

# Exact algorithm for the Reliability Fixed-Charge Location Problem with Capacity constraints

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# RFLP

- Introduced by Snyder & Daskin in *Reliability models for facility location: the expected failure cost case. Transportation Science*, 39 (2.005).
- **Fixed-charge facility location problem.**
- Unsplittable demands.
- Facilities can independently fail with homogeneous probability.
- For each customer, a sequence of assignments to opened facilities is defined and, at each scenario, the customer is served from the first facility in the sequence that has not failed.
- An extra dummy non-failing facility with large assignment costs is used to model situations where a customer is lost or outsourced.
- Facilities have unlimited capacity.

# CRFLP

- *CRFLP* was introduced by Albareda-Sambola et al. in *Introducing capacities in the location of unreliable facilities. European Journal of Operational Research, 259 (2.017)*
- **It could have facilities with limited capacity.**
- Usually, capacities are considered as strict limits. However, in many situations it is possible to increase the capacity of a facility during emergency situations. In this work different models were explored **allowing to serve a demand slightly over the capacity** of the facilities, but keeping a limit on these excesses.
- **Stability** in the assignment of customers to facilities is compulsory. Then, the orders of the assignments of customers to facilities is predefined and provided by the best solution. The **reassignments are not allowed.**

# Sets and parameters

## Sets

- $I$ : set of customers.
- $J$ : set of possible locations.
- $F$ : subset of locations of  $J$  that could fail.
- $NF$ : subset of locations of  $J$  that can not fail.

## Parameters

- $q$ : probability of fail for each facility  $F$ .
- $h_i \geq 0$ : demand of each customer  $i \in I$ .
- $d_{ij} \geq 0$ : cost of sending one unity of product from facility  $j \in J$  to customer  $i$ .
- $\theta_i \geq 0$ : non-service cost of customer  $i \in I$ .
- $f_j \geq 0$ : open cost for location  $j$ .

# CRFLP Model

## Variables

- $X_j$ : binary variables indicating if facility  $j$  is open.
- $Y_{ijr}$ : binary variables indicating if  $j$  is the  $(r + 1)$ -th backup-facility of customer  $i$ .

## Objective function

$$\min \quad \alpha w_1 + (1 - \alpha) w_2$$

where  $\alpha$  is a value between  $[0, 1]$ ,  $R = \{0, \dots, |F|\}$  and

$$w_1 = \sum_{j \in J} f_j X_j + \sum_{i \in I} \sum_{j \in J} h_i d_{ij} Y_{ij0}$$

$$w_2 = \sum_{i \in I} h_i \left[ \sum_{j \in NF} \sum_{r \in R} d_{ij} q^r Y_{ijr} + \sum_{j \in F} \sum_{r \in R} d_{ij} q^r (1 - q) Y_{ijr} \right].$$

# CRFLP Model

## Constraints

$$\text{s.a} \quad \sum_{j \in F} Y_{ijr} + \sum_{j \in NF} \sum_{s=0}^r Y_{ijs} = 1 \quad \forall i \in I, r \in R \quad (1)$$

$$\sum_{r \in R} Y_{ijr} \leq X_j \quad \forall i \in I, j \in J \quad (2)$$

$$X_u = 1 \quad (3)$$

$$\sum_{i \in I} h_i Y_{ij0} \leq Q_j X_j \quad \forall j \in J \quad (4)$$

$$\text{Capacity constraints} \quad (5)$$

$$X_j \in \{0, 1\} \quad \forall j \in J \quad (6)$$

$$Y_{ijr} \in \{0, 1\} \quad \forall i \in I, j \in J, r \in R \quad (7)$$

# Expected overload

$$\sum_{j \in O(X)} \mathbb{E} \left[ \left( \underbrace{\xi_j \cdot \sum_{i \in I} h_i \left( \sum_{r \in R} Y_{ijr} \cdot \prod_{s < r} \left( \sum_{j' \in O(X)} Y_{ij's} (1 - \xi_{j'}) \right) \right)}_{\text{demand at } j \text{ according to } \xi} \right) - Q_j \right)^+ \right]$$

- $O(X) \subset J$  is the set of locations where facilities have been placed
- $\xi_j \sim \text{Bernoulli}(1 - q)$  for  $j \in O_F(X) = O(X) \cap F$ ,
- $\xi_j = 1$  for  $j \in O_{NF}(X) = O(X) \cap NF$

**Modeling expected overload requires full scenario enumeration being hard to solve it even for small instances.**



# Capacity constraints

- ① **CRFLP-S( $\theta$ )** is based on staggered capacities.

$$\sum_{s=0}^r \sum_{i \in I} h_i Y_{ijs} \leq \theta^r Q_j \quad \forall j \in J, r > 1$$

this model does not manage the overload.

- ② **CRFLP-B1( $\beta$ )** bounds an upper bound for expected overload, then their solutions could not be optimal.

$$\sum_{j \in F} \sum_{r > 0} q^r (1 - q) \lambda_{jr} + \sum_{j \in NF} \sum_{r > 0} q^r \lambda_{jr} \leq \beta$$

where  $\lambda_{jr}$ : overload at facility  $j$  at level  $r$

- ③ **CRFLP-LR( $\beta$ )** bounds a linear estimation of expected overload being an approximated model:

$$2.67827q\bar{\lambda}_{\bullet,1} + 1.66348q^2\bar{\lambda}_{\bullet,2} + 1.92325q^3\bar{\lambda}_{\bullet,3} + 4.43350q^4\bar{\lambda}_{\bullet,4} \leq \beta$$

where  $\bar{\lambda}_{\bullet,r}$ : average overload at level  $r$ .

# Proposition 1

## Proposition

*For any set  $O(X)$  of open facilities it is possible to obtain an assignment  $Y$  such that the expected overload is bounded by  $\beta$ .*

### **Proof:**

*Given that in any feasible solution the dummy facility is open, the demand that produces excess over the expected overload cannot be served.* □

# The key

Case A

	r=0	r=1	r=2
i=0			
i=1			

$E(X,Y) = 7.2$   
 non-service cost = 100.0  
 overcost = 0.0

Case B

	r=0	r=1	r=2
i=0			
i=1			

$E(X,Y) = 3.6$   
 non-service cost = 550.0  
 overcost = 445.3

Case C

	r=0	r=1	r=2
i=0			
i=1			

$E(X,Y) = 0.0$   
 non-service cost = 1000.0  
 overcost = 805.3

If we make a new assignment so that the expected overload is bounded:

- 1 The non-service expected cost increases. This only depends on the assignment dummy cost and it is the same for solutions of the 'same type'. Later, we will refer it as **cost of the type of solution**.
- 2 The overcost increases, too. This depends on the specific solution. In the following, we will refer to this overcost as **overcost of the specific solution**.

# Partition of $J$

Let  $\mathcal{P} = \{p_0, \dots, p_{K-1}\}$  be a partition in  $K$  classes of the set  $J$ .

Each class  $p_k$  contains facilities with:

- same type of service disruption,
- same capacity level.

## Example 1

$J = \{A, B, C, u\}$  such that  $Q_A = Q_B = Q_C = 50$ ,  $Q_u = \infty$ ,

$F = \{A, B\}$ ,  $NF = \{C, u\}$

then  $\mathcal{P} = \{p_1, p_2, p_u\}$  with  $p_1 = \{A, B\}$ ,  $p_2 = \{C\}$  and  $p_u = \{u\}$

Let  $n(X)$  be the array containing the number of opened facilities for each class. Two solutions  $X_1$  and  $X_2$  are of the same type if  $n(X_1) = n(X_2)$ .

$O(X)$	$\bar{O}(X)$	$n(X)$
A, u	B, C	(1, 0, 1)
B, u	A, C	(1, 0, 1)
A, B, C, u	$\emptyset$	(2, 1, 1)

# Example of the exact approach

$$J = \{A, B, C, u\} \text{ such that}$$

$$Q_A = Q_B = Q_C = 50, Q_u = \infty,$$

$$F = \{A, B\}, NF = \{C, u\}$$

then  $\mathcal{P} = \{p_1, p_2, p_u\}$  with  $p_1 = \{A, B\}$ ,  $p_2 = \{C\}$  and  $p_u = \{u\}$

	Master Problem				From the solution		
It.	v	$O(X)$	$\bar{O}(X)$	$n_i$	$w_i$	$z_i$	Overall
1	100	A, u	B, C	(1, 0, 1)	400	450	550
2	150	B, u	A, C	(1, 0, 1)	*	350	500
3	400	A, C, u	B	(1, 1, 1)	100	150	550
4	410	B, C, u	A	(1, 1, 1)	*	100	510
<b>5</b>	<b>500</b>	<b>B, u</b>	<b>A, C</b>	<b>(1, 0, 1)</b>	<b>*</b>	<b>*</b>	<b>500</b>

# Master Problem

$$(\text{MASTER}) \min \alpha w_1 + (1 - \alpha) w_2 + Z$$

$$(1) - (4), (6), (7)$$

$$\sum_{r \in R} \sum_{i \in I} h_i d_{iu} q^r Y_{iur} \geq W \quad (8)$$

$$W \text{ constraints} \quad (9)$$

$$Z \text{ constraints} \quad (10)$$

$$W, Z \in \mathbb{R} \quad (11)$$

- $W$  represents **the cost of the type of solution**
- $Z$  represents **the overcost of the specific solution.**

# W constraints

$$\sum_{r \in R} \sum_{i \in I} h_i d_{iu} q^r Y_{iur} \geq W \quad (12)$$

$$\sum_{j \in p_k} X_j = \sum_{i=0}^{|p_k|} i c_i^k; \quad \sum_{i=0}^{|p_k|} c_i^k = 1; p_k \in \mathcal{P} \quad (13)$$

$$\sum_{k=0}^{|\mathcal{P}|-1} c_{n_k}^k - b_a \leq |\mathcal{P}| - 1 \quad (14)$$

$$\sum_{i=1}^a b_i \leq 1; \quad \sum_{i=1}^a w_i b_i = W; \quad (15)$$

$$c_i^k \in \{0, 1\}; b_1 \in \{0, 1\}; k \in \{0, \dots, |\mathcal{P}| - 1\}, i \in \{0, \dots, |p_k|\} \quad (16)$$

**$w_i$  is the cost of the type of solution.**

# W constraints

## Example 2

Suppose for *Example 1*:

- 2 previous iterations:  $w_1 = 10.5$  and  $w_2 = 7.5$  were obtained,
- current iteration (#3):  $n(X) = (2, 0, 1)$  and  $w_3 = 6.5$ .

Then, the constraints to be added are:

$$c_2^0 + c_0^1 + c_1^2 - b_3 \leq 2$$

$$b_1 + b_2 + b_3 \leq 1$$

$$10.5b_1 + 7.5b_2 + 6.5b_3 = W$$

$$b_3 \in \{0, 1\}$$









# Z constraints






$$(\text{MASTER}) \quad \min \alpha w_1 + (1 - \alpha) w_2 + Z$$

$$\sum_{j \in J \setminus O(X)} z X_j + Z \geq z$$

## Example 3

	r=0	r=1	r=2
i=0			
i=1			

$E(X, Y) = 7.2$   
 non-service cost = 100.0  
 overcost = 0.0

	r=0	r=1	r=2
i=0			
i=1			

$E(X, Y) = 3.6$   
 non-service cost = 550.0  
 overcost = 445.3

**Target:  $E(X, Y) < 4$  ( $\beta = 4$ )**

$J = \{A, B, C, u\}$ ,  $O(X) = \{A, u\}$ ,  $\bar{O}(X) = \{B, C\}$

$$445.3X_B + 445.3X_C + Z \geq 445.3$$

# Slave problem AP-D(X)

$$\min \sum_{i \in I} h_i d_{iu} \sum_{r \geq 1} q^r Y'_{iur}$$

$$\text{s.t.} \quad \sum_{j \in O_F(X)} Y'_{ijr} + \sum_{j \in O_{NF}(X)} \sum_{s=0}^r Y'_{ijs} = 1 \quad i \in I, r \in R \quad (17)$$

$$\sum_{r \in R} Y'_{ijr} \leq 1 \quad i \in I, j \in O(X) \quad (18)$$

$$h_i (\xi_j^s Y'_{ijr} - \sum_{k \in O(X): k \neq j} \sum_{t=0}^{r-1} \xi_k^s Y'_{ikt}) \leq \delta_{ij}^s, i \in I, j \in O(X), r \in R, s \in S \quad (19)$$

$$\sum_{i \in I} \delta_{ij}^s - Q_j \leq \theta_j^s \quad j \in O(X), s \in S \quad (20)$$

$$\sum_{j \in O(X)} \sum_{s \in S} p^s \theta_j^s \leq B \quad (21)$$

$$Y'_{ijr} \in \{0, 1\} \quad i \in I, j \in O(X), r \in R \quad (22)$$

$$\delta_{ij}^s, \theta_j^s \in \mathbb{R} \quad i \in I, j \in O(X), r \in R \quad (23)$$

$AP - D(X)$  model is based on scenarios taken into account only the open facilities, then the number of combinations has been highly reduced.

# Slave problem AP-A(X)

$$\begin{aligned} \min \quad & \alpha \left( \sum_{i \in I} \sum_{j \in O(X)} h_i d_{ij} Y'_{ij0} \right) + (1 - \alpha) \sum_{i \in I} h_i \left( \sum_{j \in O_{NF}(X)} \sum_{r \in R} d_{ij} q^r Y'_{ijr} + \sum_{j \in O_F(X)} \sum_{r \in R} d_{ij} q^r (1 - q) Y'_{ijr} \right) \\ \text{s.t.} \quad & (17) - (23) \end{aligned}$$

# Proposition 2

## Proposition

*If the non-service costs are higher than other assignment costs, i.e.,  $d_{iu} > d_{ij}$  for all  $i \in I, j \in J \setminus \{u\}$ , then any optimal solution of  $AP-A(X)$  is also an optimal solution of  $AP-D(X)$ .*

**Implications:** in cases which  $d_{iu} > d_{ij}$  (usual cases) we also employ  $AP - A(X)$  for obtaining the minimum non-service expected cost capturing the assignments to the dummy facility. Then, we do not solve  $AP - D(X)$  problem for these cases.

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**Algorithm 1:**  $(v^*, X^*, Y^*) = \text{main\_algorithm}()$ 

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```

1 master = model(QRFLP);
2  $(c, X, Y) = \text{solve}(\text{master})$ ;
3 overload =  $E(X, Y)$ ;
4  $a = 1$ ;
5 if overload >  $\beta$  then
6    $v^* = +\text{inf}$ ;
7 else
8    $v^* = c$ ;
9    $(X^*, Y^*) = (X, Y)$ 
10 while  $v^* > c$  & time <  $t_{\text{limit}}$  do
11    $(w_a, z, Y') = \text{new\_assignments}(O(X), c, \beta)$ ;
12   add_overcost(master,  $z, X$ );
13   if  $c + v < v^*$  then
14      $v^* = c + z$ ;
15      $(X^*, Y^*) = (X, Y')$ 
16   if is_new_distribution_of_open_facilities( $O(X)$ ) then
17     add_min_non_service_cost(master,  $O(X)$ ,  $\mathcal{P}, w, a$ );
18      $a = a + 1$ ;
19    $(c, X, Y) = \text{solve}(\text{master})$ ;
20 return  $(v^*, X^*, Y^*)$ 
```

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# Generated instances

	#	Instance #	Customers	F	NF  <sup>(*)</sup>	q	$f_F$ (×1000)	$f_{NF}/f_F$
S20_50_a	180	1 - 10	20	50	0	0.05, 0.10, 0.20	1, 2, 3	1, 2
S20_50_b	180	1 - 10	20	35	15	0.05, 0.10, 0.20	1, 2, 3	1, 2
S50_50_a	10	1 - 10	50	50	0	0.05	2	2
S50_50_b	10	1 - 10	50	35	15	0.05	2	2
S20_75_a	10	11 - 20	20	75	0	0.05	2	2
S20_75_b	10	11 - 20	20	45	30	0.05	2	2

(\*) : excluding dummy

Instances built from the capacitated p-median instances of the  
OR-LIBRARY.

$\alpha = 0.5$ , non-service cost:  $\rho = 400$ .

# Average values S20\_50 instances

	$v^*$	$E(X, Y)$	$\mathbb{P}(\text{overload})$	Dummy	# Open	Time
MASTER	8997.20	5.19	0.07	0.26	3.44	7.75
CRFLP-B1(3)	9378.19	1.64	0.06	1.92	3.67	30.20
CRFLP-B1(6)	9143.23	3.90	0.07	0.94	3.52	32.33
CRFLP-LR(3)	9287.02	2.53	0.07	1.68	3.57	31.71
CRFLP-LR(6)	9051.44	4.65	0.07	0.56	3.47	17.82
CRFLP-EX(3)	9313.96	2.15	0.10	1.52	3.63	62.82
CRFLP-EX(6)	9143.23	3.90	0.07	0.94	3.52	23.13

# Average values S50\_50 instances

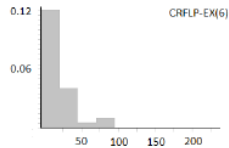
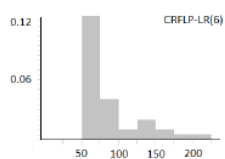
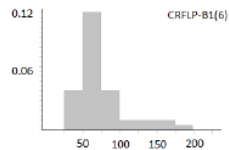
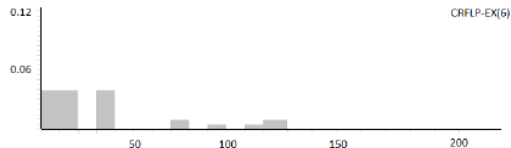
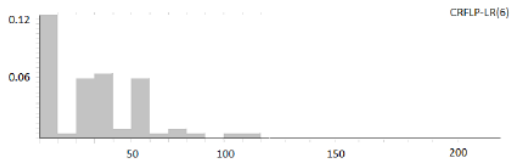
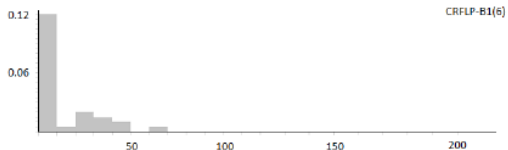
	$v^*$	$E(X, Y)$	$\mathbb{P}(\text{overload})$	Dummy	#Open	Time	Solved
MASTER	17955.67	22.06	0.23	0.00	6.10	719.03	18
CRFLP-B1(3)	21428.69	2.33	0.15	16.37	6.75	187.00	20
CRFLP-B1(6)	20870.85	4.71	0.19	13.37	6.75	215.00	20
CRFLP-LR(3)	21198.76	3.31	0.16	15.12	6.75	1152.60	18
CRFLP-LR(6)	20449.32	6.41	0.21	11.07	6.75	1188.75	16
CRFLP-EX(3)	19961.25	3.00	0.21	10.37	6.10	3600.00	2
CRFLP-EX(6)	19671.84	5.99	0.22	8.68	6.10	3600.00	3



# Average values S20\_75 instances

	$v^*$	$E(X, Y)$	$\mathbb{P}(\text{overload})$	Dummy	#Open	Time	Solved
MASTER	9806.13	5.4	0.12	0.22	3.6	349.25	20
CRFLP-B1(3)	11090.57	1.32	0.10	2.44	4.4	1412.03	19
CRFLP-LR(3)	10885.10	2.57	0.12	1.91	4.3	1337.10	17
CRFLP-EX(3)	10496.21	2.84	0.15	1.17	4.1	1398.65	18

# Distribution of overload and non-service demand



# Conclusions

- We have proposed a **dynamic approach** in order to provide the best solution strictly bounding the expected overload of the *CRFLP*.
- The approach proposed highly **reduces the combinatorial difficulty** inherent to the problem by:
  - Introducing the minimum overcost for each combination among facilities of the same type ( $W$  constraints).
  - Associating the overcost due to the assignment for a given set of open facilities that bound the overload ( $Z$  constraints).
- This approach has provided the most promising results not only in terms of the cost for strictly limiting the expected overload, but **in many cases even in less time than the approximated methods**, too.
- Even in all of the instances in which the exact method has not finished in time, **the solution returned has worked better than the solution provided by the other methods**.

# Future research lines

- We can consider **developing heuristic algorithms** based on this dynamic method, and so applying these for solving larger instances.
- Since the idea of controlling the expected overload by exact dynamic approach has worked efficiently, we can also consider **extending this idea to other reliability problems**.

# Some references

- Snyder, L. & Daskin, M.S. (2005). Reliability models for facility location: The expected failure cost case. *Transportation Science*, 39 (3), 400 - 416 .
- Albareda-Sambola, M. & Landete, M. & Monge, J.F. & Sainz-Pardo, J.L. (2017) Introducing capacities in the location of unreliable facilities. *European Journal of Operational Research*, 259, 175 - 188
- Espejo, I. & Marín, A. & Rodríguez-Chía, A.M. (2015). Capacitated p-center problem with failure foresight. *European Journal of Operational Research*, 247 , 229 - 244.

# Thanks!

