Column generation and Benders' Decomposition to maximize the lifetime in connected wireless sensor networks

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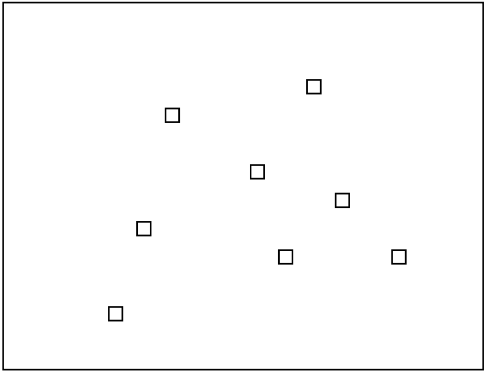
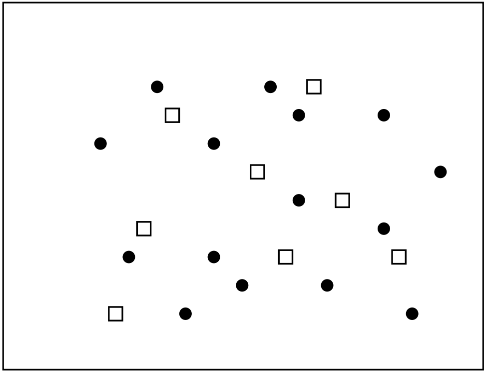
Maximum network lifetime problem with connectivity and coverage constraints (CMLP)

- A set of targets T



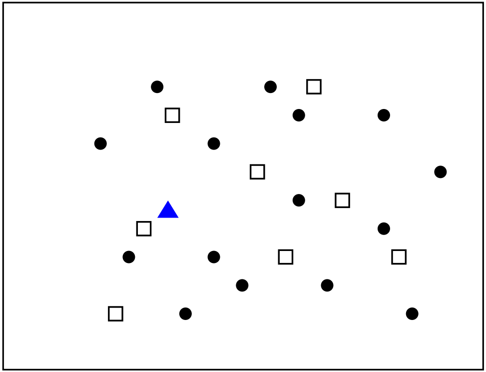
Maximum network lifetime problem with connectivity and coverage constraints (CMLP)

- A set of targets T
- A set of sensors S



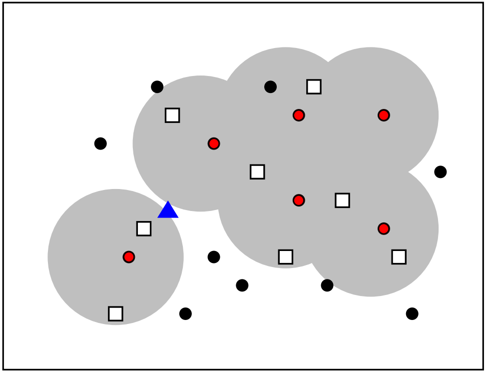
Maximum network lifetime problem with connectivity and coverage constraints (CMLP)

- A set of targets T
- A set of sensors S
- A base station B



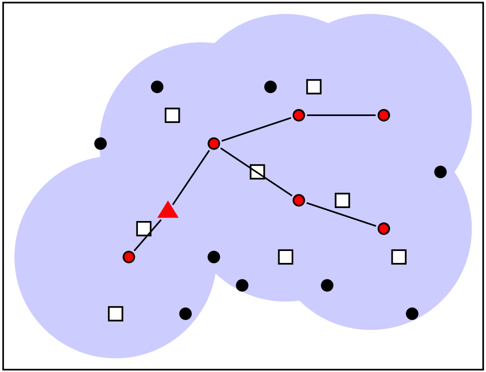
Maximum network lifetime problem with connectivity and coverage constraints (CMLP)

- A set of targets T
- A set of sensors S
- A base station B
- Sensing range R_s

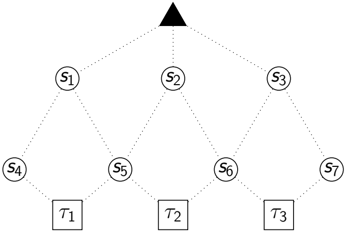


Maximum network lifetime problem with connectivity and coverage constraints (CMLP)

- A set of targets T
- A set of sensors S
- A base station B
- Sensing range R_s
- Communication range R_c
- Cover set
- Connectivity required

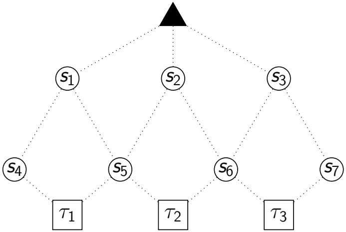


Strategies to extend network lifetime

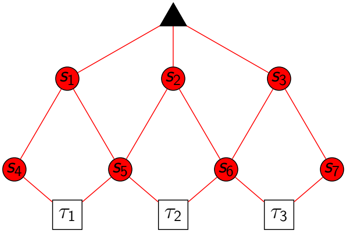


Potential network

Strategies to extend network lifetime

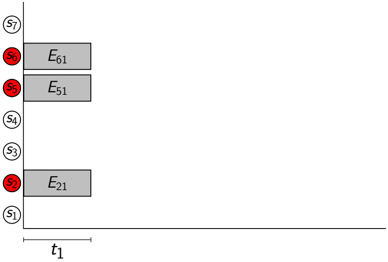


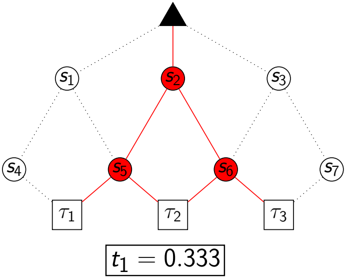
Potential network



Total Lifetime=1

Strategies to extend network lifetime





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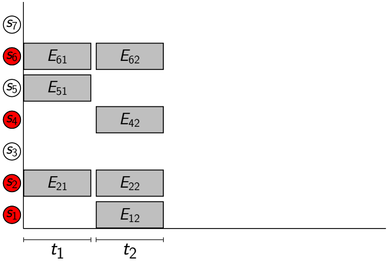

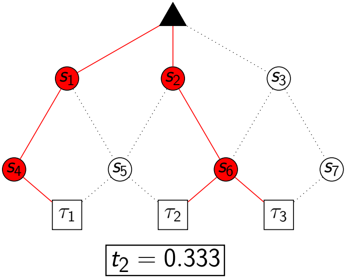

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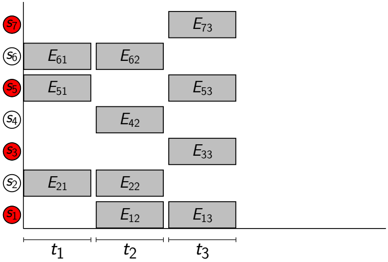

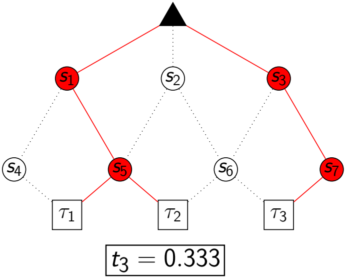

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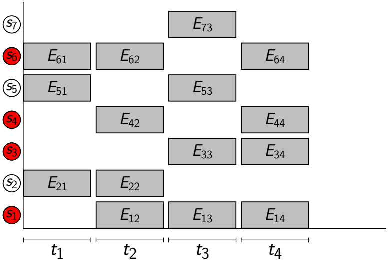

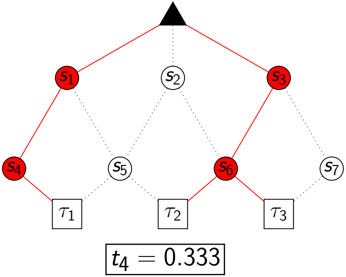

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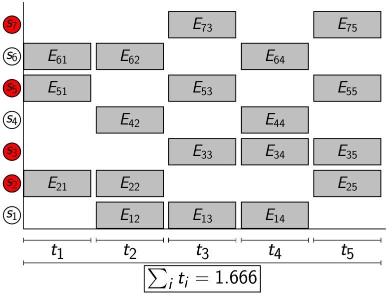
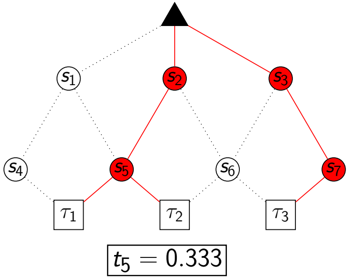
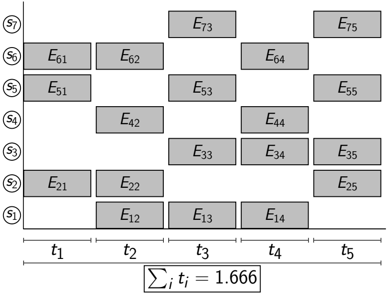




Strategies to extend network lifetime

Representation



$$\begin{pmatrix} 0 & 0 & E_{73} & 0 & E_{75} \\ E_{61} & E_{62} & 0 & E_{64} & 0 \\ E_{51} & 0 & E_{53} & 0 & E_{55} \\ 0 & E_{42} & 0 & E_{44} & 0 \\ 0 & 0 & E_{33} & E_{34} & E_{35} \\ E_{21} & E_{22} & 0 & 0 & E_{25} \\ 0 & E_{12} & E_{13} & E_{14} & 0 \end{pmatrix} \begin{pmatrix} t_1 \\ t_2 \\ t_3 \\ t_4 \\ t_5 \end{pmatrix}$$

Lifetime maximization in wireless sensor networks

Problem representation

Representation

$$\begin{pmatrix} 0 & 0 & E_{73} & 0 & E_{75} \\ E_{61} & E_{62} & 0 & E_{64} & 0 \\ E_{51} & 0 & E_{53} & 0 & E_{55} \\ 0 & E_{42} & 0 & E_{44} & 0 \\ 0 & 0 & E_{33} & E_{34} & E_{35} \\ E_{21} & E_{22} & 0 & 0 & E_{25} \\ 0 & E_{12} & E_{13} & E_{14} & 0 \end{pmatrix} \begin{pmatrix} t_1 \\ t_2 \\ t_3 \\ t_4 \\ t_5 \end{pmatrix}$$

Model

Maximize:

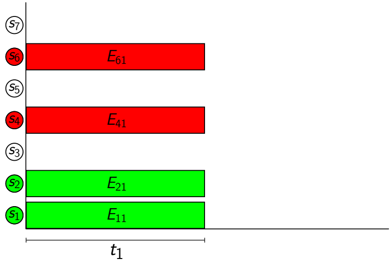
$$t_1 + t_2 + t_3 + t_4 + t_5$$

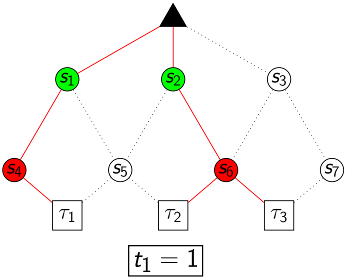
Subject to:

$$\begin{aligned} E_{73} t_3 + E_{75} t_5 &\leq b_7 && (1) \\ E_{61} t_1 + E_{62} t_2 + E_{64} t_4 &\leq b_6 && (2) \\ E_{51} t_1 + E_{53} t_3 + E_{55} t_5 &\leq b_5 && (3) \\ E_{41} t_2 + E_{44} t_4 &\leq b_4 && (4) \\ E_{33} t_3 + E_{34} t_4 + E_{35} t_5 &\leq b_3 && (5) \\ E_{21} t_1 + E_{22} t_2 + E_{25} t_5 &\leq b_2 && (6) \\ E_{11} t_2 + E_{13} t_3 + E_{14} t_4 &\leq b_1 && (7) \\ t_1, t_2, t_3, t_4, t_5 &\geq 0 && (8) \end{aligned}$$

Strategies to extend network lifetime

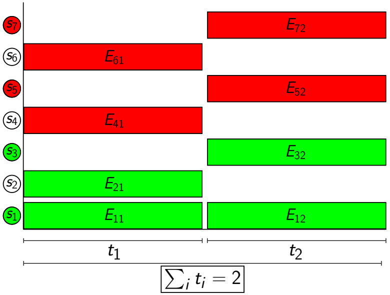
Multiple role allocation (MR-CMLP)

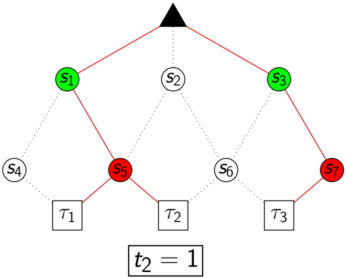




Strategies to extend network lifetime

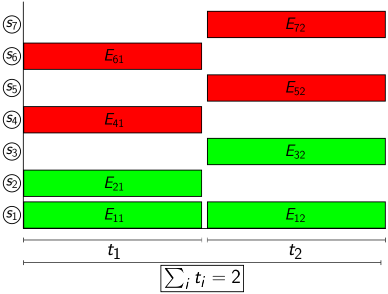
Multiple role allocation (MR-CMLP)





Strategies to extend network lifetime

Multiple role allocation (MR-CMLP)



Representation

$$\begin{pmatrix} 0 & E_{72} \\ E_{61} & 0 \\ 0 & E_{52} \\ E_{41} & 0 \\ 0 & E_{32} \\ E_{21} & 0 \\ E_{11} & E_{12} \end{pmatrix} \begin{pmatrix} t_1 \\ t_2 \end{pmatrix}$$

Lifetime maximization in wireless sensor networks

Problem representation

Representation

$$\begin{pmatrix} 0 & E_{72} \\ E_{61} & 0 \\ 0 & E_{52} \\ E_{41} & 0 \\ 0 & E_{32} \\ E_{21} & 0 \\ E_{11} & E_{12} \end{pmatrix} \begin{pmatrix} t_1 \\ t_2 \end{pmatrix}$$

Model

Maximize:

$$t_1 + t_2$$

Subject to:

$$\begin{aligned} E_{72} t_2 &\leq b \\ E_{61} t_1 &\leq b \\ E_{52} t_2 &\leq b \\ E_{41} t_1 &\leq b \\ E_{32} t_2 &\leq b \\ E_{21} t_1 &\leq b \\ E_{11} t_1 + E_{12} t_2 &\leq b \\ t_1, t_2 &\geq 0 \end{aligned}$$

Lifetime maximization in wireless sensor networks

General model for MLP

Representation

$$\begin{pmatrix} E_{51} & E_{52} & E_{53} & E_{54} & E_{51} \\ E_{41} & E_{42} & E_{43} & E_{44} & E_{45} \\ E_{31} & E_{32} & E_{33} & E_{34} & E_{35} \\ E_{21} & E_{22} & E_{23} & E_{24} & E_{25} \\ E_{41} & E_{12} & E_{13} & E_{14} & E_{15} \end{pmatrix} \begin{pmatrix} t_1 \\ t_2 \\ t_3 \\ t_4 \\ t_5 \end{pmatrix}$$

Model

Maximize:

$$t_1 + t_2 + t_3 + t_4 + t_5$$

Subject to:

$$\begin{aligned} E_{51}t_1 + E_{52}t_1 + E_{53}t_1 + E_{54}t_1 + E_{55}t_1 &\leq b_5 \\ E_{41}t_1 + E_{42}t_1 + E_{43}t_1 + E_{44}t_1 + E_{45}t_1 &\leq b_4 \\ E_{31}t_1 + E_{32}t_1 + E_{33}t_1 + E_{34}t_1 + E_{35}t_1 &\leq b_3 \\ E_{21}t_1 + E_{22}t_1 + E_{23}t_1 + E_{24}t_1 + E_{25}t_1 &\leq b_2 \\ E_{11}t_1 + E_{12}t_1 + E_{13}t_1 + E_{14}t_1 + E_{15}t_1 &\leq b_1 \\ t_1, t_2, t_3, t_4, t_5 &\geq 0 \end{aligned}$$

Lifetime maximization in wireless sensor networks

General model for MLP

Representation

$$\begin{pmatrix} E_{51} & E_{52} & E_{53} & E_{54} & E_{51} \\ E_{41} & E_{42} & E_{43} & E_{44} & E_{45} \\ E_{31} & E_{32} & E_{33} & E_{34} & E_{35} \\ E_{21} & E_{22} & E_{23} & E_{24} & E_{25} \\ E_{41} & E_{12} & E_{13} & E_{14} & E_{15} \end{pmatrix} \begin{pmatrix} t_1 \\ t_2 \\ t_3 \\ t_4 \\ t_5 \end{pmatrix}$$

Model

Maximize:

$$\sum_{j|C_j \in \Omega} t_j$$

Subject to:

$$\sum_{j|C_j \in \Omega} E_{s_u j} t_j \leq b_{s_u} \qquad \forall\ s_u \in S$$

$$t_j \geq 0 \qquad \forall\ j|C_j \in \Omega$$

Maximum network lifetime problem (CMLP)

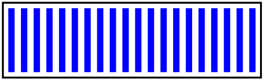
Considerations

Problem decomposition

The problem has been reduced to identify subset of sensors and to create schedules for them.

Drawback:

- The number of subsets is too large



Maximum network lifetime problem (CMLP)

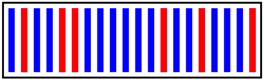
Considerations

Problem decomposition

The problem has been reduced to identify subset of sensors and to create schedules for them.

Drawback:

- The number of subsets is too large
- Only part of them will be in the optimal solution



Maximum network lifetime problem (CMLP)

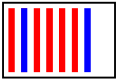
Considerations

Problem decomposition

The problem has been reduced to identify subset of sensors and to create schedules for them.

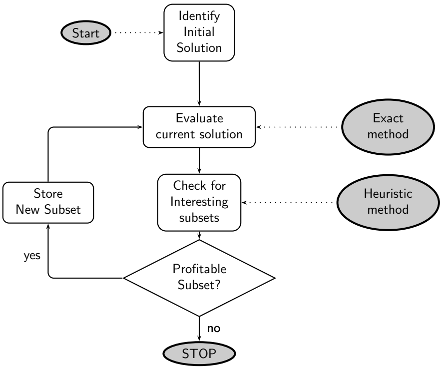
Drawback:

- The number of subsets is too large
- Only part of them will be in the optimal solution
- Gradually generate them is a more efficient strategy



Iterative improvement of lifetime

Column generation algorithm



Iterative improvement of lifetime

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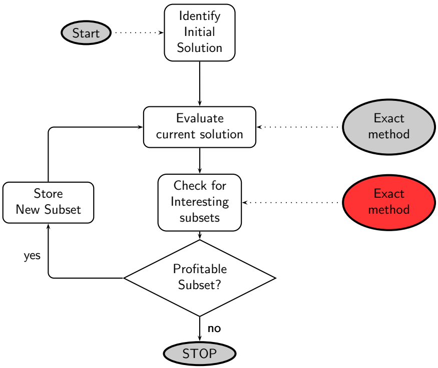
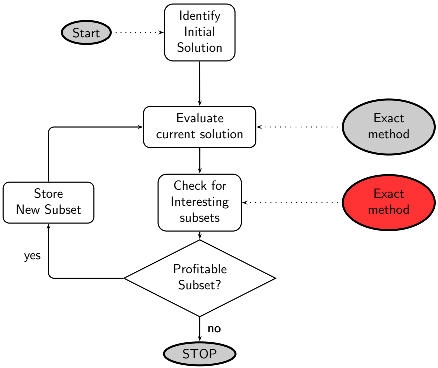


Iterative improvement of lifetime

Column generation algorithm

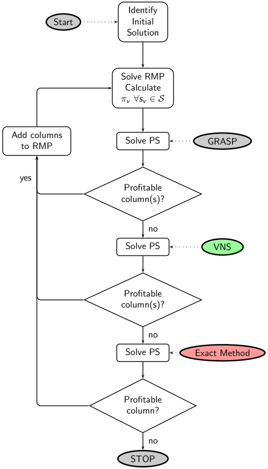


Check for subsets?

- Set covering
- Facility location
- Minimum Steiner tree
- Minimum power multicast tree
- Node weighted Steiner tree

Efficient implementations?

Hybrid approaches

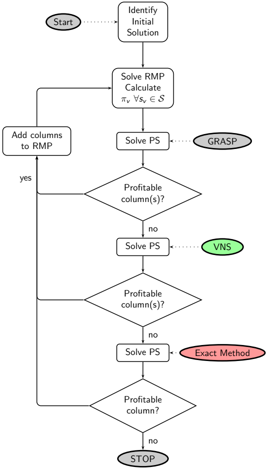


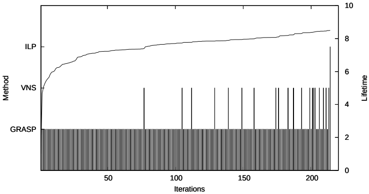
Ideas (Castaño *et al.*, 2013)

- Use fast heuristic approaches to solve pricing subproblem as much as possible
- Improve the performance of the exact approaches by using advanced techniques

Efficient implementations?

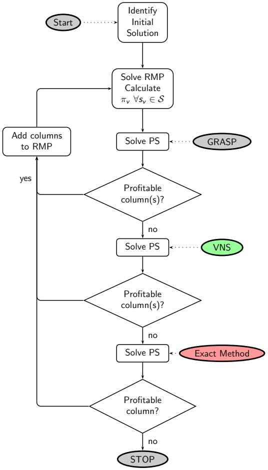
Hybrid approaches

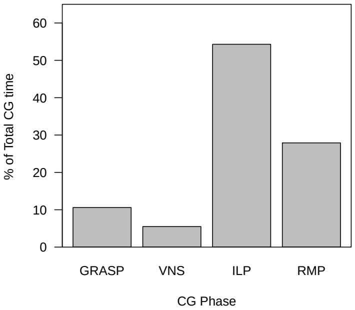




Efficient implementations?

Hybrid approaches





Decomposition based approach

General approach

Restricted Master Problem (Scheduling decisions)

$$\text{Maximize:} \quad \sum_{j|C_j \in \Omega} t_j$$

$$\sum_{j|C_j \in \Omega} E_{s_u j} t_j \leq b_{s_u} \qquad \forall\ s_u \in S$$

$$t_j \geq 0 \qquad \forall\ j|C_j \in \Omega$$

Decomposition based approach

General approach

Restricted Master Problem (Scheduling decisions)

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$$t_j \geq 0 \qquad \forall\, j|C_j \in \Omega$$

Considerations

- Ω: set of feasible covers
- $|\Omega|$:Exponential (number of variables)
- Use a reduced set $\Omega' \subseteq \Omega$

Decomposition based approach

General approach

Restricted Master Problem (Scheduling decisions)

$$\text{Maximize:} \quad \sum_{j|C_j \in \Omega} t_j$$

$$\sum_{j|C_j \in \Omega} E_{s_u j} t_j \leq b_{s_u} \qquad \forall\ s_u \in S$$

$$t_j \geq 0 \qquad \forall\ j|C_j \in \Omega$$

Pricing subproblem (MR-CMLP)

$$Maximize : 1 - \sum_{v \in \mathcal{S}} \sum_{l \in \mathcal{E}} l y_{vlj} \pi_v$$

Subject to:

$$\sum_{u \in \mathcal{S}|\exists a(v,u)} x_{vu} - \sum_{u \in \mathcal{S}|\exists a(u,v)} x_{uv} = 1 \qquad \forall\ v \in \mathcal{T}$$

$$\sum_{u \in \mathcal{N}|\exists a(v,u)} x_{vu} - \sum_{u \in \mathcal{N}|\exists a(u,v)} x_{uv} = 0 \qquad \forall\ v \in \mathcal{S}$$

$$\sum_{u \in \mathcal{N}|\exists a(S_0,u)} x_{S_0 u} - \sum_{u \in \mathcal{N}|\exists a(u,S_0)} x_{u S_0} = -|\mathcal{T}|$$

$$x_{uv} \leq |\mathcal{T}|(y_{vE_r j} + y_{vE_s j}) \qquad \forall\ u, v \in \mathcal{S}|\exists a(u,v)$$

$$x_{vu} \leq |\mathcal{T}|(y_{vE_r j} + y_{vE_s j}) \qquad \forall\ v, u \in \mathcal{S}|\exists a(v,u)$$

$$x_{uv} \leq y_{vE_s j} \qquad \forall\ u \in \mathcal{T}, \forall\ v \in \mathcal{S}|\exists a(u,v)$$

$$\sum_{l \in \mathcal{E}} y_{vlj} = 1 \qquad \forall\ v \in \mathcal{S}$$

$$x_{uv} \in \mathbb{Z}^+ \cup \{0\} \qquad \forall\ u, v \in \mathcal{N}$$

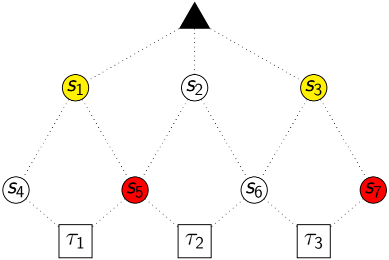
$$y_{vlj} \in \{0,1\} \qquad \forall\ v \in \mathcal{N}, l \in \mathcal{E}$$

Column generation appproach

Strategies to solve PS

Facts

- If sensor role were fixed, resulting PS is a network flow problem

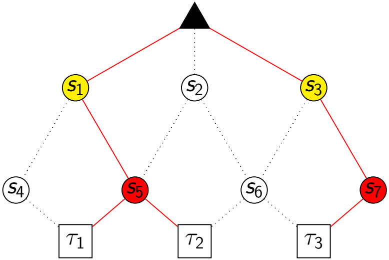


Column generation appproach

Strategies to solve PS

Facts

- If sensor role were fixed, resulting PS is a network flow problem
- Feasibility is easy to check

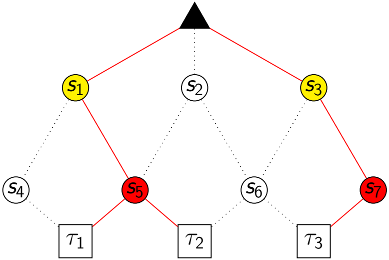


Column generation appproach

Strategies to solve PS

Facts

- If sensor role were fixed, resulting PS is a network flow problem
- Feasibility is easy to check
- Connectivity and coverage can be solved at different stages



Column generation approach

Bender's reformulation

Consider the problem . . .

$$z = \min cx + hy$$

$$Ax + Gy \leq b$$

$$x \in \mathbb{R}^n_+, y \in Y$$

Remarks:

- $(y \in Y)$ are complicating variables

Column generation approach

Bender's reformulation

Linear version

$$z_{LP} = \min cx$$

$$Ax \leq b - Gy$$

$$x \in \mathbb{R}^n_+$$

Remarks:

- $(y \in Y)$ are complicating variables
- When variables $(y \in Y)$ are fixed

Column generation approach

Bender's reformulation

Associated dual

$$\max u(b - Gy)$$

$$uA \geq c$$

$$u \in \mathbb{R}^n_+$$

Remarks:

- $(y \in Y)$ are complicating variables
- When variables $(y \in Y)$ are fixed
- Extreme points: $\{u^k \in \mathbb{R}^m_+ : k \in K\}$
- Extreme rays: $\{v^d \in \mathbb{R}^m_+ : d \in D\}$

Column generation approach

Bender's reformulation

New problem reformulation

$$z = \min(hy + \max_{k \in K} u^k(b - Gy))$$

$$v^d(b - Gy) \geq 0 \qquad \forall d \in D$$

$$y \in Y \subseteq \mathbb{Z}_+^n$$

- If cost associated to "easy variables" is zero

$$z = \min(hy)$$

$$v^d(b - Gy) \geq 0 \qquad \forall d \in D$$

$$y \in Y \subseteq \mathbb{Z}_+^n$$

Column generation appproach

Solution appproach for Bender's reformulation

Remarks

- $\mathcal{D}$ is a set of constraints (exponential size)
- Only a subset of the cut constraints will be active in the optimal solution
- A cut generation algorithm can be adapted to identify interesting cuts

Column generation appproach

Solution appproach for Bender's reformulation

Remarks

- $\mathcal{D}$ is a set of constraints (exponential size)
- Only a subset of the cut constraints will be active in the optimal solution
- A cut generation algorithm can be adapted to identify interesting cuts

Cut generation algorithm

1. $y \leftarrow \bar{y}$, $Upper\_Bound \leftarrow f(\bar{y})$
2. Solve Bender's Master Z_M, $Lower\_Bound \leftarrow Z_M^*$
3. Solve Z_{LP} with fixed $\bar{y}$

4a. If Z_{LP} is feasible:

- $Upper\_Bound \leftarrow Z_{LP}^*$, Add Bender's cut

4b. Else if Z_{LP} is Infeasible:

- Obtain extreme ray (by retrieving Farkas duals) and add feasibility cut

5. If $Upper\_Bound = Lower\_Bound$, stop. Otherwise, go to step 2

Column generation approach

Bender's reformulation of PS

Pricing subproblem (MR-CMLP)

$$Maximize : 1 - \sum_{v \in \mathcal{S}} \sum_{l \in \mathcal{E}} l y_{vlj} \pi_v$$

Subject to:

$$\sum_{u \in \mathcal{S} | \exists a(v,u)} x_{vu} - \sum_{u \in \mathcal{S} | \exists a(u,v)} x_{uv} = 1 \qquad \forall\ v \in \mathcal{T}$$

$$\sum_{u \in \mathcal{N} | \exists a(v,u)} x_{vu} - \sum_{u \in \mathcal{N} | \exists a(u,v)} x_{uv} = 0 \qquad \forall\ v \in \mathcal{S}$$

$$\sum_{u \in \mathcal{N} | \exists a(S_0,u)} x_{S_0 u} - \sum_{u \in \mathcal{N} | \exists a(u,S_0)} x_{uS_0} = -|\mathcal{T}|$$

$$x_{uv} \leq |\mathcal{T}|(y_{vE_r j} + y_{vE_s j}) \qquad \forall\ u, v \in \mathcal{S} | \exists a(u,v)$$

$$x_{vu} \leq |\mathcal{T}|(y_{vE_r j} + y_{vE_s j}) \qquad \forall\ v, u \in \mathcal{S} | \exists a(v,u)$$

$$x_{uv} \leq y_{vE_s j} \qquad \forall\ u \in \mathcal{T}, \forall\ v \in \mathcal{S} | \exists a(u,v)$$

$$\sum_{l \in \mathcal{E}} y_{vlj} = 1 \qquad \forall\ v \in \mathcal{S}$$

$$x_{uv} \in \mathbb{Z}^+ \cup \{0\} \qquad \forall\ u, v \in \mathcal{N}$$

$$y_{vlj} \in \{0,1\} \qquad \forall\ v \in \mathcal{N}, l \in \mathcal{E}$$

Benders Reformulation (MR-CMLP)

$$\min Z_{BMP} = \sum_{v \in \mathcal{S}} \sum_{l \in \mathcal{E}} y_{vlj} l \pi_v$$

Subject to:

$$\sum_{v \in S} \theta_v^d - |\mathcal{T}|\theta_B^d + \sum_{u \in \mathcal{N}, v \in \mathcal{N}} (y_{vE_r j} + y_{vE_s j})\beta_{uv}^d |\mathcal{T}| +$$

$$\sum_{v \in \mathcal{N}, u \in \mathcal{N}} (y_{vE_r j} + y_{vE_s j})\beta_{vu}^d |\mathcal{T}| + \sum_{u \in \mathcal{N}, v \in \mathcal{N}} (y_{vE_s j})\eta_{uv}^d \geq 0 \qquad \forall d \in \mathbb{D}$$

$$\sum_{l \in \mathcal{E}} y_{vlj} = 1 \qquad \forall\ v \in \mathcal{S}$$

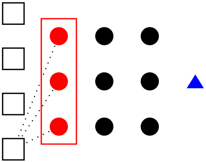
$$y_{vlj} \in \{0,1\} \qquad \forall\ v \in \mathcal{N}, \forall\ l \in \mathcal{E}$$

Column generation approach

Valid inequalities to improve convergence

Coverage

$$\sum_{v \in \mathcal{S} | \exists a(u,v)} y_{vE_sj} \geq 1 \qquad \forall\ u \in \mathcal{T}$$

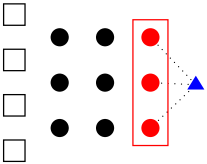


Column generation approach

Valid inequalities to improve convergence

Base Station connectivity

$$\sum_{v \in \mathcal{S} | \exists a(v, S_0)} (y_{vE_r j} + y_{vE_S j}) \geq 1$$

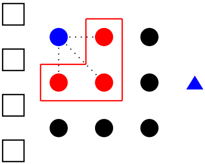


Column generation approach

Valid inequalities to improve convergence

No isolation

$$\sum_{v|\exists a(u,v)} (y_{vE_rj} + y_{vE_Sj}) \geq (y_{uE_rj} + y_{uE_Sj}) \qquad \forall\ u \in \mathcal{S}|\nexists a(u, S_0)$$

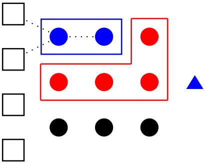


Column generation approach

Valid inequalities to improve convergence

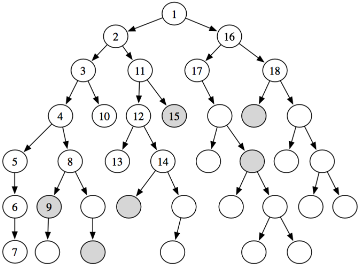
Single connected component

$$\sum_{s_u \in cc_i} (y_{uE_rj} + y_{uE_Sj}) \leq |cc_i| \sum_{s_u \in cc_i, s_v \in \mathcal{S} \setminus cc_i | \exists a(u,v)} (y_{vE_rj} + y_{vE_Sj}) \qquad \forall\ cc_i \in CC$$



Column generation approach

Further improvements

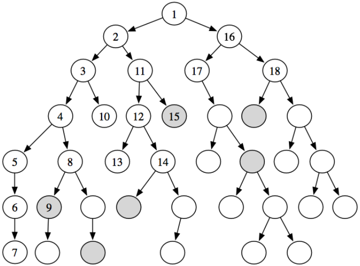


Improvements

- Embed cuts within a Branch & Bound

Column generation approach

Further improvements



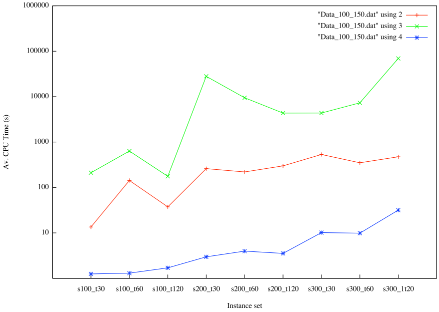
Improvements

- Embed cuts within a Branch & Bound
- Complementary connectivity constraints

Computational results

A comparison of Bender's decomposition and ILP to solve PS

Up to 1000 less time is consumed to solve PS.



Computational results

Comparison of strategies used to solve efficiently the CG approach

Instance	$\lvert S \rvert$	$\lvert \mathcal{K} \rvert$	R_s		ILP Solver				BBC			
				Opt	Sol	Time	n iters	GAP	Sol	Time	n iters	GAP
CMLP_MR_001	100	15	100	5,40	1,00	3600,0	2	81%	5,40	600,6	76	0%
CMLP_MR_002	100	15	100	4,00	4,00	119,2	43	0%	4,00	21,7	32	0%
CMLP_MR_003	100	15	100	3,75	3,50	63,3	24	7%	3,75	485,3	127	0%
CMLP_MR_004	100	15	100	4,00	4,00	214,1	31	0%	4,00	26,8	35	0%
CMLP_MR_005	100	30	100	5,00	4,30	3600,0	40	14%	5,00	3.9	108	0%
CMLP_MR_006	100	30	100	4,00	4,00	99,2	42	0%	4,00	2.9	71	0%
CMLP_MR_007	100	30	100	3,00	3,00	66,2	24	0%	3,00	2.6	48	0%
CMLP_MR_008	100	30	100	4,00	4,00	73,6	32	0%	4,00	3.0	70	0%
CMLP_MR_009	200	15	100	8,00	1,00	3600,0	2	88%	8,00	29,8	88	0%
CMLP_MR_010	200	15	100	12,00	5,23	3600,0	22	56%	12,00	78,2	105	0%
CMLP_MR_011	200	15	100	9,00	1,00	3600,0	2	89%	9,00	35,4	137	0%
CMLP_MR_012	200	15	100	14,60	2,00	3600,0	5	86%	10,86	3600,0	137	**26%**
CMLP_MR_013	200	30	100	8,00	8,00	485,6	63	0%	8,00	23,5	159	0%
CMLP_MR_014	200	30	100	7,00	7,00	225,4	46	0%	7,00	16,3	133	0%
CMLP_MR_015	200	30	100	9,00	1,00	3600,0	1	89%	9,00	44,8	157	0%
CMLP_MR_016	200	30	100	11,40	10,81	3600,0	173	5%	10,07	3600,0	347	**12%**
CMLP_MR_017	300	15	100	15,00	2,00	3600,0	6	87%	15,00	76,9	183	0%
CMLP_MR_018	300	15	100	21,25	1,00	3600,0	1	95%	18,16	3600,0	1342	**15%**
CMLP_MR_019	300	15	100	12,00	1,00	3600,0	1	92%	12,00	114,8	516	0%
CMLP_MR_020	300	15	100	16,00	4,00	3600,0	13	75%	16,00	153,5	144	0%
CMLP_MR_021	300	30	100	15,00	1,00	3600,0	1	93%	15,00	153,7	368	0%
CMLP_MR_022	300	30	100	13,20	13,00	2141,6	109	2%	13,20	223,7	866	0%
CMLP_MR_023	300	30	100	12,00	12,00	3600,0	92	0%	12,00	63,5	163	0%
CMLP_MR_024	300	30	100	13,00	1,00	3600,0	1	92%	13,00	120,2	413	0%
CMLP_MR_025	400	15	100	18,60	1,00	3600,0	2	95%	18,60	2619,1	4104	0%
CMLP_MR_026	400	15	100	18,00	1,00	3600,0	3	94%	18,00	168,5	792	0%
CMLP_MR_027	400	15	100	22,00	12,36	3600,0	57	44%	22,00	64,0	280	0%
CMLP_MR_028	400	15	100	17,00	1,00	3600,0	1	94%	17,00	202,0	898	0%
CMLP_MR_029	400	30	100	17,60	1,00	3600,0	1	94%	17,60	1600,4	1916	0%
CMLP_MR_030	400	30	100	18,00	1,00	3600,0	1	94%	18,00	205,1	789	0%
CMLP_MR_031	400	30	100	21,00	1,00	3600,0	1	95%	21,00	166,6	575	0%
CMLP_MR_032	400	30	100	17,00	1,00	3600,0	1	94%	17,00	190,3	725	0%
Number of optimals						8				29		

Conclusions & future work

- A column generation strategy combined with an efficient branch and cut based on benders decomposition
- The experiments indicate that the exact approach improves previous results obtained with hybrid approaches
- The method can be "easily" adpated to cover a wide range of WSN problems.
- Enhancements with (meta)heuristic approaches are expected to be successful in more sophisticated WSN models

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