

An Exact Solution Framework for Multi-Trip Vehicle Routing Problems with Time Windows

Autumn School on Advanced BCP Tools

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Mathematical Models for the MTVRP

Variants of the MTVRP

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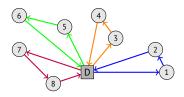
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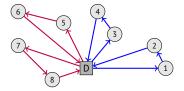
Conclusions and Open Questions

- Most of the literature on the Vehicle Routing Problem (VRP) addresses problems where each vehicle can perform at most one trip per day
- Many contributions on VRPs where vehicles can perform multiple trips have been published in the last decade
- These problems are called Multi-Trip Vehicle Routing Problems (MTVRP)

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Motivation

- Such an increasing interest in MTVRPs is due to new practices in, e.g., city logistics and last-mile delivery
- The need of limiting noise and pollution in city centers requires the usage of small vans, electric vehicles, and/or drones and forbids large trucks from entering city centers
- The limited capacity/autonomy of these vehicles forces them to perform multiple trips and to return to the depot to reload multiple times over the day



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Research Question



Main Research Question to Address in this Talk

What is the best model to solve an MTVRP (with side constraints) to optimality?

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What is the best model to solve an MTVRP (with side constraints) to optimality?

Based on the state-of-the-art exact methods for lots of VRPs...

Set Partitioning Models!

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Definition of the Multi-Trip VRP I

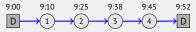
Input Data

- N set of customers
- V vertex set, $V = N \cup \{0\}$, where 0 is the depot
- \mathcal{A} arc set, $\mathcal{A} = \{(i,j) \mid i, j \in V : i \neq j\}$
- \mathcal{G} directed graph, $\mathcal{G} = (V, \mathcal{A})$
- t_{ij} travel time of arc $(i,j) \in A$
- K fleet of identical capacitated vehicles, |K| = m
- q_i demand of customer $i \in N$
- Q vehicle capacity
- *T* length of the planning horizon

Definition of the Multi-Trip VRP II

Definitions

• A trip is a sequence of customers, whose total demand does not exceed *Q*, that can be visited by a vehicle in between two visits at the depot, and that has a fixed departure time from the depot



• A journey is a sequence of non-overlapping trips assigned to a vehicle whose total travel time does not exceed *T*



The MTVRP aims at defining a set of at most *m* journeys such that:

- 1. each customer is visited exactly once
- 2. the total traveled time is minimized

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Models with 3- and 4-index Variables

4-index Variables

 $x_{ij}^{kh} \in \{0, 1\}$ equal to 1 if trip h of vehicle $k \in K$ traverses arc $(i, j) \in A$ (0 otherwise)

3-index Variables with Vehicle Index (without Trip Index)

 $x_{ij}^k \in \{\mathbf{0},\mathbf{1}\}$ equal to 1 if vehicle $k \in K$ traverses arc $(i,j) \in \mathcal{A}$ (0 otherwise)

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 $x_{ii}^h \in \{0,1\}$ equal to 1 if trip *h* traverses arc $(i,j) \in \mathcal{A}$ (0 otherwise)

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Models with 3- and 4-index Variables Pros and Cons



- Polynomial number of variables
- Can be solved with commercial solvers
- Easy to embed additional side constraints

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- High integrality gaps
- BigM constraints
- Symmetries in the vehicles

Mathematical Models for the MTVRP

2-Index Arc-based Model (Koc and Karaoglan (2011)) I

Variables	
$x_{ij} \in \{0,1\}$	equal to 1 if arc $(i,j)\in \mathcal{A}$ is traversed (0 otherwise)
$x'_{ij} \in \{0,1\}$	equal to 1 if a vehicle visits customers $i, j \in N$ ($i \neq j$) consecutively with a stop at the depot in between (0 otherwise)
$\ell_i \in \mathbb{R}_+$	load on board after visiting customer $i \in N$
$a_i \in \mathbb{R}_+$	arrival time at customer $i \in N$

2-Index Arc-based Model (Koc and Karaoglan (2011)) II

$$\begin{array}{ll} \min\sum_{(i,j)\in\mathcal{A}} t_{ij}x_{ij} & [\text{Minimize travel times}] & (1a) \\ \text{s.t.} \sum_{(i,j)\in\mathcal{A}} x_{ij} = 1 & i \in \mathbb{N} & [\text{Serve each customer}] & (1b) \\ \sum_{(i,j)\in\mathcal{A}} x_{ij} = \sum_{(j,i)\in\mathcal{A}} x_{ji} & i \in \mathbb{V} & [\text{Flow conservation}] & (1c) \\ \sum_{(i,j)\in\mathcal{A}} x_{ij} = \sum_{(j,i)\in\mathcal{A}} x_{ji} & i \in \mathbb{V} & [\text{Flow conservation}] & (1c) \\ i \in q_i \neq q_i \leq \ell_i + Q(1 - x_{ij}) & i \in \mathbb{N} j \in \mathbb{V} & [\text{Subtour + Load on board}] & (1d) \\ a_i + t_{ij} \leq a_i + T(1 - x_{ij}) & i \in \mathbb{V} j \in \mathbb{N} & [\text{Subtour + Arrival time}] & (1e) \\ a_i + (t_{i0} + t_{0j}) \leq a_j + T(1 - x'_{ij}) & i, j \in \mathbb{N} : i \neq j & [\text{Arrival time depot visit}] & (1f) \\ t_{0i} \leq a_i \leq T - t_{i0} & i \in \mathbb{N} & [\text{Planning horizon}] & (1g) \\ \sum_{j \in \mathbb{N}} x'_{ij} \leq x_{i0} & i \in \mathbb{N} & [\text{Link x with } x'] & (1h) \\ \sum_{j \in \mathbb{N}} x'_{ij} \leq x_{0j} & j \in \mathbb{N} & [\text{Link x with } x'] & (1i) \\ \sum_{j \in \mathbb{N}} x_{ij} \in \{0, 1\} & (i, j) \in \mathcal{A} & (1k) \\ x'_{ij} \in \{0, 1\} & i, j \in \mathbb{N} : i \neq j & (1l) \\ q_i \leq \ell_i \leq Q, \quad a_i \in \mathbb{R}_+ & i \in \mathbb{N} & (1m) \end{array}$$

2-Index Arc-based Model (Koc and Karaoglan (2011)) Pros and Cons



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- BigM constraints
- Instances with 50 customers are already difficult to close

Trip-based Model (Mingozzi, Roberti, and Toth (2013))

 $\mathcal H$ set of all feasible trips

 c_h cost of trip $h \in \mathcal{H}$

 α_{ih} trip $h \in \mathcal{H}$ serves customer $i \in N$ ($\alpha_{ih} = 1$) or not ($\alpha_{ih} = 0$)

 d_h duration of trip $h \in \mathcal{H}$

Variables

 $x_{hk} \in \{0,1\}$ trip $h \in \mathcal{H}$ is assigned to vehicle $k \in K$ ($x_{hk} = 1$) or not ($x_{hk} = 0$)

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 [Minimize travel costs] (2a)
s.t.
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 $i \in N$ [Serve each customer] (2b)

$$\sum_{h \in \mathcal{H}} d_h x_{hk} \leq T$$
 $k \in K$ [Planning horizon] (2c)

$$x_{hk} \in \{0, 1\}$$
 $h \in \mathcal{H}$ $k \in K$ (2d)

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- Small integrality gaps
- Instances with 100-120 customers can be closed
- Easy to embed side constraints

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- Column generation/branch(-and-cut)-and-price needed
- Additional constraints can make the pricing problem difficult



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- Column generation/branch(and-cut)-and-price needed
- Pricing problem more difficult than trip-based model
- Additional constraints can make the pricing problem (even more) difficult



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Main Side Constraints and Academic Extensions

- Time Windows: each customer *i* ∈ *N* must be visited within a time interval [*a_i*, *b_i*]
- Service-Dependent Loading Times: vehicle loading time at the depot depends on the customers visited in the next trip
- Limited Trip Duration: maximum time between the departure from the depot and the arrival time at the last customer of the trip
- Profits: a profit *p_i* is associated with each customer *i* ∈ *N*; hierarchical objective function: maximize profit first; minimize routing cost second

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Reference	Time Windows	Service-Dependent Loading Times	Limited Trip Duration	Profits
Exact Methods				
Azi, Gendreau, and Potvin (2010)	\checkmark	\checkmark	\checkmark	\checkmark
Macedo et al. (2011)	\checkmark	\checkmark	\checkmark	\checkmark
Hernandez et al. (2014)	\checkmark	\checkmark	\checkmark	
Hernandez et al. (2016)	\checkmark	\checkmark		
Heuristic Methods				
Azi, Gendreau, and Potvin (2014)	\checkmark	\checkmark	\checkmark	\checkmark
Wang, Liang, and Hu (2014)	\checkmark	\checkmark	\checkmark	\checkmark
Cattaruzza, Absi, and Feillet (2016a)	\checkmark	\checkmark		
Anaya-Arenas et al. (2016)	\checkmark		\checkmark	

From Cattaruzza, Absi, and Feillet (2016b)

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Variables

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$$\sum_{\substack{h \in \mathcal{H} \\ x_h \in \{0, 1\}}} \tau_{th} x_h \leq m \quad t \in [a_0, b_0] \qquad [\text{No overlaps}] \qquad (4c)$$

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- Exponential number of variables
- Column generation/branch(-and-cut)-and-price needed
- Side constraints make the pricing problem difficult
- Constraints (4c) to add in a cutting plane fashion
- Instances with 25 customers can be out of reach

Journey-based Model (Hernandez et al. (2014, 2016))

 $\mathcal R$ set of all feasible journeys

 c_r cost of journey $r \in \mathcal{R}$

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(5b)

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$$\sum_{\substack{r \in \mathcal{R} \\ x_r \in \{0, 1\}}} x_r \leq m \qquad [\text{Number of vehicles}] \qquad (5c)$$

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Journey-based Model (Hernandez et al. (2014, 2016)) Pros and Cons



- Small integrality gaps (smaller than trip-based model)
- Easy to embed additional side constraints both related to trips and journeys

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- Exponential number of variables
- Column generation/branch(and-cut)-and-price needed
- Pricing problem more difficult than trip-based model
- Instances with 25 customers can be out of reach

The Concept of Structure

Definition of Structure

A structure $s = (0, i_1, i_2, ..., i_{\mu_s}, 0)$ is an ordered set of μ_s customers that can be visited in between two visits at the depot and can start from the depot within time interval $[e_s, \ell_s]$, such that:

- 1. capacity constraints are satisfied
- 2. the duration d_s and the cost c_s are constant for each departure time from the depot within $[e_s, \ell_s]$
- 3. the duration d_s is the minimum duration to serve the set of customers in the given order



Structure-based Model (Paradiso et al. (2019))

 ${\mathcal S}\,$ set of all feasible structures

 c_s cost of structure $s \in S$

 α_{is} structure $s \in S$ serves $i \in N$ ($\alpha_{is} = 1$) or not ($\alpha_{is} = 0$)

Variables

 $x_s \in \{0, 1\}$ structure $s \in S$ is selected ($x_s = 1$) or not ($x_s = 0$)

$$\min \sum_{s \in S} c_s x_s$$
 [Minimize travel costs] (6a)
s.t. $\sum_{s \in S} \alpha_{is} x_s = 1$ $i \in N$ [Serve each customer] (6b)
 $\sum_{s \in \widehat{S}} x_s \le \eta_m(\widehat{S})$ $\widehat{S} \subseteq S$ [Structure feasibility constraints] (6c)
 $x_s \in \{0, 1\}$ $s \in S$ (6d)

where $\eta_m(\widehat{S})$ is the maximum number of structures of the set \widehat{S} that can be simultaneously in a solution given the number of vehicles *m*

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- Column generation/branch(-and-cut)-and-price needed
- Constraints (6c) to add in a cutting plane fashion

Trip vs Journey vs Structure (-based Models)

	Trip	Journey	Structure
Integrality gap	്	රාථ	心(心)
Number of variables	\mathbf{r}	\mathbf{r}	Ģ
Number of constraints	Ģ	ம்	\mathbf{r}
Trip-related constraints	ப	ம்	്
Journey-related constraints	Ģ	ம்	Ģ
Complexity of algorithms	Ģ	Ģ	Ģ

Sketch of an Exact Method based on Structure-based Model Paradiso et al. (2019)

- Compute SP Bound: solve LP relaxation of (7) without (7c) to compute dual sol. u¹ of cost LB₁
- 2. Enumerate Structures: enumerate structures (\tilde{S}) of red. cost \leq UB LB₁ w.r.t. u^1 , where UB is a guessed upper bound
- 3. Compute SP plus Relaxed SFC: solve LP relaxation of (7) with relaxed (7c) to compute dual sol. u^2 of cost LB₂
- 4. Reduce set of structures: remove from \tilde{S} structures of red. cost > UB LB₂ w.r.t. u^2
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$$\min\sum_{s\in\mathcal{S}}c_s x_s \tag{7a}$$

s.t.
$$\sum_{s \in S} \alpha_{is} x_s = 1$$
 $i \in N$ (7b)

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Group	N	Inst	%Gap	Opt	T _{tot}	%Gap	Opt	T _{tot}	%Gap	Opt	T _{tot}	
С	25	8	2.24	8	108	2.12	7	805	0.73	8	19	
R	25	11	2.41	11	646	1.19	7	6,925	0.78	11	115	
RC	25	8	5.41	6	6,671	2.86	5	2,963	1.91	8	880	
С	40	8							1.51	7	2,170	
R	40	11							0.41	10	418	
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MTVRP with Time Windows, Loading Times, Limited Trip Duration

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R	25	22	0.76	22	33	0.25	22	2
RC	25	16	2.35	11	18	0.49	16	2
С	40	16	1.25	13	511	0.48	16	151
R	40	19	1.43	12	1,738	1.06	19	220
RC	40	2	-	0	-	0.67	2	11
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N	Inst	%Gap	Opt	T _{tot}	%Gap	Opt	T _{tot}
10	10	4.49	10	0	0.40	10	0
15	10	5.47	4	9	1.28	10	1
20	10	3.69	5	18	0.86	10	2
25	37	2.68	22	59	0.62	37	1
30	10		0		0.52	10	4
35	10		0		0.44	10	11
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- Research on MTVRPs is scarce and 50-customer instances are already challenging, how can large instances be solved?
- Are there better models (maybe models not based on arcs, structures, trips, or journeys)?
- Can we use models not based on arcs or routes to solve other VRPs?

R. Paradiso, R. Roberti, D. Laganá, W. Dullaert. An Exact Solution Framework for Multi-Trip Vehicle Routing Problems with Time Windows. *Operations Research* (forthcoming)

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