2009), Subramanian et al. (2012), Penna et al. (2013).
  - Hiermann et al. (2014) and Goeke and Schneider (2015) use some form of vehicle heterogeneity in the electric VRP.
Related Literature

Related Stochastic IRP Literature

- Early research on optimal replenishment policies in a stochastic setting:

- Robust optimization:
  - Solyalı et al. (2012).

- Chance constraints:

- Scenario based:
Contributions

- Dynamic probabilistic information on overflows and route failures.
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- Demand forecasting model tested and validated on real data (Markov et al., 2015).
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- A rich IRP with features traditionally absent or rarely considered in the IRP literature.
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- Dynamic probabilistic information on overflows and route failures.

- Demand forecasting model tested and validated on real data (Markov et al., 2015).

- A rich IRP with features traditionally absent or rarely considered in the IRP literature.

- ALNS algorithm performs very well on IRP benchmarks from the literature.

- Benefit of considering uncertainty in the objective function evaluated on instances derived from real data.
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Nomenclature

Sets

\( o \) origin
\( \mathcal{D} \) set of dumps
\( \mathcal{N} = \{ o \} \cup \{ d \} \cup \mathcal{D} \cup \mathcal{P} \)
\( \mathcal{T} = \{ 0, \ldots, u \} \)
\( d \) destination
\( \mathcal{P} \) set of containers
\( \mathcal{K} \) set of vehicles
\( \mathcal{T}^+ = \{ 1, \ldots, u + 1 \} \)

Parameters

\( \pi_{ij} \) length of arc \((i, j)\)
\( \tau_{ijk} \) travel time of vehicle \(k\) on arc \((i, j)\)
\( \lambda_i, \mu_i \) lower and upper time window bound at point \(i\)
\( \delta_i \) service duration at point \(i\)
\( \rho_{it} \) demand of container \(i\) on day \(t\) (random variable)
\( \omega_i \) capacity of container \(i\)
\( \chi \) container overflow cost (monetary)
\( \zeta \) emergency collection cost (monetary)
Nomenclature

Sets

\( o \) \hspace{1cm} \text{origin} \hspace{1cm} \( d \) \hspace{1cm} \text{destination} \\
\( \mathcal{D} \) \hspace{1cm} \text{set of dumps} \hspace{1cm} \( \mathcal{P} \) \hspace{1cm} \text{set of containers} \\
\( \mathcal{N} = \{o\} \cup \{d\} \cup \mathcal{D} \cup \mathcal{P} \) \hspace{1cm} \( \mathcal{K} \) \hspace{1cm} \text{set of vehicles} \\
\( \mathcal{T} = \{0, ..., u\} \) \hspace{1cm} \( \mathcal{T}^+ = \{1, ..., u + 1\} \)

Parameters

\( \sigma_{it} \) \hspace{1cm} = 1 \text{ if container } i \text{ is in a state of full and overflowing on day } t, 0 \text{ otherwise} \\
\( \Omega_k \) \hspace{1cm} \text{capacity of vehicle } k \\
\( \varphi_k \) \hspace{1cm} \text{daily deployment cost of vehicle } k \text{ (monetary)} \\
\( \beta_k \) \hspace{1cm} \text{unit-distance running cost of vehicle } k \text{ (monetary)} \\
\( \theta_k \) \hspace{1cm} \text{unit-time running cost of vehicle } k \text{ (monetary)} \\
\( \alpha_{kt} \) \hspace{1cm} = 1 \text{ if vehicle } k \text{ is available on day } t, 0 \text{ otherwise} \\
\( \alpha_{ik} \) \hspace{1cm} = 1 \text{ if point } i \text{ is accessible by vehicle } k, 0 \text{ otherwise} \\
\( H \) \hspace{1cm} \text{maximum tour duration}
Nomenclature

Decision variables: binary

\[ x_{ijkl} = \begin{cases} 1 & \text{if vehicle } k \text{ traverses arc } (i,j) \text{ on day } t \\ 0 & \text{otherwise} \end{cases} \]

\[ y_{ikt} = \begin{cases} 1 & \text{if vehicle } k \text{ visits point } i \text{ on day } t \\ 0 & \text{otherwise} \end{cases} \]

\[ z_{kt} = \begin{cases} 1 & \text{if vehicle } k \text{ is used on day } t \\ 0 & \text{otherwise} \end{cases} \]

Decision variables: continuous

\[ q_{ikt} \quad \text{expected pickup quantity by vehicle } k \text{ at point } i \text{ on day } t \]
\[ Q_{ikt} \quad \text{expected cumulative quantity on vehicle } k \text{ at point } i \text{ on day } t \]
\[ I_{it} \quad \text{expected inventory at point } i \text{ at the start of day } t \]
\[ S_{ikt} \quad \text{start-of-service time of vehicle } k \text{ at point } i \text{ on day } t \]
Forecasting Model

- Demand is the amount deposited in a container on each day, and is random and non-stationary.
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We can use any forecasting model that gives us:
- the expected container demands $\mathbb{E}(\rho_{it})$ on each day,
- a consistent estimate of the forecasting error $\varsigma$.

The forecasting error is the standard deviation of the residuals based on a historical fit. Its distribution can be approximated as a normal, and is used to calculate probabilities of container overflows and route failures. The probabilities are dynamic and conditional, and depend on:
- the evolution of container states over the planning horizon,
- and the vehicle visits on each day.
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  - the evolution of container states over the planning horizon,
  - and the vehicle visits on each day.
Formulation

Objective Function

Routing cost + Expected overflow and emergency visit cost + Expected route failure cost

Lower routing cost is counterbalanced by more overflows and route failures, and vice versa.

Our goal is to minimize the expected monetary value of all components.
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- Our goal is to minimize the expected monetary value of all components.
Objective Function: Main Concepts

- **Two container states:**
  - $\sigma_{it} = 0$: not full,
  - $\sigma_{it} = 1$: full and overflowing.
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  - $\sigma_{it} = 0$: not full,
  - $\sigma_{it} = 1$: full and overflowing.

- **Two types of container collection:**
  - regular collection of container $i$ on day $t$: $\exists k \in K : y_{ikt} = 1$,
  - emergency collection of container $i$ on day $t$: $\sigma_{it} = 1$ and $y_{ikt} = 0$, $\forall k \in K$. 

- **Related costs:**
  - overflow cost $\chi$: paid in state $\sigma_{it} = 1$,
  - emergency collection cost $\zeta$: paid in state $\sigma_{it} = 1$ when $y_{ikt} = 0$, $\forall k \in K$. 

Objective Function: Main Concepts

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  - Emergency collection of container \( i \) on day \( t \):
    \( \sigma_{it} = 1 \) and \( y_{ikt} = 0, \forall k \in K \).

- **Related costs:**
  - Overflow cost \( \chi \): paid in state \( \sigma_{it} = 1 \),
  - Emergency collection cost \( \zeta \): paid in state \( \sigma_{it} = 1 \) when \( y_{ikt} = 0, \forall k \in K \).
Figure 1: Container state probability tree

\[
\begin{align*}
\sigma_{i0} = 0 & \quad \mathbb{P}(i_0 + \rho i_0 + \rho i_1 + \rho i_2 < \omega_i) \quad \mathbb{P}(i_0 + \rho i_0 + \rho i_1 < \omega_i) \quad \mathbb{P}(i_0 + \rho i_0 + \rho i_1 + \rho i_2 < \omega_i) \\
\sigma_{i1} = 0 & \quad \mathbb{P}(i_0 + \rho i_0 + \rho i_1 + \rho i_2 \geq \omega_i) \quad \mathbb{P}(i_0 + \rho i_0 + \rho i_1 \geq \omega_i) \\
\sigma_{i0} = 1 & \quad \mathbb{P}(i_0 + \rho i_0 + \rho i_1 < \omega_i) \quad \mathbb{P}(i_0 + \rho i_0 + \rho i_1 \geq \omega_i) \\
\sigma_{i1} = 1 & \quad \mathbb{P}(i_0 + \rho i_0 + \rho i_1 + \rho i_2 < \omega_i) \quad \mathbb{P}(i_0 + \rho i_0 + \rho i_1 + \rho i_2 \geq \omega_i)
\end{align*}
\]
Objective Function: Formulation

- Routing cost (RC):
  \[
  \sum_{t \in T} \sum_{k \in K} \left( \varphi_k z_{kt} + \beta_k \sum_{i \in N} \sum_{j \in N} \pi_{ij} x_{ijkt} + \theta_k \left( S_{dkt} - S_{okt} \right) \right)
  \] (1)

- Expected overflow and emergency collection cost (EOECC):
  \[
  \sum_{t \in T} \sum_{i \in P} \left( \lambda_t \sigma_{it} \left\{ \max(0, g - t) : \exists k \in K : y_{ikt} = 1 \right\} \right) \left( \chi + \zeta - \zeta \sum_{k \in K} y_{ikt} \right)
  \] (2)
Objective Function: Formulation

- Routing cost (RC):
  \[
  \sum_{t \in T} \sum_{k \in K} \left( \varphi_k z_{kt} + \beta_k \sum_{i \in N} \sum_{j \in N} \pi_{ij} x_{ijkt} + \theta_k \left( S_{dkt} - S_{okt} \right) \right) \tag{1}
  \]

- Expected overflow and emergency collection cost (EOECC):
  \[
  \sum_{t \in T \cup T^+} \sum_{i \in P} \left( \mathbb{P} (\sigma_{it} = 1 \mid \max (0, g < t : \exists k \in K : y_{ikg} = 1)) \left( \chi + \zeta - \zeta \sum_{k \in K} y_{ikt} \right) \right) \tag{2}
  \]
Objective Function: Formulation

- **Expected route failure cost (ERFC):**

  \[
  \sum_{t \in T \setminus 0} \sum_{k \in K} \sum_{S \in \mathcal{I}_{kt}} \left( C_S \mathbb{P}\left( \sum_{s \in S} I_{st} > \Omega_k \left| \max(0, g < t: y_{skg} = 1) \right) \right) \right), \tag{3}
  \]

  where
  - \( \mathcal{I}_{kt} = \mathcal{I}_{kt}(y_{ikt}, \forall i \in D) \) is the set of depot-to-dump or dump-to-dump trips for vehicle \( k \) on day \( t \),
  - \( S \) is the set of containers in a particular trip,
  - \( C_S \) is the average routing cost of going from this set to the nearest dump and back.
Objective Function: Formulation

- **Expected route failure cost (ERFC):**

\[
\sum_{t \in T \setminus 0} \sum_{k \in K} \sum_{S \in \mathcal{I}_{kt}} \left( C_S \cdot P \left( \sum_{s \in S} l_{st} > \Omega_k \left| \max(0, g < t: y_{skg} = 1) \right. \right) \right), \tag{3}
\]

where

- \( \mathcal{I}_{kt} = \mathcal{I}_{kt}(y_{ikt}, \forall i \in D) \) is the set of depot-to-dump or dump-to-dump trips for vehicle \( k \) on day \( t \),
- \( S \) is the set of containers in a particular trip,
- \( C_S \) is the average routing cost of going from this set to the nearest dump and back.

- The objective function becomes

\[
z(\cdot) = RC + EOECC + ERFC \tag{4}
\]

and is non-linear, thus resulting in an MINLP.
Formulation

Constraints: Basic routing

\[
\sum_{j \in N} x_{ojkt} = \alpha_{kt} z_{kt}, \quad \forall t \in T, k \in K
\]

\[
\sum_{i \in D} x_{idkt} = \alpha_{kt} z_{kt}, \quad \forall t \in T, k \in K
\]

\[
y_{ikt} = \sum_{j \in N} x_{ijkt} = \sum_{j \in N} x_{jikt}, \quad \forall t \in T, k \in K, i \in P
\]

\[
\sum_{k \in K} y_{ikt} \leq 1, \quad \forall t \in T, i \in P
\]

\[
y_{ikt} \leq \alpha_{ik}, \quad \forall t \in T, k \in K, i \in P
\]

\[
\sum_{i \in N} x_{ijkt} = \sum_{i \in N} x_{jikt}, \quad \forall t \in T, k \in K, j \in D \cup P
\]

\[
l_{it} = l_{i(t-1)} - \sum_{k \in K} q_{ik(t-1)} + \mathbb{E}(\rho_{i(t-1)}), \quad \forall t \in T^+, i \in P
\]

\[
l_{it} \leq \omega_{i}, \quad \forall t \in T^+, i \in P
\]

\[
l_{i0} - \omega_{i} \leq \omega_{i} \sum_{k \in K} y_{ik0}, \quad \forall i \in P
\]

\[
q_{ikt} \leq M y_{ikt}, \quad \forall t \in T, k \in K, i \in P
\]

\[
q_{ikt} \leq l_{it}, \quad \forall t \in T, k \in K, i \in P
\]

\[
q_{ikt} \geq l_{it} - M(1 - y_{ikt}), \quad \forall t \in T, k \in K, i \in P
\]
**Formulation**

**Constraints: Inventory balance**

\[
\sum_{j \in N} x_{ojkt} = \alpha_{kt} z_{kt}, \quad \forall t \in T, k \in K \tag{5}
\]

\[
\sum_{i \in D} x_{idkt} = \alpha_{kt} z_{kt}, \quad \forall t \in T, k \in K \tag{6}
\]

\[
y_{ikt} = \sum_{j \in N} x_{ijkt} = \sum_{j \in N} x_{jikt}, \quad \forall t \in T, k \in K, i \in P \tag{7}
\]

\[
\sum_{k \in K} y_{ikt} \leq 1, \quad \forall t \in T, i \in P \tag{8}
\]

\[
y_{ikt} \leq \alpha_{ik}, \quad \forall t \in T, k \in K, i \in P \tag{9}
\]

\[
\sum_{i \in N} x_{ijkt} = \sum_{i \in N} x_{jikt}, \quad \forall t \in T, k \in K, j \in D \cup P \tag{10}
\]

\[
l_{it} = l_{i(t-1)} - \sum_{k \in K} q_{ikt(t-1)} + \mathbb{E}(\rho_{i(t-1)}), \quad \forall t \in T^+, i \in P \tag{11}
\]

\[
l_{it} \leq \omega_{i}, \quad \forall t \in T^+, i \in P \tag{12}
\]

\[
l_{i0} - \omega_{i} \leq \omega_{i} \sum_{k \in K} y_{ik0}, \quad \forall i \in P \tag{13}
\]

\[
q_{ikt} \leq M y_{ikt}, \quad \forall t \in T, k \in K, i \in P \tag{14}
\]

\[
q_{ikt} \leq l_{it}, \quad \forall t \in T, k \in K, i \in P \tag{15}
\]

\[
q_{ikt} \geq l_{it} - M(1 - y_{ikt}), \quad \forall t \in T, k \in K, i \in P \tag{16}
\]
Constraints: Capacity related

\begin{align*}
q_{ikt} & \leq Q_{ikt} \leq \Omega_k, & \forall t \in T, k \in K, i \in P \\
Q_{ikt} &= 0, & \forall t \in T, k \in K, i \in N \setminus P \\
Q_{ikt} + q_{jkt} & \leq Q_{jkt} + \Omega_k (1 - x_{ijkt}), & \forall t \in T, k \in K, i \in N \setminus \{d\}, j \in P \\
S_{ikt} + \delta_i + \tau_{ijk} & \leq S_{jkt} + (\mu_i + \delta_i + \tau_{ijk}) (1 - x_{ijkt}), & \forall t \in T, k \in K, i \in N \setminus \{d\}, j \in N \setminus \{o\} \\
\lambda_i \sum_{j \in N} x_{ijkt} & \leq S_{ikt}, & \forall t \in T, k \in K, i \in N \setminus \{d\} \\
S_{jkt} & \leq \mu_j \sum_{i \in N} x_{ijkt}, & \forall t \in T, k \in K, j \in N \setminus \{o\} \\
0 & \leq S_{dkt} - S_{okt} \leq H & \forall t \in T, k \in K \\
x_{ijkt}, y_{ikt}, z_{kt} & \in \{0, 1\}, & \forall t \in T, k \in K, i, j \in N \\
q_{ikt}, Q_{ikt}, I_{it}, S_{ikt} & \geq 0, & \forall t \in T, k \in K, i \in N 
\end{align*}
Constraints: Time related

\[ q_{ikt} \leq Q_{ikt} \leq \Omega_k, \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, i \in \mathcal{P} \quad (17) \]
\[ Q_{ikt} = 0, \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, i \in \mathcal{N} \setminus \mathcal{P} \quad (18) \]
\[ Q_{ikt} + q_{jkt} \leq Q_{jkt} + \Omega_k (1 - x_{ijkt}), \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, i \in \mathcal{N} \setminus \{d\}, j \in \mathcal{P} \quad (19) \]
\[ S_{ikt} + \delta_i + \tau_{ijk} \leq S_{jkt} + (\mu_i + \delta_i + \tau_{ijk})(1 - x_{ijkt}), \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, i \in \mathcal{N} \setminus \{d\}, j \in \mathcal{N} \setminus \{o\} \quad (20) \]
\[ \lambda_i \sum_{j \in \mathcal{N}} x_{ijkt} \leq S_{ikt}, \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, i \in \mathcal{N} \setminus \{d\} \quad (21) \]
\[ S_{jkt} \leq \mu_j \sum_{i \in \mathcal{N}} x_{ijkt}, \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, j \in \mathcal{N} \setminus \{o\} \quad (22) \]
\[ 0 \leq S_{dkt} - S_{okt} \leq H, \quad \forall t \in \mathcal{T}, k \in \mathcal{K} \quad (23) \]
\[ x_{ijkt}, y_{ikt}, z_{kt} \in \{0, 1\}, \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, i, j \in \mathcal{N} \quad (24) \]
\[ q_{ikt}, Q_{ikt}, I_{it}, S_{ikt} \geq 0, \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, i \in \mathcal{N} \quad (25) \]
Constraints: Domain

\[ q_{ikt} \leq Q_{ikt} \leq \Omega_k, \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, i \in \mathcal{P} \]  
\[ Q_{ikt} = 0, \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, i \in \mathcal{N} \setminus \mathcal{P} \]  
\[ Q_{ikt} + q_{jkt} \leq Q_{jkt} + \Omega_k (1 - x_{ijkt}), \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, i \in \mathcal{N} \setminus \{d\}, j \in \mathcal{P} \]  
\[ S_{ikt} + \delta_i + \tau_{ijk} \leq S_{jkt} + (\mu_i + \delta_i + \tau_{ijk})(1 - x_{ijkt}), \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, i \in \mathcal{N} \setminus \{d\}, j \in \mathcal{N} \setminus \{o\} \]  
\[ \lambda_i \sum_{j \in \mathcal{N}} x_{ijkt} \leq S_{ikt}, \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, i \in \mathcal{N} \setminus \{d\} \]  
\[ S_{jkt} \leq \mu_j \sum_{i \in \mathcal{N}} x_{ijkt}, \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, j \in \mathcal{N} \setminus \{o\} \]  
\[ 0 \leq S_{dkt} - S_{okt} \leq H, \quad \forall t \in \mathcal{T}, k \in \mathcal{K} \]  
\[ x_{ijkt}, y_{ikt}, z_{kt} \in \{0, 1\}, \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, i, j \in \mathcal{N} \]  
\[ q_{ikt}, Q_{ikt}, I_{it}, S_{ikt} \geq 0, \quad \forall t \in \mathcal{T}, k \in \mathcal{K}, i \in \mathcal{N} \]
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Adaptive Large Neighborhood Search (ALNS)

Solved by ALNS with the following operators:

**Destroy operators:**
- remove $\rho$ containers randomly,
- remove $\rho$ worst containers,
- Shaw removals (Shaw, 1997),
- empty a random day,
- empty a random vehicle,
- remove a random dump,
- remove the worst dump,
- remove consecutive visits.

**Repair operators:**
- insert $\rho$ containers randomly,
- insert $\rho$ containers in the best way,
- Shaw insertions (Shaw, 1997),
- swap $\rho$ random containers,
- insert a dump randomly,
- swap random dumps,
- replace a random dump,
- reorder dumps DP operator.
Reorder dumps DP Operator (Hemmelmayr et al., 2013)

Figure 2: Feasibility graph of the reorder dumps DP operator

- Preserves/restores vehicle capacity feasibility.
- Removes all dump visits and reinserts them in a locally optimal way solving a shortest path problem using the Bellman-Ford algorithm.
- Followed by local search improvement using 2-opt.
The Search Strategy

- Accepting intermediate infeasible solutions facilitates the exploration of the search space of tightly constrained problems.

- We allow the following feasibility violations of the solution $s$:
  - $V^Ω(s)$: vehicle capacity violation
  - $V^μ(s)$: time window violation
  - $V^H(s)$: duration violation
  - $V^ω(s)$: container capacity violation
  - $V^0(s)$: backorder limit violation
  - $V^α(s)$: accessibility violation

The solution representation during the search is:

$$\text{f}(s) = z(s) + L^Ω V^Ω(s) + L^μ V^μ(s) + L^H V^H(s) + L^ω V^ω(s) + L^0 V^0(s) + L^α V^α(s)$$

with the penalties $L^Ω$ through $L^α$ dynamically adjusted during the search to encourage or discourage infeasible solutions.
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  - $V_\Omega(s)$: vehicle capacity violation
  - $V_\mu(s)$: time window violation
  - $V^H(s)$: duration violation
  - $V_\omega(s)$: container capacity violation
  - $V^0(s)$: backorder limit violation
  - $V^\alpha(s)$: accessibility violation

- The solution representation during the search is:

$$f(s) = z(s) + L_\Omega V_\Omega(s) + L_\mu V_\mu + L^H V^H(s) + L_\omega V_\omega(s) + L^0 V^0(s) + L^\alpha V^\alpha(s)$$

(26)

with the penalties $L_\Omega$ through $L^\alpha$ dynamically adjusted during the search to encourage or discourage infeasible solutions.
Outline

1 Introduction
2 Related Literature
3 Formulation
4 Methodology
5 Numerical Experiments
6 Conclusion
Archetti et al. (2007) Instances

- First classical IRP testbed.
- 160 instances in total.
- 5 to 50 customers.
- 3 or 6 periods in the planning horizon.
- Single vehicle.
- Low and high inventory holding costs.
Archetti et al. (2007) Instances

- First classical IRP testbed.
- 160 instances in total.
- 5 to 50 customers.
- 3 or 6 periods in the planning horizon.
- Single vehicle.
- Low and high inventory holding costs.

- Heuristic solutions by Archetti et al. (2012), Coelho et al. (2012a), Coelho et al. (2012b), etc...
- We solve each instance 10 times and report best and average results.
## Archetti et al. (2007) Instances

### Table 1: Results on instances with high inventory holding cost

<table>
<thead>
<tr>
<th>$u$</th>
<th>$n$</th>
<th>ALNS fast version</th>
<th></th>
<th>ALNS slow version</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
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<td>Runtime(s.)</td>
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<td>Avg Gap(%)</td>
<td>Runtime(s.)</td>
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### Table 2: Results on instances with low inventory holding cost

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<tr>
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<th>ALNS fast version</th>
<th></th>
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<tbody>
<tr>
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<td>Avg Gap(%)</td>
<td>Runtime(s.)</td>
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<tr>
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<td>28</td>
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<td>0.02</td>
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<td>0.03</td>
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</tbody>
</table>
Archetti et al. (2012) Instances

- 60 instances in total.
- 50, 100 and 200 customers.
- 6 periods in the planning horizon.
- Single vehicle.
- Low and high inventory holding costs.
Archetti et al. (2012) Instances

- 60 instances in total.
- 50, 100 and 200 customers.
- 6 periods in the planning horizon.
- Single vehicle.
- Low and high inventory holding costs.

Solved by Archetti et al. (2012) using a hybrid heuristic algorithm.
For the moment we have solved the 50-customer instances 10 times and provide best and average results.
## Archetti et al. (2012) Instances

Table 3: Results on 50-customer instances with high inventory holding cost

<table>
<thead>
<tr>
<th>Instance</th>
<th>Archetti et al. (2012)</th>
<th>Runtime(s.)</th>
<th>Best Cost</th>
<th>Avg Cost</th>
<th>Best Gap(%)</th>
<th>Avg Gap(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>abs1n50</td>
<td>31,147.82</td>
<td>670</td>
<td>30,708.05</td>
<td>30,809.31</td>
<td>-1.41</td>
<td>-1.09</td>
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<tr>
<td>abs2n50</td>
<td>30,192.51</td>
<td>676</td>
<td>30,226.23</td>
<td>30,271.07</td>
<td>0.11</td>
<td>0.26</td>
</tr>
<tr>
<td>abs3n50</td>
<td>30,420.96</td>
<td>667</td>
<td>30,388.68</td>
<td>30,515.79</td>
<td>-0.11</td>
<td>0.31</td>
</tr>
<tr>
<td>abs4n50</td>
<td>31,898.84</td>
<td>671</td>
<td>32,103.17</td>
<td>32,213.62</td>
<td>0.64</td>
<td>0.99</td>
</tr>
<tr>
<td>abs5n50</td>
<td>29,518.68</td>
<td>666</td>
<td>29,646.74</td>
<td>29,797.79</td>
<td>0.43</td>
<td>0.95</td>
</tr>
<tr>
<td>abs6n50</td>
<td>32,394.50</td>
<td>652</td>
<td>32,336.81</td>
<td>32,420.63</td>
<td>-0.18</td>
<td>0.08</td>
</tr>
<tr>
<td>abs7n50</td>
<td>30,165.00</td>
<td>661</td>
<td>30,222.28</td>
<td>30,269.23</td>
<td>0.19</td>
<td>0.35</td>
</tr>
<tr>
<td>abs8n50</td>
<td>26,416.46</td>
<td>652</td>
<td>26,409.83</td>
<td>26,537.19</td>
<td>-0.03</td>
<td>0.46</td>
</tr>
<tr>
<td>abs9n50</td>
<td>30,671.88</td>
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<td>30,543.31</td>
<td>30,630.53</td>
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<td>-0.13</td>
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<tr>
<td>abs10n50</td>
<td>32,362.01</td>
<td>635</td>
<td>31,937.51</td>
<td>32,065.85</td>
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<td>-0.92</td>
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<tr>
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<td>30,518.87</td>
<td>661</td>
<td>30,452.26</td>
<td>30,553.10</td>
<td>-0.21</td>
<td>0.13</td>
</tr>
</tbody>
</table>
## Table 4: Results on 50-customer instances with low inventory holding cost

<table>
<thead>
<tr>
<th>Instance</th>
<th>Archetti et al. (2012)</th>
<th>Runtime(s.)</th>
<th>Best Cost</th>
<th>Avg Cost</th>
<th>Best Gap(%)</th>
<th>Avg Gap(%)</th>
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</thead>
<tbody>
<tr>
<td>abs1n50</td>
<td>10,409.13</td>
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<td>10,377.36</td>
<td>10,449.91</td>
<td>-0.31</td>
<td>0.39</td>
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<tr>
<td>abs2n50</td>
<td>10,881.35</td>
<td>643</td>
<td>10,927.83</td>
<td>11,014.20</td>
<td>0.43</td>
<td>1.22</td>
</tr>
<tr>
<td>abs3n50</td>
<td>10,767.39</td>
<td>622</td>
<td>10,702.05</td>
<td>10,924.09</td>
<td>-0.61</td>
<td>1.46</td>
</tr>
<tr>
<td>abs4n50</td>
<td>10,656.21</td>
<td>632</td>
<td>10,711.86</td>
<td>10,875.98</td>
<td>0.52</td>
<td>2.06</td>
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<tr>
<td>abs5n50</td>
<td>10,234.60</td>
<td>624</td>
<td>10,332.55</td>
<td>10,458.54</td>
<td>0.96</td>
<td>2.19</td>
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<tr>
<td>abs6n50</td>
<td>10,533.63</td>
<td>620</td>
<td>10,388.66</td>
<td>10,485.72</td>
<td>-1.38</td>
<td>-0.45</td>
</tr>
<tr>
<td>abs7n50</td>
<td>10,460.82</td>
<td>626</td>
<td>10,388.08</td>
<td>10,497.06</td>
<td>-0.70</td>
<td>0.35</td>
</tr>
<tr>
<td>abs8n50</td>
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<td>623</td>
<td>10,683.31</td>
<td>10,771.40</td>
<td>2.61</td>
<td>3.46</td>
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<td>10,305.69</td>
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<td>10,416.97</td>
<td>10,472.96</td>
<td>1.08</td>
<td>1.62</td>
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<tr>
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<td>10,047.06</td>
<td>10,153.50</td>
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<tr>
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<td>10,497.57</td>
<td>10,610.33</td>
<td>-0.14</td>
<td>0.93</td>
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</tbody>
</table>
Instances Based on Real Data

- 63 instances, each covering a week of white glass collections in Geneva, Switzerland in 2014, 2015, or 2016.
- Maximum tour duration of 4 hours.
- Time windows from 8h00 to 12h00.
- Planning horizon of 7 days.
- Up to 2 heterogeneous vehicles.
- Up to 53 containers (41 on average).
- 2 dumps located far apart from each other.
Instances Based on Real Data

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- Time windows from 8h00 to 12h00.
- Planning horizon of 7 days.
- Up to 2 heterogeneous vehicles.
- Up to 53 containers (41 on average).
- 2 dumps located far apart from each other.

- We solve each instance 10 times and provide best and average results.
- We simulate the forecasting error realizations and evaluate the relevance of the probability information captured by the objective function.
Real Data: The Relevant Costs

- **Truck related:**
  - vehicle per day: 100 CHF,
  - vehicle per km: 2.95 CHF,
  - driver per hour: 40 CHF.

- **Container related:**
  - overflow cost $\chi$: 100 CHF,
  - emergency collection cost $\zeta$: 100 CHF, 50 CHF, 25 CHF.

- **Route failure related:**
  - cost of visiting the nearest dump from a cluster $C_S$, multiplied by a
    *route failure cost multiplier* (RFCM): 1.00, 0.50, 0.25.
Two Problem Types

- **Routing-only:**
  - Optimizes the routing cost only in the objective function, disregarding all probability information.
  - In other words, it ignores the risk of container overflows and route failures.

- **Complete:**
  - Optimizes the complete objective function as previously defined.
## Table 5: Basic results for real data instances

<table>
<thead>
<tr>
<th>Type</th>
<th>Emergency Cost</th>
<th>RFCM</th>
<th>Runtime (s.)</th>
<th>Avg Num Tours</th>
<th>Avg Num Containers</th>
<th>Avg Num Dump Visits</th>
<th>Best Cost (CHF)</th>
<th>Avg Cost (CHF)</th>
<th>Gap Best (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complete</td>
<td>100.00</td>
<td>1.00</td>
<td>781.71</td>
<td>1.96</td>
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<td>2.31</td>
<td>664.76</td>
<td>679.54</td>
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<tr>
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<td>0.50</td>
<td>862.13</td>
<td>1.96</td>
<td>43.43</td>
<td>2.30</td>
<td>664.82</td>
<td>678.84</td>
<td>2.11</td>
</tr>
<tr>
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<td>806.52</td>
<td>1.95</td>
<td>43.52</td>
<td>2.28</td>
<td>664.34</td>
<td>677.81</td>
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<td>650.55</td>
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<tr>
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<td>0.25</td>
<td>809.76</td>
<td>1.91</td>
<td>41.19</td>
<td>2.19</td>
<td>650.72</td>
<td>661.88</td>
<td>1.71</td>
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<td>652.04</td>
<td>1.60</td>
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<tr>
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<td>789.40</td>
<td>1.90</td>
<td>39.57</td>
<td>2.15</td>
<td>641.42</td>
<td>651.85</td>
<td>1.63</td>
</tr>
<tr>
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<td>16.77</td>
<td>1.87</td>
<td>422.64</td>
<td>425.08</td>
<td>0.58</td>
</tr>
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</table>
### Table 6: Cost breakdown and KPI for real data instances

<table>
<thead>
<tr>
<th>Type</th>
<th>Emergency Cost</th>
<th>RFCM</th>
<th>Avg Routing Cost (CHF)</th>
<th>Avg Overflow Cost (CHF)</th>
<th>Avg Rte Failure Cost (CHF)</th>
<th>Avg Collected Volume (L)</th>
<th>Liters per Unit Cost</th>
<th>Liters per Unit Routing Cost</th>
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</thead>
<tbody>
<tr>
<td>Complete</td>
<td>100.00</td>
<td>1.00</td>
<td>579.78</td>
<td>99.73</td>
<td>0.03</td>
<td>47,234.59</td>
<td>69.51</td>
<td>81.47</td>
</tr>
<tr>
<td>Complete</td>
<td>100.00</td>
<td>0.50</td>
<td>579.46</td>
<td>99.33</td>
<td>0.05</td>
<td>47,225.62</td>
<td>69.57</td>
<td>81.50</td>
</tr>
<tr>
<td>Complete</td>
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<td>82.13</td>
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<td>0.50</td>
<td>558.37</td>
<td>103.82</td>
<td>0.09</td>
<td>45,852.89</td>
<td>69.24</td>
<td>82.12</td>
</tr>
<tr>
<td>Complete</td>
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<td>0.25</td>
<td>558.47</td>
<td>103.35</td>
<td>0.07</td>
<td>45,949.94</td>
<td>69.42</td>
<td>82.28</td>
</tr>
<tr>
<td>Complete</td>
<td>25.00</td>
<td>0.50</td>
<td>548.10</td>
<td>103.83</td>
<td>0.11</td>
<td>44,653.66</td>
<td>68.48</td>
<td>81.47</td>
</tr>
<tr>
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<td>0.25</td>
<td>547.75</td>
<td>104.05</td>
<td>0.06</td>
<td>44,678.38</td>
<td>68.54</td>
<td>81.57</td>
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<tr>
<td>Routing-only</td>
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<td>425.08</td>
<td>0.00</td>
<td>0.00</td>
<td>25,286.94</td>
<td>59.49</td>
<td>59.49</td>
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</table>
### Real Data: Occurrence of Rare Events

**Table 7:** Average number of overflows at various percentiles for real data instances for 10,000 simulations

<table>
<thead>
<tr>
<th>Type</th>
<th>Cost</th>
<th>RFCM</th>
<th>75th perc.</th>
<th>90th perc.</th>
<th>95th perc.</th>
<th>99th perc.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complete</td>
<td>100.00</td>
<td>1.00</td>
<td>0.98</td>
<td>1.78</td>
<td>2.40</td>
<td>3.58</td>
</tr>
<tr>
<td>Complete</td>
<td>100.00</td>
<td>0.50</td>
<td>0.99</td>
<td>1.78</td>
<td>2.39</td>
<td>3.55</td>
</tr>
<tr>
<td>Complete</td>
<td>100.00</td>
<td>0.25</td>
<td>0.97</td>
<td>1.80</td>
<td>2.38</td>
<td>3.56</td>
</tr>
<tr>
<td>Complete</td>
<td>50.00</td>
<td>0.50</td>
<td>1.28</td>
<td>2.19</td>
<td>2.84</td>
<td>4.16</td>
</tr>
<tr>
<td>Complete</td>
<td>50.00</td>
<td>0.25</td>
<td>1.28</td>
<td>2.18</td>
<td>2.83</td>
<td>4.15</td>
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<tr>
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<td>0.50</td>
<td>1.48</td>
<td>2.46</td>
<td>3.14</td>
<td>4.58</td>
</tr>
<tr>
<td>Complete</td>
<td>25.00</td>
<td>0.25</td>
<td>1.51</td>
<td>2.50</td>
<td>3.18</td>
<td>4.61</td>
</tr>
<tr>
<td>Routing-only</td>
<td>0.00</td>
<td>0.00</td>
<td>16.97</td>
<td>20.45</td>
<td>22.56</td>
<td>26.70</td>
</tr>
</tbody>
</table>
Table 8: Average number of route failures at various percentiles for real data instances for 10,000 simulations

<table>
<thead>
<tr>
<th>Type</th>
<th>Emergency Cost</th>
<th>RFCM</th>
<th>75th perc.</th>
<th>90th perc.</th>
<th>95th perc.</th>
<th>99th perc.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Complete</td>
<td>100.00</td>
<td>1.00</td>
<td>0.03</td>
<td>0.03</td>
<td>0.04</td>
<td>0.05</td>
</tr>
<tr>
<td>Complete</td>
<td>100.00</td>
<td>0.50</td>
<td>0.04</td>
<td>0.05</td>
<td>0.05</td>
<td>0.07</td>
</tr>
<tr>
<td>Complete</td>
<td>100.00</td>
<td>0.25</td>
<td>0.04</td>
<td>0.05</td>
<td>0.06</td>
<td>0.10</td>
</tr>
<tr>
<td>Complete</td>
<td>50.00</td>
<td>0.50</td>
<td>0.06</td>
<td>0.07</td>
<td>0.08</td>
<td>0.09</td>
</tr>
<tr>
<td>Complete</td>
<td>50.00</td>
<td>0.25</td>
<td>0.04</td>
<td>0.06</td>
<td>0.07</td>
<td>0.10</td>
</tr>
<tr>
<td>Complete</td>
<td>25.00</td>
<td>0.50</td>
<td>0.05</td>
<td>0.07</td>
<td>0.07</td>
<td>0.10</td>
</tr>
<tr>
<td>Complete</td>
<td>25.00</td>
<td>0.25</td>
<td>0.04</td>
<td>0.07</td>
<td>0.07</td>
<td>0.09</td>
</tr>
<tr>
<td>Routing-only</td>
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<td>0.00</td>
<td>0.01</td>
<td>0.03</td>
<td>0.04</td>
<td>0.05</td>
</tr>
</tbody>
</table>
Figure 3: Average cost percentiles of container overflows

Objective
Routing-only
Complete, $\chi=100$, RFCM=1
Real Data: Taking Advantage of Probability Information

Figure 4: Container overflow percentiles for routing-only objective
Real Data: Taking Advantage of Probability Information

Figure 5: Container overflow percentiles for complete objective, $\chi=100$, RFCM=1
Real Data: Taking Advantage of Probability Information

Figure 6: Route failure percentiles for routing-only objective
Real Data: Taking Advantage of Probability Information

**Figure 7:** Route failure percentiles for complete objective, $\chi=100$, RFCM=1
Outline

1. Introduction
2. Related Literature
3. Formulation
4. Methodology
5. Numerical Experiments
6. Conclusion
Conclusions

- A rich stochastic IRP with the relevant dynamic uncertainty components in the objective.
- An ALNS that produces very good results on IRP benchmarks.
- Computational experiments on real-data instances demonstrate the practical relevance of our approach.
Conclusions

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- An ALNS that produces very good results on IRP benchmarks.
- Computational experiments on real-data instances demonstrate the practical relevance of our approach.

Future research directions:
- decomposition methods,
- scenario generation,
- robust optimization,
- location-routing, open tours, online re-optimization, multiple flows...
Thank you.
Questions?


