

Heuristics and models for the stochastic uncapacitated r -allocation p -hub median problem

Some managerial insights

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The uncapacitated r -allocation p -hub median problem

The uncapacitated r -allocation p -hub median problem

- Given a network $G = (V, E)$, for each pair of nodes i and $j \in V$, there is a traffic $t_{ij} \geq 0$ to be transported
- p , the number of hubs to be open, is an input
- Each node i is assigned to at most r of the p hubs (r is also an input)
- No capacity constraints
- Direct transportation between nodes is not common but possible. Traffic t_{ij} travels along a path $i \rightarrow k \rightarrow l \rightarrow j$ or uses a non-stop service.

The uncapacitated r -allocation p -hub median problem

It was originally formulated as a MILP by Hande Yaman:



European Journal of Operational Research, 211: 442–451,
2011.

We extend the model, using decision variables:

- Binary variables of opening hubs and assigning nodes to hubs:
 - $z_{kk} = 1$ if $k \in V$ is a hub, and 0 otherwise.
 - $z_{ik} = 1$ if node i is assigned to node k , and 0 otherwise.
 - $w_{kl} = 1$ to connect hubs k and l , and 0 otherwise.
- Continuous variables to route the traffics
 - x_{ijkl} the proportion of the traffic t_{ij} that travels along the path $i \rightarrow k \rightarrow l \rightarrow j$.
 - y_{ij} for the proportion of the traffic t_{ij} that travels using a non-stop service between i and j

We have extended the model

Objective:

$$\min \sum_{i,k \in V} a_{ik} z_{ik} + \sum_{k,\ell \in V, k < \ell} f_{k\ell} w_{k\ell} + \sum_{i,j,k,\ell \in V} c_{ijk\ell} t_{ij} x_{ijk\ell} + \sum_{i,j \in V} (d_{ij} t_{ij} + b_{ij}) y_{ij}, \quad (1)$$

Subject to: $\sum_{k \in V} z_{kk} = p,$ (2)

$$\sum_{k \in V} z_{ik} \leq r, \quad \forall i \in V, \quad (3)$$

$$z_{ik} \leq z_{kk}, \quad \forall i, k \in V, \quad (4)$$

$$\sum_{\ell \in V} x_{ijk\ell} \leq z_{ik}, \quad \forall i, j, k \in V, \quad (5)$$

$$\sum_{k \in V} x_{ijk\ell} \leq z_{j\ell}, \quad \forall i, j, \ell \in V, \quad (6)$$

$$\sum_{k,\ell \in V} x_{ijk\ell} + y_{ij} = 1, \quad \forall i, j \in V : t_{ij} > 0, \quad (7)$$

We have extended the model

$$w_{k\ell} \leq z_{kk}, \quad \forall k, \ell \in V, k < \ell, \quad (8)$$

$$w_{k\ell} \leq z_{\ell\ell}, \quad \forall k, \ell \in V, k < \ell, \quad (9)$$

$$z_{kk} + z_{\ell\ell} \leq w_{k\ell} + 1, \quad \forall k, \ell \in V, k < \ell, \quad (10)$$

$$\sum_{j \in V} y_{ij} + \sum_{j \in V} y_{ji} \leq M(1 - z_{ii}), \quad \forall i \in V, \quad (11)$$

$$x_{ijkl} \geq 0, \quad \forall i, j, k, \ell \in V, \quad (12)$$

$$y_{ij} \geq 0, \quad \forall i, j \in V, \quad (13)$$

$$z_{ik} \in \{0, 1\}, \quad \forall i, k \in V, \quad (14)$$

$$w_{k\ell} \in \{0, 1\}, \quad \forall k, \ell \in V, k < \ell. \quad (15)$$

We introduce uncertainty in the model

We will assume that **demands** and **costs** are **NOT KNOWN** in advance, but can be captured by a probability distribution.

We will use a two-stage stochastic programming model.

For every $i, j \in V$, we assume t_{ij} , c_{ij} , b_{ij} , and d_{ij} to be random.

The random vector is

$$\xi = \left[[t_{ij}]_{i,j \in V}, [c_{ij}]_{(i,j) \in E}, [b_{ij}]_{(i,j) \in E}, [d_{ij}]_{(i,j) \in E} \right].$$

Each realization of ξ is a scenario.

A two-stage stochastic version of the UrApHMP-NSS

$$\min \sum_{i,k \in V} a_{ik} z_{ik} + \sum_{k,\ell \in V, k < \ell} f_{k\ell} w_{k\ell} + Q(\mathbf{z}, \mathbf{w}), \quad (16)$$

s. t. (2) – (4), (8) – (10), (14), (15).

where $Q(\mathbf{z}, \mathbf{w}) = E_\xi[Q(\mathbf{z}, \mathbf{w}, \xi)]$ is the mathematical expectation with respect to ξ , and

each $Q(\mathbf{z}, \xi) =$

$$Q(\mathbf{z}, \mathbf{w}, \xi) = \min \sum_{i,j,k,\ell \in V} c_{ijk\ell} t_{ij} x_{ijk\ell} + \sum_{i,j \in V} (d_{ij} t_{ij} + b_{ij}) y_{ij}, \quad (17)$$

$$\text{s. t. } \sum_{\ell \in V} x_{ijk\ell} \leq z_{ik}, \quad \forall i, j, k \in V, \quad (18)$$

$$\sum_{k \in V} x_{ijk\ell} \leq z_{j\ell}, \quad \forall i, j, \ell \in V, \quad (19)$$

$$\sum_{k,\ell \in V} x_{ijk\ell} + y_{ij} = 1, \quad \forall i, j \in V : t_{ij} > 0, \quad (20)$$

$$\sum_{j \in V} y_{ij} + \sum_{j \in V} y_{ji} \leq M(1 - z_{ii}), \quad \forall i \in V, \quad (21)$$

$$x_{ijk\ell} \geq 0, \quad \forall i, j, k, \ell \in V, \quad (22)$$

$$y_{ij} \in \{0, 1\}, \quad \forall i, j \in V. \quad (23)$$

The deterministic equivalent model if the support of ξ is finite

$$\begin{aligned} \min \sum_{i,k \in V} a_{ik} z_{ik} + \sum_{k,\ell \in V, k < \ell} f_{k\ell} w_{k\ell} \\ + \sum_{s \in S} \pi_s \left[\sum_{i,j,k,\ell \in V} c_{ijk\ell s} t_{ij s} x_{ijk\ell s} + \sum_{i,j \in V} (d_{ijs} t_{ijs} + b_{ijs}) y_{ijs} \right], \end{aligned} \quad (24)$$

s. t. (2) – (4), (8) – (10), (14), (15),

$$\sum_{\ell \in V} x_{ijk\ell s} \leq z_{ik}, \quad \forall i, j, k \in V, s \in S, \quad (25)$$

$$\sum_{k \in V} x_{ijk\ell s} \leq z_{j\ell}, \quad \forall i, j, \ell \in V, s \in S, \quad (26)$$

$$\sum_{k,\ell \in V} x_{ijk\ell s} + y_{ijs} = 1, \quad \forall i, j \in V, s \in S, \quad (27)$$

$$\sum_{j \in V} y_{ijs} + \sum_{j \in V} y_{jis} \leq M(1 - z_{ii}), \quad \forall i \in V, s \in S, \quad (28)$$

$$x_{ijk\ell s} \geq 0, \quad \forall i, j, k, \ell \in V, s \in S, \quad (29)$$

$$y_{ijs} \in \{0, 1\}, \quad \forall i, j \in V, s \in S. \quad (30)$$

Our proposal: Heuristic optimization

Our assumption:

Good solutions for the single-scenario problems \mathcal{P}_s , $s \in S$, may contain information about good attributes of a solution to \mathcal{P}

- Build solutions to \mathcal{P} using the solutions of \mathcal{P}_s , $s \in S$.
- Note that solutions for problems \mathcal{P}_s , $s \in S$, may render different network designs:
 - distinct hubs selection
 - distinct allocations of terminals
 - the number of hubs to which a terminal is assigned to may be different for one scenario to another

Name: Greedy Attributive Scenario Based Constructive Method

Computational experiments and some managerial insights

Competitive testing for CAB-based instances

n	p	r	Heuristic								
			CPLEX			CPU (sec.)			Dev (%)		
			#solved	CPU (sec.)		min	avg	max	min	avg	max
15	3	3	10	456		20	27	34	0.1	1.2	2.3
15	3	2	10	745		22	25	33	0.5	1.4	2.3
15	3	1	10	1118		20	28	34	0.4	2.0	4.9
20	3	3	10	3986		117	127	138	0.3	1.6	2.4
20	3	2	10	4150		119	128	138	0.6	1.8	3.0
20	3	1	3	6970		126	134	137	2.3	2.8	3.4
20	4	4	10	4924		297	331	365	0.9	1.9	2.7
20	4	3	10	6437		301	328	354	0.1	1.6	2.7
20	4	2	10	6414		297	338	368	0.1	2.2	4.1
20	4	1	2	7352		322	326	329	3.8	4.0	4.1

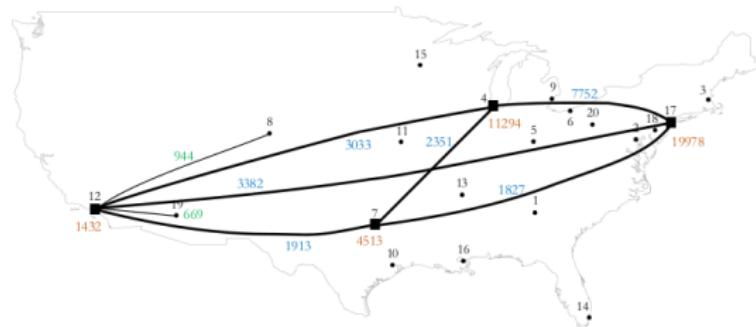
Competitive testing for AP-based instances

n	p	r	Heuristic								
			CPLEX			CPU (sec.)			Dev (%)		
			#solved	CPU (sec.)		min	avg	max	min	avg	max
15	3	3	3	575		31	32	33	0.2	2.3	3.5
15	3	2	3	794		23	25	28	0.1	0.4	0.9
15	3	1	3	1141		23	27	30	0.9	1.5	2.3
20	3	3	3	4878		120	122	124	1.8	2.1	2.5
20	3	2	3	5916		127	127	129	0.3	1.8	3.2
20	3	1	0	n/a		n/a	n/a	n/a	n/a	n/a	n/a
20	4	4	3	5603		268	278	288	1.1	1.6	2.1
20	4	3	3	6041		292	316	332	2.6	3.2	3.9
20	4	2	2	6711		250	277	305	1.7	2.7	3.8
20	4	1	1	7224		169	169	169	3.5	3.5	3.5

The optimal solution is not optimal for any scenario



(a) $\alpha = 1.0$.



(b) $\alpha = 0.6$.

The effect in here-and-now decisions when α changes

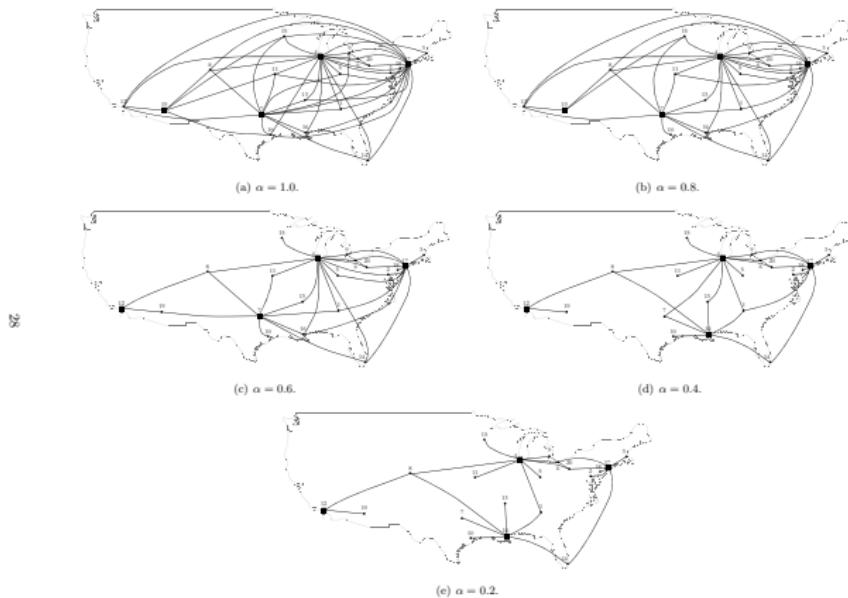


Figure 3: 20-node CAB instance with $p = 4$, $r = 4$: representation of the hubs and allocations.

Thank you very much for your attention!

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