

An exact algorithm for the Green Vehicle Routing Problem

J. Andelmin E. Bartolini

Department of Mathematics and Systems Analysis
Aalto University School of Science, Finland

EURO 2015, Glasgow, UK
July 14th 2015

Outline

Problem description

Existing literature and motivations

Modeling the G-VRP by using a multigraph

Set Partitioning formulation and valid Inequalities

Separation of k -path cuts

Exact Algorithm

Preliminary Computational Results

Instances by [Erdođan and Miller-Hooks(2012)]

New Instances

Conclusions

Bibliography

Green Vehicle Routing Problem (G-VRP)

Defined on a complete graph $G = (N \cup F, A)$ where N is a set of n customers plus a depot 0, and F is a set of s refueling stations

- An unlimited number of vehicles with fuel level Q are available at 0
- Each vehicle can be assigned a trip (called route) that visits a subset of the customers and returns back to 0
- Traversing an arc $(i, j) \in A$ (i.e., traveling from i to j) consumes a fuel amount c_{ij} (cost of (i, j)) and a travel time $t_{ij} = \kappa c_{ij}$ (κ is a constant)
- A vehicle can visit a station during its route to restore its fuel level back to Q . Refueling consumes a refueling time δ

Constraints:

- The fuel level must remain positive during each trip (fuel constraints)
- Each customer must be visited by exactly one route. A customer visit consumes a service time τ
- The duration of a route cannot exceed a maximum driving time T

Objective A set of routes that minimize the total fuel consumption

Literature Review

The G-VRP was introduced by [Erdoğ̃an and Miller-Hooks(2012)]

- Motivated by growing popularity of low-emission alternative-fuel vehicles (biodiesel, electricity, hydrogen..): limited fuel autonomy and limited refueling infrastructure
- Refueling stops, and resulting delays need to be modeled explicitly

Applications to electric vehicles: Routing of vehicles with replaceable batteries (battery swap systems)

Heuristic Algorithms

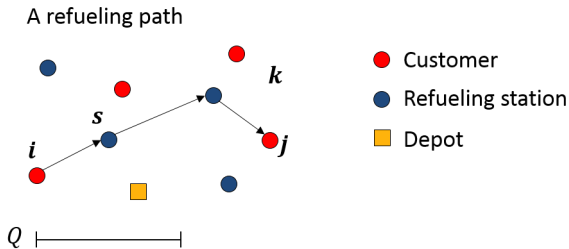
- Modified savings [Erdoğ̃an and Miller-Hooks(2012)], VNS/TS [Schneider et al.(2014a), Schneider et al.(2014b)], modified MSH [Montoya et al.(2014)], local search and SA [Felipe et al.(2014)]

Exact Algorithms

- There are no exact algorithms for the G-VRP
- [Desaulniers et al.(2014)] develop an exact algorithm for a generalization of G-VRP called Electric VRPTW. They do not consider the G-VRP

Refueling paths

A **refueling path** is a simple path $P = (i, s, \dots, k, j)$ from $i \in N$ to $j \in N$ such that s, \dots, k are refueling stations and all arcs (u, v) it traverses have cost $c_{uv} \leq Q$



The cost of a refueling path is the sum of the costs of its arcs

The time of a refueling path from i to j is the sum of the travel times of its arcs, plus the refueling times of its stations, plus the service time τ (if $i \neq 0$)

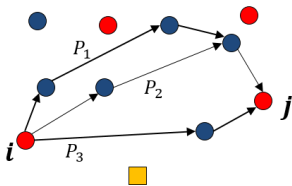
Refueling-path multigraph

Some refueling paths are **dominated**: We can assume they are not traversed by any vehicle in an optimal solution

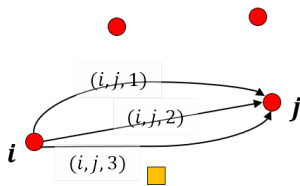
- Dominance of a refueling path depends on (i) the cost of its first and last arc, (ii) the total path cost (iii) the number of stations it visits
- The non-dominated refueling paths can be efficiently computed a-priori

We model the G-VRP on a multigraph \mathcal{G} with an arc (i, j, p) for each non-dominated refueling path p , plus the arcs $(i, j) \in A$ with $c_{ij} \leq Q$

Three refueling paths from i to j



The three corresponding arcs in \mathcal{G}



G-VRP routes and Set Partitioning formulation

A G-VRP route is a simple circuit in \mathcal{G} starting from 0, having duration less than or equal than T and satisfying the fuel constraints

Define:

- \mathcal{R} : index set of all G-VRP routes
- $x_\ell, \forall \ell \in \mathcal{R}$: 0-1 variables taking value 1 if route R_ℓ is in solution
- c_ℓ : cost of route R_ℓ
- $a_{i\ell}$: 0-1 coefficient equal to 1 if route R_ℓ visits $i \in N$

The G-VRP can be modeled as a Set Partitioning problem:

$$\begin{aligned} \text{(SP)} \quad z(SP) = \min & \sum_{\ell \in \mathcal{R}} c_\ell x_\ell \\ \text{s.t.} & \sum_{\ell \in \mathcal{R}} a_{i\ell} x_\ell = 1 \quad i \in N \setminus \{0\} \\ & x_\ell \in \{0, 1\} \quad \ell \in \mathcal{R} \end{aligned}$$

We call LSP the LP relaxation of SP

Valid Inequalities

We use three types of valid inequalities to tighten LSP

- Subset Row inequalities (SR3) [Jepsen et al.(2008)]
- Weak Subset Row inequalities (WSR3) [Baldacci et al.(2011)]
- k -path cuts [Laporte et al.(1985)]

$$\sum_{\ell \in \mathcal{R}} b_{S\ell} x_{\ell} \geq r(S) \quad \forall S \subseteq N \setminus \{0\}, |S| > 2$$

where $b_{S\ell}$ equals 1 if route R_{ℓ} visits S , and 0 otherwise, and $r(S)$ is the minimum number of routes needed to visit S

Separation of k -path cuts I

Consider any set $S \subseteq N \setminus \{0\}$. If we can find a vector $\pi \in \mathbb{R}_+^n$ satisfying

$$(i) \quad \pi_i = 0, \forall i \in N \setminus S,$$

$$(ii) \quad \sum_{i \in N \setminus \{0\}} a_{i\ell} \pi_i \leq 1, \forall \ell \in \mathcal{R}$$

$$(iii) \quad \sum_{i \in N \setminus \{0\}} \pi_i > r(S) - 1$$

then the k -path cut defined by S can be rewritten as the following rank-1 (w.r.t. LSP) Chàvatal-Gomory cut (rank-1 CG cut)

$$\sum_{\ell \in \mathcal{R}} \left[\sum_{i \in N \setminus \{0\}} a_{i\ell} \pi_i \right] x_\ell \geq \left[\sum_{i \in N \setminus \{0\}} \pi_i \right] \quad (1)$$

Moreover, we have $S = \{i \in N : \pi_i > 0\}$, and $r(S) = \left\lceil \sum_{i \in N \setminus \{0\}} \pi_i \right\rceil$

Observation:

A violated CG cut (1) defined by a π satisfying (i) – (iii) provides a violated k -path cut defined by the set $S = \{i \in N : \pi_i > 0\}$

Separation of k -path cuts II

Separation problem: Given a fractional solution $\bar{\mathbf{x}}$, find a violated rank 1 CG cut defined by a $\boldsymbol{\pi} \in \mathbb{R}_+^n$ with $\sum_{i \in N \setminus \{0\}} \pi_i \leq 1, \forall l \in \mathcal{R}$

The problem of finding a maximally violated rank-1 CG cut can be modeled as a MILP and solved by a MILP solver [Fischetti, Lodi(2007)]. In our case, it is

$$\begin{aligned} (SEP) \quad & \max z - \sum_{\ell \in \bar{\mathcal{R}}} \bar{x}_\ell y_\ell \\ & \text{s.t.} \quad \sum_{i \in N \setminus \{0\}} a_{i\ell} \pi_i \leq y_\ell, \quad \forall \ell \in \bar{\mathcal{R}} \\ & \quad \sum_{i \in N \setminus \{0\}} a_{i\ell} \pi_i \leq 1, \quad \forall \ell \in \mathcal{R} \\ & \quad \epsilon - 1 \leq \sum_{i \in N \setminus \{0\}} \pi_i - z \leq 0 \\ & \quad y_\ell \in \{0, 1\}, \quad \forall \ell \in \bar{\mathcal{R}} \\ & \quad \pi_i \geq 0, \quad \forall i \in N \setminus \{0\} \quad \text{and} \quad z \in \mathbb{Z}_+ \end{aligned}$$

where $\bar{\mathcal{R}}$ is the index set of routes R_ℓ with $\bar{x}_\ell > 0$

Exact solution algorithm I

2-phase method based on the schema proposed by [Baldacci et al. 2008, 2011] for the Capacitated VRP and VRP with Time Windows

Phase I:

- Compute a lower bound $z(\text{LB})$ as the cost of an optimal dual solution of LSP plus SR3, WSR3 and k -path cuts (called LSP_+)
- Compute an upper bound $z(\text{UB})$ by running an ALNS heuristic which uses the multigraph \mathcal{G}

Phase II:

- Enumerate all routes \mathcal{R}^* having reduced cost $\leq z(\text{UB}) - z(\text{LB})$ with respect to the dual solution obtained in Phase I
- \mathcal{R}^* is computed by dynamic programming. It is guaranteed to contain an optimal set of routes
- An optimal solution is obtained by solving SP with \mathcal{R} replaced by \mathcal{R}^*

Exact solution algorithm II

$z(\text{LB})$ in Phase I is computed by cut-and-column generation methods

Pricing problem: Find a least cost G-VRP route:

- It is an elementary shortest path problem with resource constraints in the multigraph \mathcal{G} . Solved by a forward dynamic programming algorithm
- Bounding functions based on the ng-path relaxation [Baldacci et al.(2011)] are used to fathom sub-optimal states
- The same algorithm is used when solving the separation problem for k -path cuts to detect violated constraints $\sum_{i \in N \setminus \{0\}} a_{il} \pi_i \leq 1, \forall l \in \mathcal{R}$

Computational Experiments

[Erdogan and Miller-Hooks(2012)] proposed two sets of instances with 20 and 109–500 customers, respectively

- Based on data from an U.S. medical textile supply company in Virginia
- Max. driving time of $T = 11$ hours and max. travel distance without refuel $Q = 300$ miles. Vehicles travel at a constant speed of 40 miles/h.
- Customers service time is $\tau = 30$ min., refueling time is $\delta = 15$ min.
- Each vehicle incurs an initial refueling time at the depot before starting its route (i.e., in practice $T = T - \delta$)

We have considered all Erdogan, Miller-Hooks instances with up to 109 customers, and created an additional set of problems with ~ 50 , 75 and 100 customers by extracting customers from the larger ones

Computer used: Intel Xeon X3450, 2.67 GHz with 12 GB RAM (CPLEX is used as MILP and LP solver)

Preliminary Computational Results

Instances proposed by [Erdoĝan and Miller-Hooks(2012)]

All instances with 20 customers are solved within a few seconds (Phase I always terminates with an integer solution after solving LSP_+)

Table: Instances of [Erdoĝan and Miller-Hooks(2012)] with 109 customers

Inst.	n	s	Opt	$\%LB_0$	$\%LB_{SR}$	$\%LB$	T_{LB}	# kP	# SR	Time
111c.21s	109	21	*	97.59	98.09	99.82	17994	88	509	18714
111c.22s	109	22	*	97.59	98.09	99.92	19920	89	606	20223
111c.24s §	109	24		97.59	98.09	99.70	21912	98	662	22560
111c.26s	109	26	*	97.59	98.09	99.95	16419	81	533	16547
111c.28s	109	28	*	97.58	98.09	99.90	13737	85	423	14261
Average				97.59	98.09	99.86	17996			

§: found new best known upper bound

- LB_0 : optimal cost of LSP without valid inequalities, ($\%LB_0$: % ratio of LB_0)
- LB_{SR} : optimal cost of LSP plus WSR3 and SR3 inequalities, ($\%LB_{SR}$: % ratio of LB_{SR})
- LB : optimal cost of LSP plus WSR3, SR3 and k -path cuts, ($\%LB$: % ratio of LB)
- T_{LB} : cpu time (sec.) to compute LB
- # kP and # SR: total number of k -path cuts and SR3 plus WSR3 inequalities added to LSP
- Time: Total cpu time (sec.)

Preliminary Computational Results

New instances

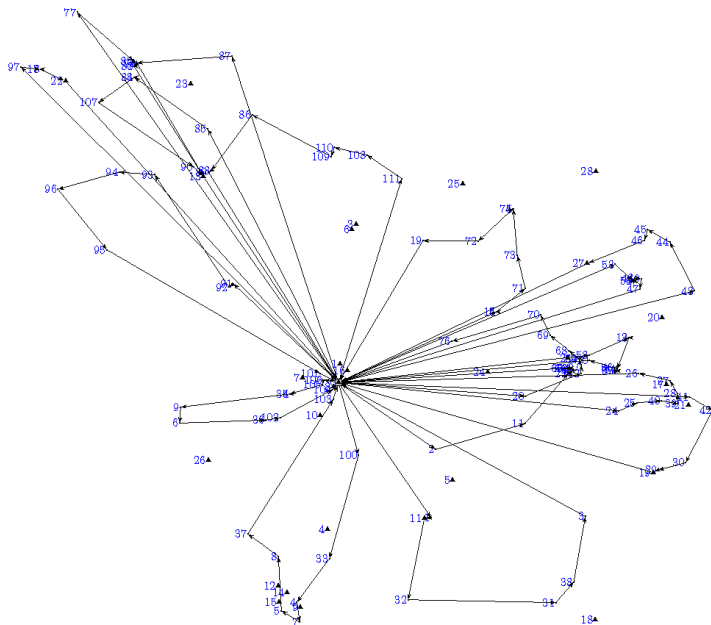
Table: Instances derived by taking the first 75 and 100 customers from 111c_21s and 111c_28s

Inst.	n	s	Opt	$\%LB_0$	$\%LB_{SR}$	$\%LB$	T_{LB}	# kP	# SR	Time
75c_21s	75	21	*	97.38	98.04	100.00	4860	41	140	4861
75c_28s	75	28	*	97.38	98.04	100.00	7999	63	140	8000
100c_21s	98	21	*	98.80	99.25	100.00	9850	74	124	9852
100c_28s	98	28	*	98.80	99.25	99.89	9894	17	335	10166
Average				98.09	98.64	99.97	8151			

Table: Average results on new instances derived by randomly extracting customers from the large [Erdoğan and Miller-Hooks(2012)] instances

# of inst.	n	s	$\%LB_0$	$\%LB_{SR}$	$\%LB$	T_{LB}	# kP	# SR	Time	Opt
7	50	21	95.98	97.87	99.84	2464	50	108	2477	7/7
8	75	22	97.24	99.16	99.67	2988	45	179	4384	8/8
8	98	24	97.62	99.11	99.56	7068	27	466	10409	7/8

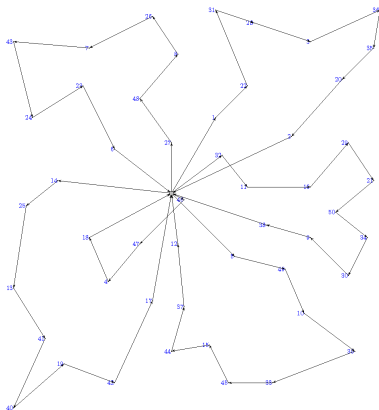
Optimal solution of instance 111c_28s



Conclusions

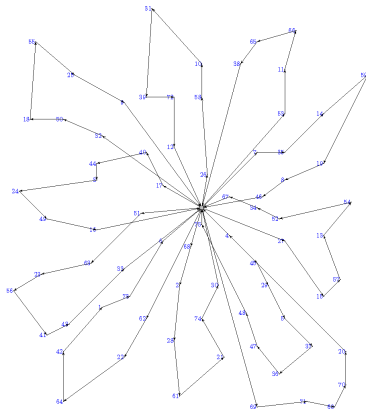
- We have proposed an exact algorithm for solving the **Green Vehicle Routing Problem** which can be viewed as a basic model for alternative-fuel vehicle routing optimization
- We have modeled the problem by using a multigraph which does not explicitly model the refueling stations and excludes a-priori sub-optimal refueling paths
- We have characterized a subset of the k -path cuts as Chàvatal-Gomory cuts of rank 1. This permitted to use k -path cuts within a cut-and-column generation algorithm
- We reported computational results on benchmark instances based on a case study from [**Erdoğan and Miller-Hooks(2012)**]
- The exact algorithm provides tight lower bounds and optimally solves instances with up to 109 customers

Optimal solution of the distance-constrained CVRP instance CMT6



Inst.	n	s	UB^*	Opt	$\%LB_0$	$\%LB_{SR}$	$\%LB$	T_{LB}	# kP	# SR	Time
CMT6	50	0	555.43	*	96.83	99.01	100.00	573	9	294	573

Optimal solution of the distance-constrained CVRP instance CMT7



Inst.	n	s	UB^*	Opt	$\%LB_0$	$\%LB_{SR}$	$\%LB$	T_{LB}	# kP	# SR	Time
CMT7	75	0	909.68	*	98.35	99.81	99.85	1272	3	317	1290

Bibliography I

- [Baldacci et al.(2008)] Baldacci, R., N. Christofides, A. Mingozzi. 2008. An exact algorithm for the vehicle routing problem based on the set partitioning formulation with additional cuts. *Mathematical Programming Ser. A*, **115**, 351–385.
- [Baldacci et al.(2011)] Baldacci, R., A. Mingozzi, R. Roberti. 2011. New Route Relaxation and Pricing Strategies for the Vehicle Routing Problem. *Operations Research*, **59**, 1269–1283.
- [Desaulniers et al.(2014)] Desaulniers, G., F. Errico, S. Irnich, M. Schneider. 2014. Exact algorithms for electric vehicle-routing problems with time windows . *Les Cahiers du GERAD*, **G-2014-110**, Montréal, Canada.
- [Erdoğan and Miller-Hooks(2012)] Erdoğan, S., E. Miller-Hooks. 2012. A Green Vehicle Routing Problem. *Transportation Research, Part E*, **48**, 100–114.
- [Felipe et al.(2014)] Felipe, A., M. T. Ortuño, G. Righini, G. Tirado. 2014. A heuristic approach for the green vehicle routing problem with multiple technologies and partial recharges. *Transportation Research Part E: Logistics and Transportation Review*, **71**, 111–128.
- [Fischetti, Lodi(2007)] Fischetti, M., A.Lodi. 2007. Optimizing over the first Chvtal closure. *Mathematical Programming, Ser. B*, **110**, 3–20.

Bibliography II

- [Montoya et al.(2014)] Montoya, A., C. Guéret, J. E. Mendoza, J. G. Villegas. 2014. A modified multi-space sampling heuristic for the green vehicle routing problem. *Technical Report LARIS-EA 7315*, Laboratoire Angevin de Recherche en Ingénierie des Systèmes, Université d'Angers.
- [Jepsen et al.(2008)] Jepsen, M., B. Petersen, S. Spoorendonk, D. Pisinger. 2008. Subset-Row Inequalities Applied to the Vehicle-Routing Problem with Time Windows. *Operations Research*, **56**, 497–511.
- [Laporte et al.(1985)] Laporte, G., Y. Nobert, M. Desrochers. 1985. Optimal Routing under Capacity and Distance Restrictions. *Operations Research*, **33**, 1050–1073.
- [Schneider et al.(2014a)] Schneider, M., A. Stenger, D. Goetze. 2014. The Electric Vehicle-Routing Problem with Time Windows and Recharging Stations. *Transportation Science*, **48**, 500–520.
- [Schneider et al.(2014b)] Schneider, M., A. Stenger, J. Hof. 2014. An adaptive VNS algorithm for vehicle routing problems with intermediate stops. *OR Spectrum*, 2014. doi: 10.1007/s00291-014-0376-5.