

A Branch-and-Price Algorithm for the Vehicle Routing Problem with Stochastic Demands, Optimal Restocking Policy, and Probabilistic Duration Constraints

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Capacitated Vehicle Routing Problem (VRP)

Input:

- $1 + n$ locations: 0 depot and n customers,
- There is a **known** travel cost (**duration**) between 2 locations,
- There are m identical vehicles with a **known** capacity Q ,
- Each customer i has a **known** demand d_i .

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- **CLUSTER**: Partition of customers into m groups such that the total demand of each group is not larger than Q ,
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to **minimize** the total travel cost.

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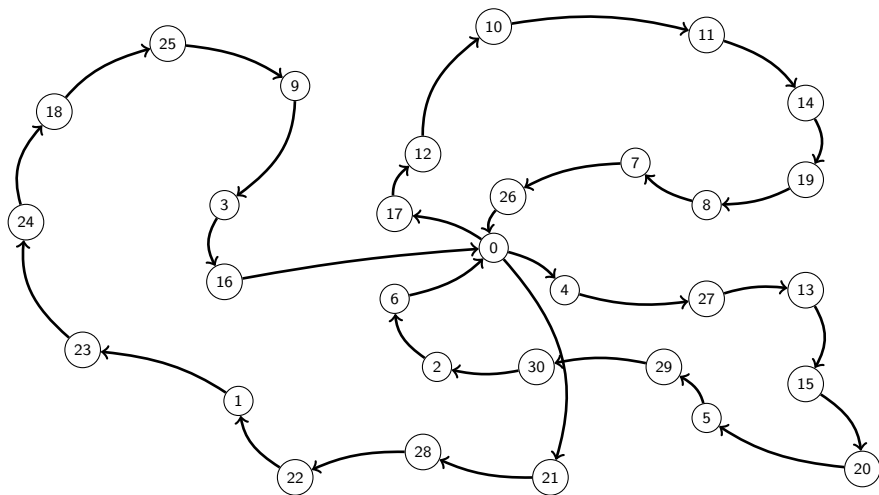
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See e.g. the book by Toth & Vigo “Vehicle Routing: problems, methods, and applications” SIAM Series on Optimization 2014.

E031-09h: Optimal solution of VRP: length = 358



VRP with stochastic demands (VRP-SD)

Input:

- Now each customer i has a demand ξ_i which is a **random number** with a known probability distribution
- The vehicle must go-and-return to the depot when it **fails** to serve a customer (split demand).

Output:

- Again **CLUSTER & ROUTE** to minimize the total travel cost of the solution **plus expected** cost due to failures.

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- Each demand is a **discrete** random number taking the non-negative value k with probability $p_i^k := \mathbb{P}[\xi_i = k]$.
- These random numbers are **independent**.

We also assume restocking actions (i.e. preventive returns)

We must **CLUSTER & ROUTES** again, but also find a **threshold value τ_i** for each customer so the driver will go to the depot before the next customer if the load of the vehicle exceeds that threshold.

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- **Failure returns:** The vehicle must go-and-return to the depot when it fails serving a customer
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We must design the **a-priori solution** to minimize the **expected** total travel cost of the **a-posteriori solution**: $\sum_r \mathbb{E}[T_r]$.

(see Louveaux & Salazar (2018))

VRP-SD: probabilistic duration constraints

The duration of a route r is a random variable T_r .

Objective function: minimize $\sum_{r=1}^m \mathbb{E}[T_r]$

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Literature:

Mendoza, Rousseau and Villegas, “A hybrid metaheuristic for the vehicle routing problem with stochastic demand and duration constraints” J. of Heuristics 22 (2016) 539–566.

Expected duration of a given route r

Let us assume that the route is $0, 1, \dots, n_r, 0$.

The initialization stage defines $f_r(q) = c_{n_r,0}$ for $q = 0, 1, \dots, Q$.

Assuming $0 \leq \xi_j \leq Q$, and using $i = j - 1$, the recursion defines

$$f_i(q) = \min \left\{ \begin{array}{l} c_{i,0} + c_{0,j} + \sum_{k=0}^Q f_j(Q - k) \cdot p_j^k \quad ; \\ c_{i,j} + \sum_{k \leq q} f_j(q - k) \cdot p_j^k + \sum_{k > q} (c_{j,0} + c_{0,j} + f_j(q + Q - k)) \cdot p_j^k \end{array} \right\}$$

for $j = n_r, \dots, 2$ and $q = 0, 1, \dots, Q$.

The expected penalty of the route is then

$$\mathbb{E}[T_r] := c_{0,1} + \sum_{k=0}^Q f_1(Q - k) \cdot p_1^k$$

Expected duration of a given route r

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Without assuming $\xi_j \leq Q$, we need to use:

$$\Gamma_{k,q} = \left\lceil \frac{k-q}{Q} \right\rceil$$

the number of go-and-return to 0 when the demand to serve is k and the remaining load is q ($0 \leq q \leq Q$).

The recursion is

$$f_i(q) = \min \left\{ c_{i,0} + c_{0,j} + \sum_{k=0}^{\infty} (c_{i,0} + c_{0,i}) \Gamma_{k,q} + f_j(Q + Q\Gamma_{k,q} - k) \cdot p_j^k; \right. \\ \left. c_{i,j} + \sum_{k=0}^{\infty} ((c_{i,0} + c_{0,i}) \Gamma_{k,q} + f_j(q + Q\Gamma_{k,q} - k)) \cdot p_j^k \right\}$$

for $j = n_r, \dots, 2$ and $q = 0, 1, \dots, Q$, and using $i = j - 1$.

The branch-and-price approach

$$\begin{aligned} & \text{minimize} && \sum_{r \in \mathcal{R}} \mathbb{E}[T_r] \theta_r, \\ & \text{subject to} && \sum_{r \in \mathcal{R}} a_{ir} \theta_r = 1 && \forall i \in \{1, \dots, N\}, && (1) \\ & && \theta_r \in \{0, 1\} \end{aligned}$$

where \mathcal{R} is the set of all feasible a priori routes and a_{ir} is a binary value that indicates whether i is visited by the a priori route r .

Checking the feasibility of a route r : Strategy I

Using the **Cantelli's inequality** (one-sided Chebyshev's bound):

$$\mathbb{P}[T_r > D] = \mathbb{P}[T_r - \mathbb{E}[T_r] > D - \mathbb{E}[T_r]] \leq \frac{\mathbb{V}(T_r)}{\mathbb{V}(T_r) + (D - \mathbb{E}[T_r])^2}$$

where $\mathbb{V}(T_r)$ can be computed using the **law of total variance**:

$$\begin{aligned} \mathbb{V}(T_r^{i,q}) &= \sum_{k=0}^{\infty} \mathbb{V}(T_r^{i,q} | \xi_j = k) \cdot p_j^k + \sum_{k=0}^{\infty} \mathbb{E}[T_r^{i,q} | \xi_j = k]^2 \cdot (1 - p_j^k) \cdot p_j^k \\ &\quad - 2 \sum_{k=1}^{\infty} \sum_{l=0}^{k-1} \mathbb{E}[T_r^{i,q} | \xi_j = k] \cdot p_j^k \cdot \mathbb{E}[T_r^{i,q} | \xi_j = l] \cdot p_j^l. \end{aligned}$$

being $\mathbb{V}(T_r^{i,q} | \xi_j = k) = \mathbb{V}(T_r^{j,q'})$ with

$$q' = \begin{cases} q + Q\Gamma_{k,q} - k, & \text{if } q > \tau_i, \\ Q + Q\Gamma_{k,Q} - k, & \text{if } q \leq \tau_i. \end{cases}$$

Checking the feasibility of a route r : Strategy II

Monte Carlo sampling and statistical inference.

(the approach becomes probabilistic because there is no guarantee that the optimal solution will always be returned:

Type I: Inferring that r is infeasible when it is feasible; or

Type II: Inferring that r is feasible when it is infeasible.)

Checking the feasibility of a route r : Strategy III

Deriving the distribution of T_r to compute $\mathbb{P}[T_r > D]$:

function ISFEASIBLE(r) ▷ returns TRUE iff r is feasible

$$p_{L,P}^{r,1}(Q + Q\Gamma_{k,Q} - k, c_{0,1} + \Gamma_{k,Q}(c_{1,0} + c_{0,1})) = p_1^k$$

for $j = 2$ **to** n_r **do**

$$p_{L,P}^{r,j}(\cdot, \cdot) \leftarrow 0 \quad \text{▷ initialize with zeros}$$

for all l, p **such that** $p_{L,P}^{r,j-1}(l, p) > 0$ **do**

for all k **such that** $p_j^k > 0$ **do**

if $l > \tau_{j-1}$ **then** ▷ visiting j directly

$$p_{L,P}^{r,j}(l + Q\Gamma_{k,l} - k, p + t_{s_{j-1}s_j} + \Gamma_{k,l}(c_{j,0} + c_{0,j})) += p_{L,P}^{r,j-1}(l, p)p_j^k$$

else ▷ restocking before visiting j

$$p_{L,P}^{r,j}(Q + Q\Gamma_{k,Q} - k, p + c_{j-1,0} + c_{0,j} + \Gamma_{k,Q}(c_{j,0} + c_{0,j})) += p_{L,P}^{r,j-1}(l, p)p_j^k$$

end if

end for

end for

end for

$$\text{return } \sum_{l=0}^Q \sum_{p \leq \bar{T} - c_{n_r,0}} p_{L,P}^{r,n_r}(l, p) \geq \alpha$$

end function

Computational Results with $\alpha = 0.95$

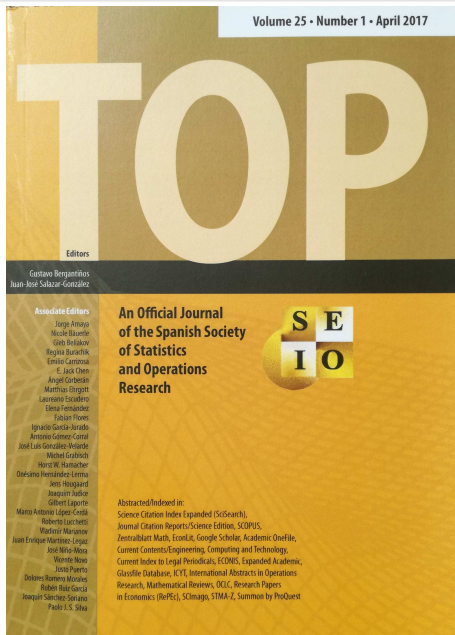
Instance	MRV-16		B&P				
	Best	#	Best	#	$\#_{>q}$	Gap	Time(h)
A-n32-k5	866.77	5	866.45	5	0		5.00
A-n33-k5	735.00	6	732.82	5	1		6.74
A-n33-k6	793.90	6	792.54	5	3		10.64
A-n34-k5	839.01	6	838.95	6	0		0.44
A-n37-k5	713.99	5	710.78	4	1	1.57%	t.l.
A-n38-k5	777.59	6	777.55	6	0		29.58
A-n39-k6	889.40	6	887.04	5	1	0.81%	t.l.
A-n48-k7	1210.79	7	1212.32	7	1	1.60%	t.l.
P-n19-k2	233.36	3	227.87	2	1		0.02
P-n20-k2	240.84	3	240.80	3	0		0.12
P-n21-k2	234.00	3	233.98	3	0		0.09
P-n22-k2	242.19	3	242.18	3	0		0.43
P-n22-k8	715.81	10	591.56	7	1		0.17
P-n23-k8	634.46	10	620.45	7	3		0.14
P-n40-k5	488.50	5	487.61	5	0		0.89
P-n45-k5	539.66	6	539.65	6	0	0.09%	t.l.
P-n50-k8	680.42	9	680.34	9	0	0.24%	t.l.
P-n50-k10	772.25	11	771.49	10	1	0.11%	t.l.
P-n51-k10	833.42	11	832.40	10	1	0.49%	t.l.
P-n55-k10	759.36	11	754.12	10	1	0.55%	t.l.
P-n55-k15	1086.44	17	1075.18	14	4	0.38%	t.l.
P-n60-k10	811.44	11	809.42	10	2	0.17%	t.l.
P-n60-k15	1110.72	17	1101.41	15	3	0.61%	t.l.

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Questions?????????????

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2016	0.899	32	64/83
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