

# Formulations and Approximation Algorithms for Multi-level Facility Location Problems

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# Outline

## Introduction

- Classes of Problems
- Submodularity

## Main Results

- Approximation Algorithms
- MILP Formulation
- Computational Results

## *Facility Location Problems*

- ◇ Location of the facilities
- ◇ Allocation of customers to open facilities

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- ▶ Uncapacitated Facility Location Problem (UFLP)  
(Kuehn and Hamburger, 1963)
- ▶  $p$ -Median Problem ( $p$ -MP)  
(Hakimi, 1964)
- ▶ Uncapacitated  $p$ -Location Problem ( $Up$ LP)  
(Cornuéjols et al., 1977)

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- ◇ Allocation of customers to open facilities

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Location Problem (UFLP)

(Kuehn and Hamburger, 1963)

▶  $p$ -Median Problem ( $p$ -MP)

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▶ Uncapacitated  $p$ -Location  
Problem ( $U_p$ LP)

(Cornuéjols et al., 1977)

▶ Multi-level Uncapacitated Facility  
Location Problem (MUFLP)

(Kaufman et al., 1977)

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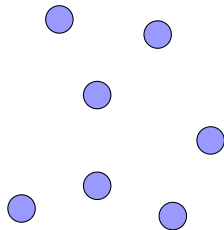
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▶ Multi-level  $p$ -median Problem  
( $Mp$ MP)

▶ Multi-level Uncapacitated  
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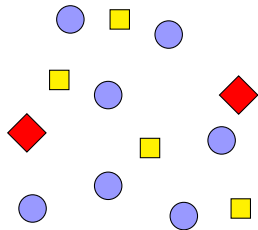
# Definitions

- ▶ Set of customers  $I$
- ▶ Sets of potential facilities of levels 1 to  $k$  ( $V_1, \dots, V_k$ )
- ▶ Setup costs  $f_{j_r}$  for each facility
- ▶ Allocation profits  $c_{ij_1 \dots j_k}$



# Definitions

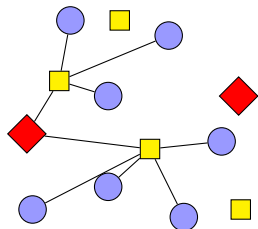
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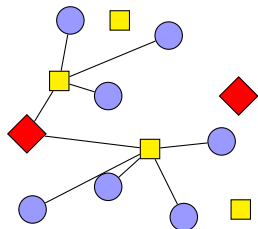
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The MUFLP consists of selecting a set of facilities to open at each of the  $k$  levels and of assigning each customer to a set of facilities, exactly one at each level, while maximizing the difference of the total profit minus the setup cost for opening the facilities.

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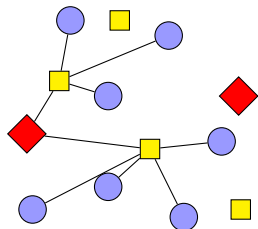
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The **MU $p$ LP** is defined as the MUFLP with the addition of satisfying the cardinality constraints.

The M $p$ MP is a particular case of MU $p$ LP when all  $f_{j_r}$  are zero.

# Submodularity

Let  $N$  be a finite set and  $z$  be a real-valued function defined on the set of subsets of  $N$  and  $\rho_e(W) = z(W \cup \{e\}) - z(W)$ .

## Definition

1.  $z$  is submodular if  $\rho_e(W) \geq \rho_e(U)$ ,  $\forall W \subseteq U \subseteq N$  and  $e \in N \setminus U$ .
2.  $z$  is nondecreasing if  $\rho_e(W) \geq \rho_e(U) \geq 0$ ,  $\forall W \subseteq U \subseteq N$  and  $e \in N$ .

## Some results for single level FLPs

- Nemhauser et al. (1978) presented a greedy heuristic for

$$\max_{S \subseteq N} \{z(S) : |S| \leq p \text{ and } z \text{ is submodular}\}. \quad (1)$$

### Proposition

*If the greedy heuristic is applied to problem (1) then*

$$\frac{Z - Z^G}{Z - z(\emptyset)} \leq \frac{p-1}{p} \text{ and } \frac{Z - Z^G}{Z - z(\emptyset) + p\theta} \leq \left(\frac{p-1}{p}\right)^p.$$

where,  $Z$  is the optimal value,  $Z^G$  the value obtained by the greedy heuristic and  $\rho_e(W) \geq \theta$  for all  $W \subseteq N$  and  $e \in N \setminus W$ .

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When  $z$  is also nondecreasing, that is  $\theta = 0$  (e.g.  $p$ -MP)

$$\frac{Z - Z^G}{Z - z(\emptyset)} \leq \left(\frac{p-1}{p}\right)^p \leq 1/e,$$

and the bound is tight.

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- MILP Formulations (Nemhauser and Wolsey, 1981)

## A Submodular Representation for the $MU_pLP$

$$\max_{R \subseteq V} \left\{ \sum_{i \in I} \max_{j_1 \in R_1, \dots, j_k \in R_k} c_{ij_1 \dots j_k} - \sum_{r=1}^k \sum_{j_r \in R_r} f_{j_r} : |R_r| \leq p_r \right\}$$

The above objective function does **not** satisfy submodularity.

Example Submodularity



## A Submodular Representation for the MUPLP

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### Example Submodularity

Let  $Q$  be the set of all possible simple paths  $(j_1, \dots, j_k)$  and  $N = Q \cup V$ .

$$z(S, R) = h(S, R) + f(S, R) = \sum_{i \in I} \max_{(j_1, \dots, j_k) \in S} c_{ij_1 \dots j_k} - \sum_{r=1}^k \sum_{j \in R_r} f_{j_r}.$$

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$$\max_{(S, R) \subseteq N} \{z(S, R) : |N_r(S)| \leq p_r \text{ and } N_r(S) = R_r \ \forall r\},$$

where  $N_r(S) = \{j_r \in V_r : j_r \in s \text{ for some } s \in S\}$  and  $z$  satisfies submodularity. However, in general,  $z$  is not nondecreasing. (Ortiz-Astorquiza et al., 2015b)

# The Greedy Heuristic for the $MUpLP$

Let  $(S, R)^0 \leftarrow \emptyset$ ,  $N^0 \leftarrow N$  and  $t \leftarrow 1$

**while**  $t < p_1 + 1$  **do**

    Select  $A_{q^*}(t) \subseteq N^{t-1}$  for which

$\rho_{A_{q^*}(t)}((S, R)^{t-1}) = \max_{A_q(t) \in N^{t-1}} \rho_{A_q(t)}((S, R)^{t-1})$  with ties broken

    arbitrarily. Set  $\rho_{t-1} \leftarrow \rho_{A_{q^*}(t)}((S, R)^{t-1})$

**if**  $\rho_{t-1} \leq 0$  **then**

        Stop with  $(S, R)^{t-1}$  as the greedy solution

**else**

        Set  $(S, R)^t \leftarrow (S, R)^{t-1} \cup A_{q^*}(t)$  and  $N^t \leftarrow N^{t-1} \setminus A_{q^*}(t)$

**end if**

**for**  $r$  such that  $|N_r(S^t)| = p_r$  **do**

        Set  $N^t \leftarrow N^t \setminus \{q : \exists j_r \in V_r \setminus R_r^t\}$

**end for**

$t \leftarrow t + 1$

**end while**

## Worst-case bounds for greedy heuristics

Under the assumption that  $c_{ij_1 \dots j_k} = c_{ij_1} + \dots + c_{j_{k-1}j_k} \geq 0$ .

### Proposition

*If the greedy heuristic for the MUpLP terminates after  $t^*$  iterations,*

$$\frac{Z - Z^G}{Z - z(\emptyset) + p_1 \theta} \leq \frac{t^*}{p_1} \left( \frac{p_1 - 1}{p_1} \right)^{p_1} \leq \left( \frac{p_1 - 1}{p_1} \right)^{p_1} \leq 1/e.$$

### Proposition

*If the greedy heuristic is applied to MpMP, then*

$$\frac{H - H^G}{H} \leq \left( \frac{p_1 - 1}{p_1} \right)^{p_1} \leq 1/e,$$

*and the bound is tight.*

## A Submodular MILP Formulation

Let  $x_q$  be 1 if path  $q \in Q$  is open and  $y_{j_r}$  be 1 if facility  $j_r \in V_r$  is open, 0 otherwise. The MUPLP can be formulated as

$$\begin{aligned} \text{(SF) } \max \quad & \eta - \sum_{r=1}^k \sum_{j_r \in V_r} f_{j_r} y_{j_r} \\ \text{s.t.} \quad & \eta \leq h(S) + \sum_{q \in Q \setminus S} \rho_q(S) x_q \quad S \subseteq Q \end{aligned} \quad (2)$$

$$\sum_{q \in Q: j_r \in q} x_q \leq M_r y_{j_r} \quad j_r \in V_r, \quad r = 1, \dots, k \quad (3)$$

$$\sum_{j_r \in V_r} y_{j_r} \leq p_r \quad r = 1, \dots, k \quad (4)$$

$$x_q \in \{0, 1\} \quad q \in Q \quad (5)$$

$$y_{j_r} \in \{0, 1\} \quad j_r \in V_r, \quad r = 1, \dots, k, \quad (6)$$

where,  $M_r = \min\{p_1, |Q|/V_r\}$  are sufficiently large values for  $r = 1, \dots, k$ .

# A Submodular MILP Formulation

Constraints (2) can be written as

$$\eta^i \leq c_{iqt} + \sum_{q \in Q} (c_{iq} - c_{iqt})^+ x_q \quad i \in I, \quad t = 0, \dots, |Q| - 1,$$

## A Submodular MILP Formulation

Constraints (2) can be written as

$$\eta^i \leq c_{iq_t} + \sum_{q \in Q} (c_{iq} - c_{iq_t})^+ x_q \quad i \in I, \quad t = 0, \dots, |Q| - 1,$$

And since we assumed that  $c_{ij_1 \dots j_k} = c_{ij_1} + \dots + c_{j_{k-1}j_k} \geq 0$ , we can add the valid cut

$$\sum_{q \in Q} x_q \leq p_1.$$

# Computational Results

Using CPLEX 12.6.1 we compare the submodular formulations for the MpMP and for the MU $p$ LP with three previously presented formulations. A Path-based formulation (PBF, Aardal et al., 1999), an Arc-based formulation (ABF, Aardal et al., 1996; Gabor and Omeren, 2010) and a Flow-based formulation (FBF, Kratica et al., 2014).

## Other Formulations

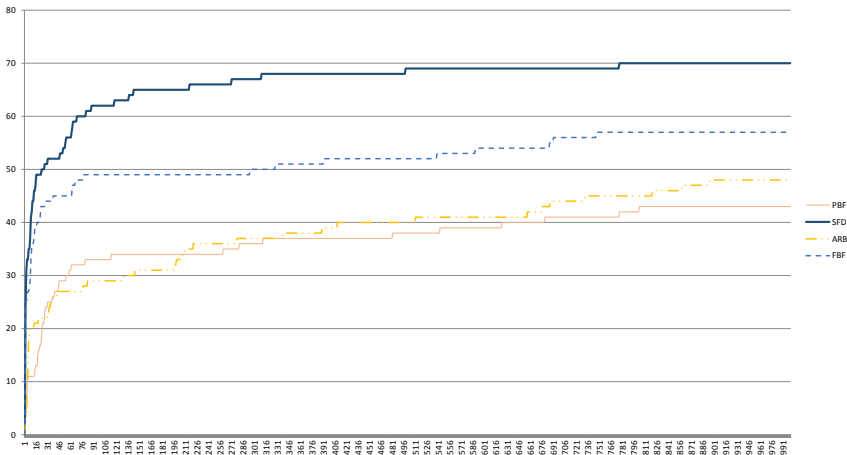
	$k = 2$	$k = 3$	$k = 4$	$ I  = 500$	$ I =1,000$	$ I =1,500$	$ I =2,000$	cap	Total	SGM sec	SGM nodes	Avg. %gap
SFD	36/39	22/25	12/12	16/16	37/37	12/16	2/4	21/21	70/76	3.46	13.44	1.24
FBF	28/39	18/25	11/12	13/16	33/37	6/16	2/4	21/21	57/76	10.54	13.70	3.19
ARB	28/39	14/25	6/12	13/16	27/37	4/16	1/4	19/21	48/76	46.91	0.14	0.01
PBF	35/39	8/25	0/12	8/16	24/37	6/16	2/4	15/21	43/76	-	-	-
Greedy	17/39	8/25	6/12	6/16	20/37	4/16	1/4	11/21	31/76	0.00	-	1.33

Table : Summary of the computational results for the MpMP.

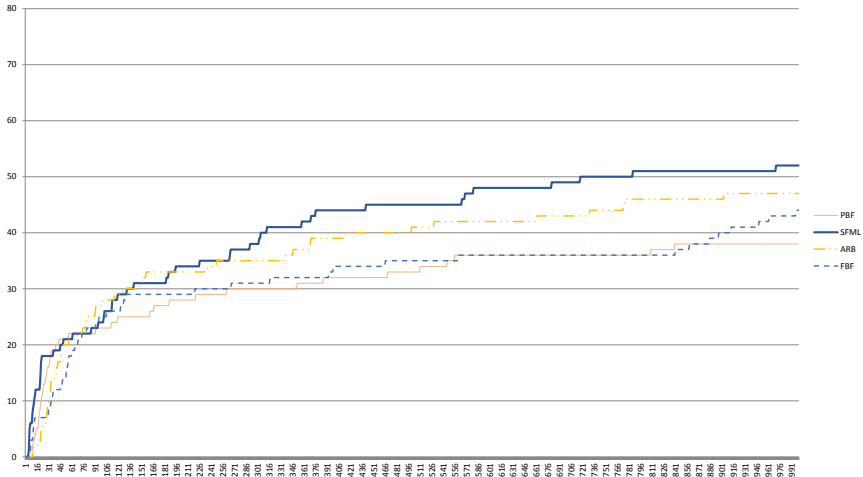
	$k = 2$	$k = 3$	$k = 4$	$ I  = 500$	$ I =1,000$	$ I =1,500$	$ I =2000$	cap	MUFLP	Total	SGM sec	SGM nodes	Avg. %gap
SFML	29/36	15/25	9/12	12/16	31/37	9/16	1/4	16/21	10/20	53/73	68.84	440.64	4.41
FBF	18/36	14/25	8/12	13/16	29/37	2/16	0/4	21/21	14/20	44/73	91.70	103.2	7.76
ARB	25/36	16/25	5/12	13/16	29/37	4/16	1/4	21/21	20/20	47/73	79.64	0.37	0.01
PBF	28/36	6/25	0/12	7/16	23/37	4/16	0/4	15/21	12/20	34/73	-	-	-
Greedy	1/36	0/25	0/12	0/16	1/37	0/16	0/4	0/21	0/20	2/73	0.00	-	5.88

Table : Summary of the Computational Results for the MU $p$ LP.





Comparison of models by number of solved instances for MpMP



Comparison of models by number of solved instances for MUpLP

- Aardal, K., Chudak, F. A., and Shmoys, D. B. (1999). A 3-approximation algorithm for the  $k$ -level uncapacitated facility location problem. *Information Processing Letters*, 72:161–167.
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Ortiz-Astorquiza, C., Contreras, I., and Laporte, G. (2015b). The multi-level facility location problem as the maximization of a submodular set function. *European Journal of Operational Research*, 247:1013–1016.

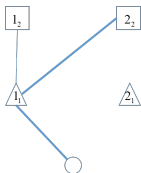
# Appendix

Greedy

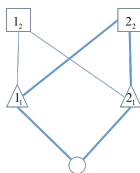
Submodular Formulations

## Example

$c$	$1_2$	$2_2$
$1_1$	1	1
$2_1$	100	1



(a)  $T = \{1_1, 1_2, 2_2\}$  and  $S = \{1_1, 2_2\}$

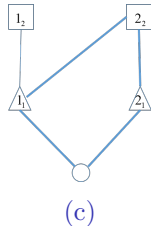
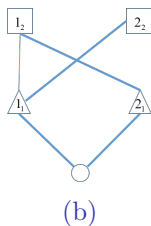
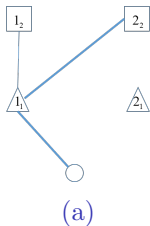


(b)  $T \cup \{2_1\}$  and  $S \cup \{2_1\}$

Vertex representation of the MUFLP

$$v(T) = 1, v(T \cup \{2_1\}) = 100 \text{ and } \rho_{2_1}(T) = 99$$

$$v(S) = 1, v(S \cup \{2_1\}) = 1 \text{ and } \rho_{2_1}(S) = 0.$$



### Path-allocation representation of the MUFLP

(a)  $T = \{(1_1, 1_2), (1_1, 2_2)\}$  and  $S = \{(1_1, 2_2)\}$

(b)  $T = \{(1_1, 1_2), (1_1, 2_2), (2_1, 1_2)\}$  and  $S = \{(1_1, 2_2), (2_1, 1_2)\}$

(c)  $T = \{(1_1, 1_2), (1_1, 2_2), (2_1, 2_2)\}$  and  $S = \{(1_1, 2_2), (2_1, 2_2)\}$

[back](#)



## Proposition

*The greedy heuristic for the MUpLP can be executed in  $O(p_1|V_1|(|V|\log|V| + E + |I|))$  time.*

Proof: At iteration  $t$  the subset  $A_{q^*}(t) \subseteq N^{t-1}$  can be efficiently identified by solving a series of shortest path problems as follows. We consider the auxiliary directed graph  $G^t = (V^t, A^t)$ , where  $A^t = \{(i, j) : i \in V_r^t, j \in V_{r+1}^t, r = 1, \dots, k-1\}$ . For each  $a \in A^t$ , we define its length as  $w_{j_r j_{r+1}} = f_{j_{r+1}} - c_{j_r j_{r+1}}$  if  $j_{r+1} \notin R^t$  and  $w_{j_r j_{r+1}} = -c_{j_r j_{r+1}}$  if  $j_{r+1} \in R^t$ . This operation takes  $O(|E|)$  time. We then compute a candidate path  $q$ , and its associated subset  $A_q(t)$ , associated with each facility  $j \in V_1 \setminus R_1^t$  by solving a shortest path problem between  $j$  and all nodes in  $V_k$ . This can be done in  $O(|V|\log|V| + |E|)$  time using the Fibonacci heap implementation of Dijkstra's algorithm (Ahuja et al., 1993). Finally, we evaluate  $\rho_{A_q(t)}((S, R)^{t-1})$  for each candidate path  $q$ . This takes  $O(|I|)$  time. Therefore, each iteration of the algorithm takes a total of  $O(|V_1|(|V|\log|V| + E + |I|))$  time. Given that there are at most  $p_1$  iterations in the algorithm, the result follows.

Property 1:

Under Assumption 1, there exists an optimal solution to the  $MUpLP$  in which every open facility at level  $r$  is assigned to exactly one facility at level  $r + 1$ , for  $r = 1, \dots, k$  (i.e. coherent structure).

Property 2:

Under Assumption 1, there exists an optimal solution to the  $MUpLP$  in which at most  $p_1$  paths are used, i.e.  $|S| \leq p_1$ .

[back](#)

Consider the polyhedron  $X$  defined as

$$\{(\eta, x, y_1, \dots, y_k) : \eta \leq h(S) + \sum_{q \in Q \setminus S} \rho_q(S)x_q, \quad \forall S \subseteq Q,$$

$$x \in \{0, 1\}^{|Q|}, \quad y_r \in \{0, 1\}^{|V_r|}, \quad \eta \in \mathbb{R}\},$$

where the binary variables  $x_q$  can be interpreted as  $x_q = 1$  if the path  $q \in Q$  is open and 0 otherwise, and  $y_r$  corresponds to the incidence vector for each level  $r$  of the facilities that are open.

## Proposition

*Let  $T \subseteq Q$ ,  $N_r(T) \subseteq V_r$  for all  $r$ , and  $(\eta, x^T, y_1^T, \dots, y_k^T)$  where  $x^T, y_1^T, \dots, y_k^T$  are the incidence vectors of  $T$  and  $N_r(T)$ , respectively. Then,  $(\eta, x^T, y_1^T, \dots, y_k^T) \in X$  if and only if  $\eta \leq h(T)$ .*

Also, note that since  $h(S)$  is the sum of  $|I|$  submodular set functions, one for each  $i \in I$ , we can replace the objective function  $\eta$  by  $\sum_{i \in I} \eta^i$  and constraints (2) with

$$\eta^i \leq h^i(S) + \sum_{q \in Q \setminus S} \rho_q^i(S) x_q \quad i \in I, S \subseteq Q, \quad (7)$$

where  $\rho_q^i(S) = h^i(S \cup \{q\}) - h^i(S)$ . Moreover, most of these inequalities are redundant. First, note that for  $S \subseteq Q$  and  $i \in I$  given, the right-hand side of their associated constraint (7) does not change if the summation is taken over all  $q \in Q$ , since  $\rho_q^i(S) = 0$  for  $q \in S$ . Also,  $h^i(S) = c_{i s_1, \dots, s_k}$  for some  $s_1, \dots, s_k \in S$ . For simplicity, we write  $c_{is}$  for  $s \in S \subseteq Q$ . Then,  $\rho_q^i(S) = c_{iq} - c_{is}$  if  $c_{iq} > c_{is}$  or  $\rho_q^i(S) = 0$  if  $c_{iq} \leq c_{is}$ . For any  $S$ , its associated constraint (7) can thus be written as

$$\eta^i \leq c_{is} + \sum_{q \in Q} (c_{iq} - c_{is})^+ x_q,$$

for some  $s \in S$  and  $\chi^+ = \max\{0, \chi\}$ . Therefore, if for each  $i \in I$  we consider the ordering  $0 = c_{iq_0} \leq c_{iq_1} \leq \dots \leq c_{iq_{|Q|-1}}$ , we may select only the sets  $S_q = \{q\}$  with  $q = q_0, \dots, q_{|Q|-1}$  in constraints (7).

## Proposition

The MpMP can be formulated as

$$\begin{aligned} & \text{maximize} && \sum_{i \in I} \eta^i \\ & \text{subject to} && (3) - (6) \\ & && \eta^i \leq c_{iqt} + \sum_{q \in Q} (c_{iq} - c_{iqt})^+ x_q \quad i \in I, \quad t = 0, \dots, |Q| \end{aligned} \quad (8)$$

Proof:

Since constraints (8) are a subset of constraints (2), we only need to show that if  $(\zeta, x^T, y^T)$  does not satisfy constraints (2) (i.e.  $\zeta > h^{\hat{i}}(T)$  for some  $\hat{i}$ , by Proposition 3.2) for a given  $T \subseteq Q$ , then  $(\zeta, x^T, y^T)$  is also infeasible with respect to constraints (8). Thus, suppose  $h^{\hat{i}}(T) = \max_{q \in T} c_{iq} = c_{iqt}$ , then the associated  $t^{\text{th}}$  inequality (8) would be

$$\zeta \leq c_{iqt-1} + \sum_{q \in Q} (c_{iq} - c_{iqt-1})^+ x_q^T = c_{iqt-1} + c_{iqt} - c_{iqt-1} = c_{iqt} = h^{\hat{i}}(T),$$

which contradicts  $\zeta > h^{\hat{i}}(T)$  and the result follows

## A Path-based Formulation

$$\begin{aligned} \text{(PBF) max} \quad & \sum_{i \in I} \sum_{q \in Q} c_{iq} x_{iq} - \sum_{r=1}^k \sum_{j_r \in V_r} f_{j_r} y_{j_r} \\ \text{s. t.} \quad & \sum_{q \in Q} x_{iq} = 1 \quad i \in I \\ & \sum_{q \in Q: j_r \in q} x_{iq} \leq y_{j_r} \quad i \in I, \quad j_r \in V_r, \quad r = 1, \dots, k \\ & \sum_{j_r \in V_r} y_{j_r} \leq p_r \quad r = 1, \dots, k \\ & x_{iq} \geq 0 \quad i \in I, \quad q \in Q \\ & y_{j_r} \in \{0, 1\} \quad j_r \in V_r, \quad r = 1, \dots, k. \end{aligned}$$

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(Aardal et al., 1999)

# An Arc-based Formulation

$$\begin{aligned} \text{(ABF) maximize} \quad & \sum_{i \in I} \sum_{j_1 \in V_1} c_{ij_1} x_{ij_1} + \sum_{i \in I} \sum_{r=1}^{k-1} \sum_{(a,b) \in V_r \times V_{r+1}} c_{ab} z_{iab} - \sum_{r=1}^k \sum_{j_r \in V_r} f_{j_r} \\ \text{subject to} \quad & \sum_{j_1 \in V_1} x_{ij_1} = 1 \quad i \in I \\ & \sum_{b \in V_2} z_{iab} = x_{ia} \quad i \in I, a \in V_1 \\ & \sum_{b \in V_{r+1}} z_{iab} = \sum_{b' \in V_{r-1}} z_{ib'a} \quad i \in I, a \in V_1, r = 2, \dots, k-1 \\ & x_{ij_1} \leq y_{j_1} \quad i \in I, j_1 \in V_1 \\ & \sum_{a \in V_{r-1}} z_{iab} \leq y_b \quad i \in I, b \in V_r, r = 2, \dots, k \\ & \sum_{j_r \in V_r} y_{j_r} \leq p_r \quad r = 1, \dots, k \\ & x_{ij_1} \geq 0, z_{iab} \geq 0 \quad i \in I, j_1 \in V_1, (a,b) \in V_r \times V_{r+1} \\ & y_{j_r} \in \{0, 1\} \quad j_r \in V_r, r = 1, \dots, k. \end{aligned}$$

# A Flow-based Formulation

$$\begin{aligned} \text{(FBF)} \quad & \text{maximize} && \sum_{r=1}^k \sum_{a \in V_{r+1}} \sum_{b \in V_r} c_{ab} z_{abr} - \sum_{r=1}^k \sum_{j_r \in V_r} f_{j_r} y_{j_r} \\ & \text{subject to} && \sum_{b \in V_1} z_{ab0} = 1 \quad a \in I \\ & && \sum_{b \in V_{r-1}} z_{abr-1} = \sum_{b \in V_{r+1}} z_{bar} \quad a \in V_r, \quad r = 1, \dots, k-1 \\ & && z_{abr} \leq m y_b \quad a \in V_{r+1}, \quad b \in V_r \quad r = 1, \dots, k \\ & && \sum_{j_r \in V_r} y_{j_r} \leq p_r \quad r = 1, \dots, k \\ & && z_{ijr} \geq 0 \quad i \in V_{r+1}, \quad j \in V_r, \quad r = 0, \dots, k \\ & && y_{j_r} \in \{0, 1\} \quad j_r \in V_r, \quad r = 1, \dots, k. \end{aligned}$$

(Kratika et al., 2014)