



**Towards a recursive graph bipartitioning algorithm
for well balanced domain decomposition.**

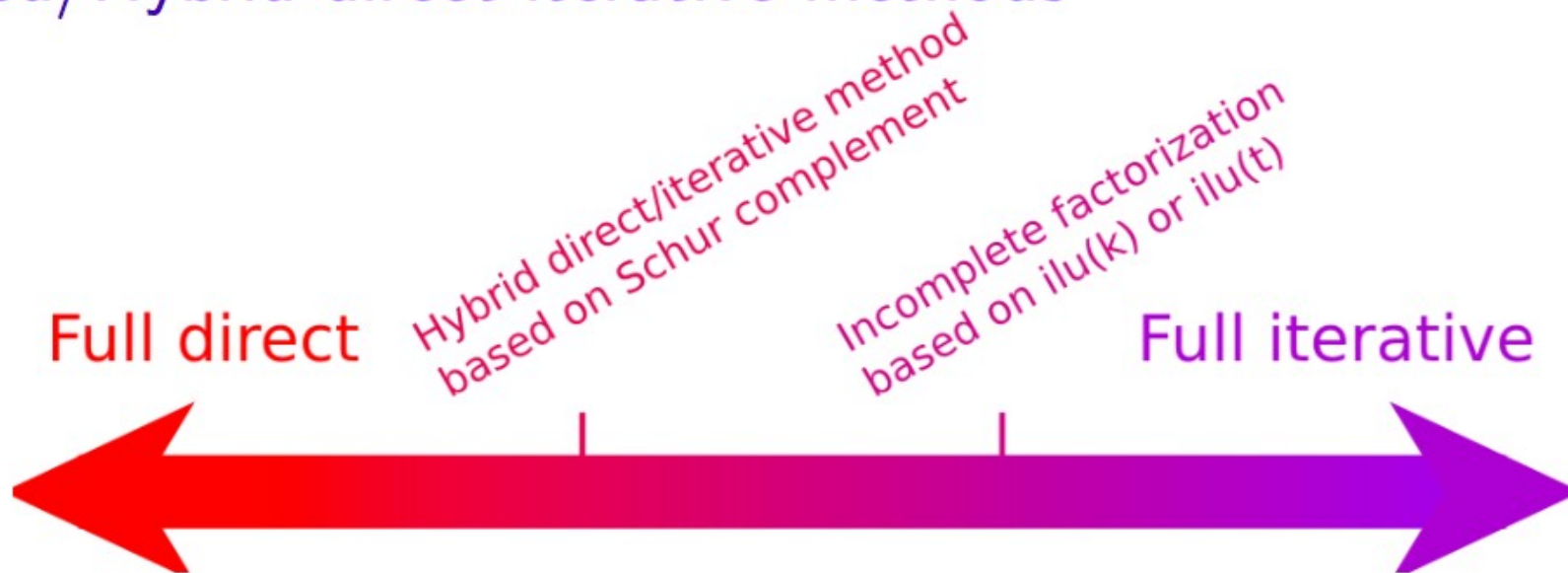
Mini-Symposium on "Combinatorial Issues in Sparse Matrix Computation"

Astrid Casadei, Pierre Ramet and Jean Roman

Plan

- 1. Context: load balancing in hybrid solvers
- 2. Nested Dissection (ND)
- 3. Multilevel framework
- 4. Algorithm to refine a separator: Fiduccia-Mattheyses (FM)
- Algorithms to build a separator:
 - 5. Greedy graph growing (GG)
 - 6. Double greedy graph growing (DG)
 - 7. Halo-first greedy graph growing (HF)
- 8. Results
- 9. Conclusion / future work

Mixed/Hybrid direct-iterative methods



The "spectrum" of linear algebra solvers

- ▶ Robust/accurate for general problems
- ▶ BLAS-3 based implementation
- ▶ Memory/CPU prohibitive for large 3D problems
- ▶ Limited parallel scalability
- ▶ Problem **dependent** efficiency/controlled accuracy
- ▶ Only mat-vec required, fine grain computation
- ▶ Less memory consumption, possible trade-off with CPU
- ▶ Attractive "build-in" parallel features

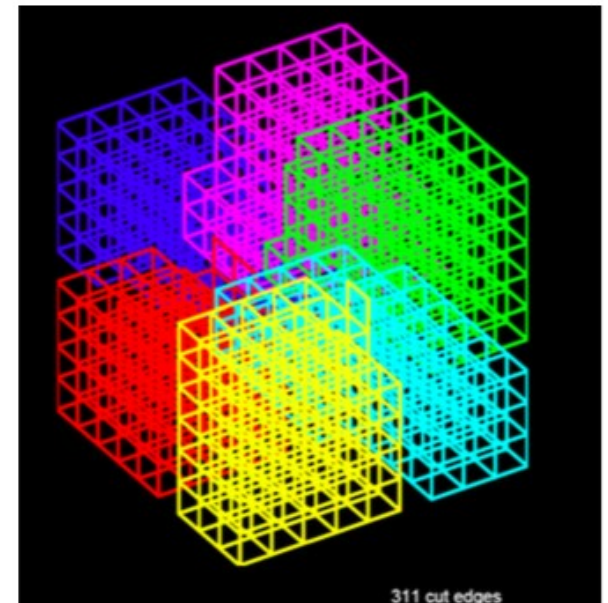
Hybrid Linear Solvers

Develop robust scalable parallel hybrid direct/iterative linear solvers

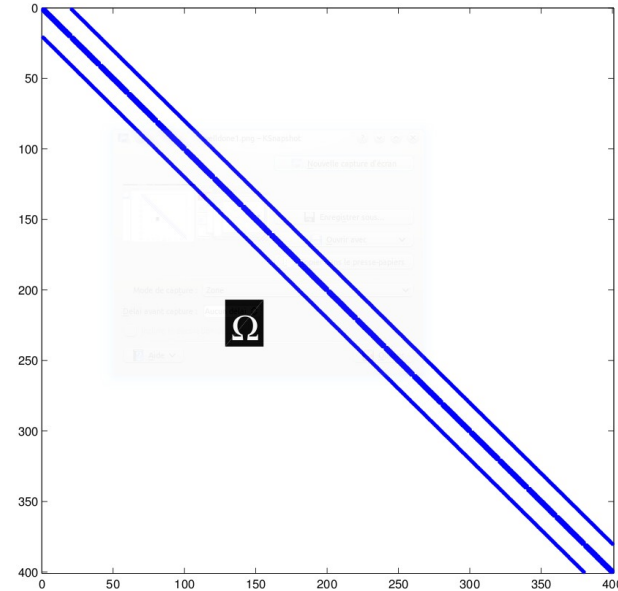
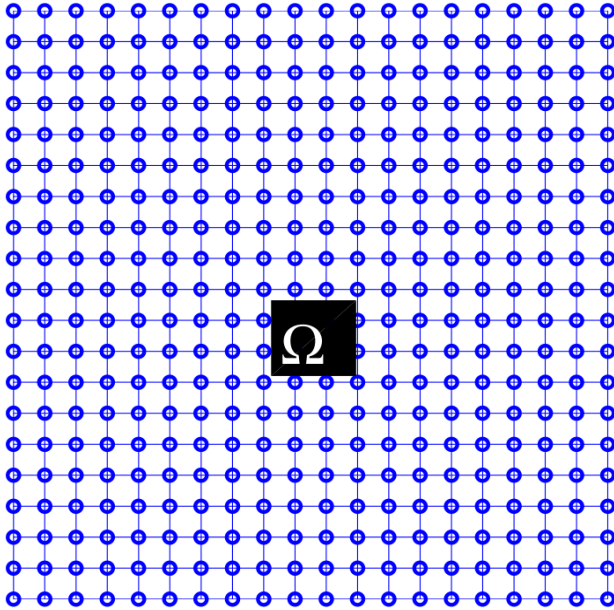
- ▶ Exploit the efficiency and robustness of the sparse direct solvers
- ▶ Develop robust parallel preconditioners for iterative solvers
- ▶ Take advantage of scalable implementation of iterative solvers

Domain Decomposition (DD)

- ▶ Natural approach for PDE's
- ▶ Extend to general sparse matrices
- ▶ Partition the problem into subdomains
- ▶ Use a direct solver on the subdomains
- ▶ Robust preconditioned iterative solver

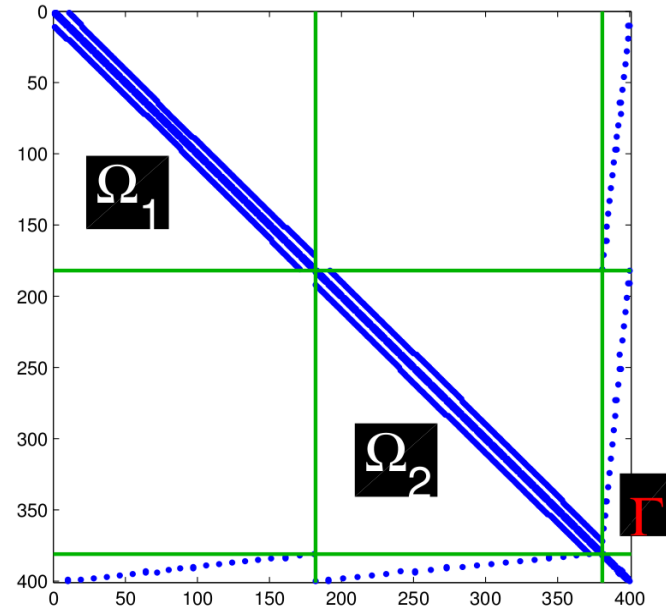
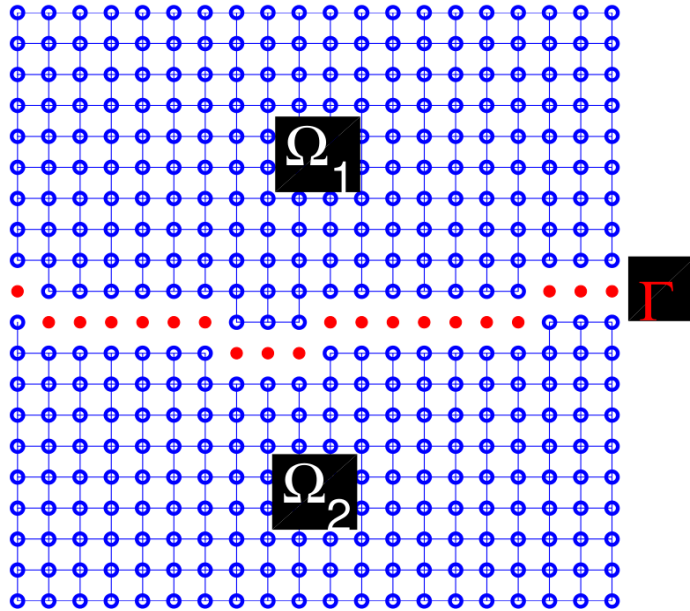


1 Context: load balancing in hybrid solvers



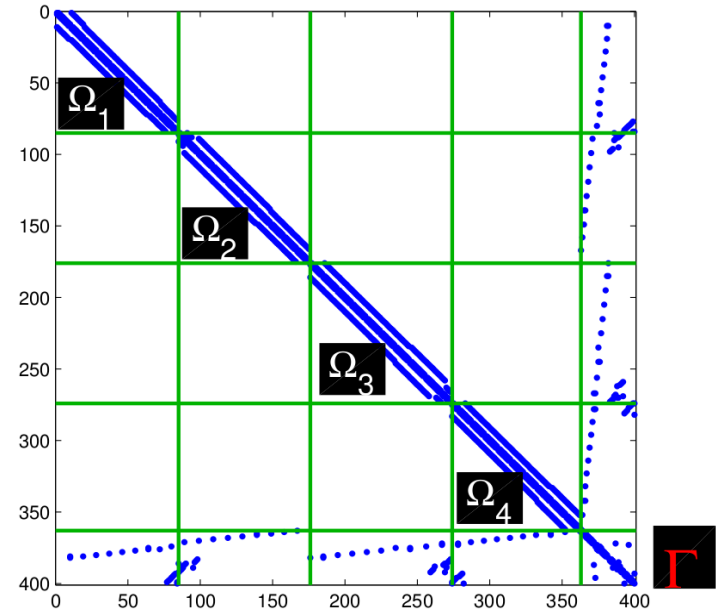
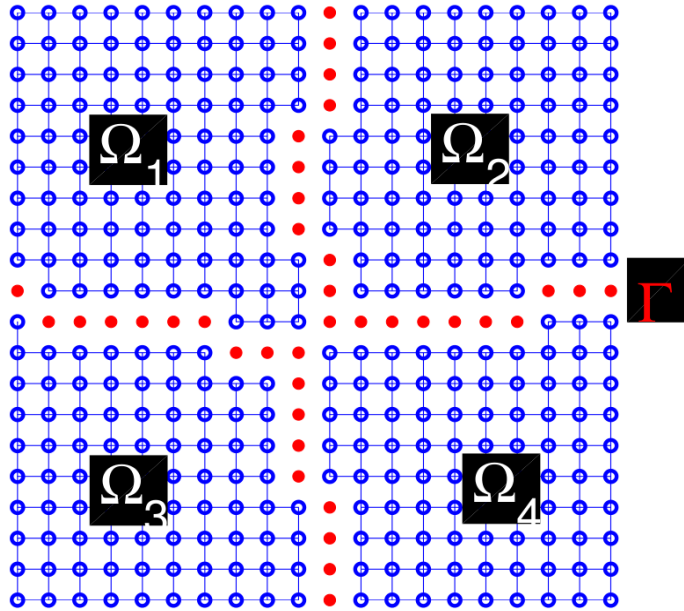
1. Building a domain decomposition
2. Factorizing each domain and computing local Schur complement (= local interface)
3. Iterating on Schur complement (= interface)

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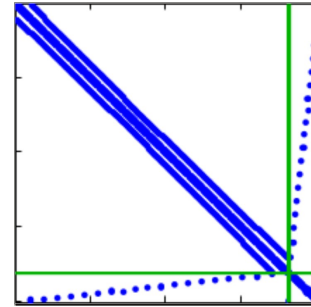
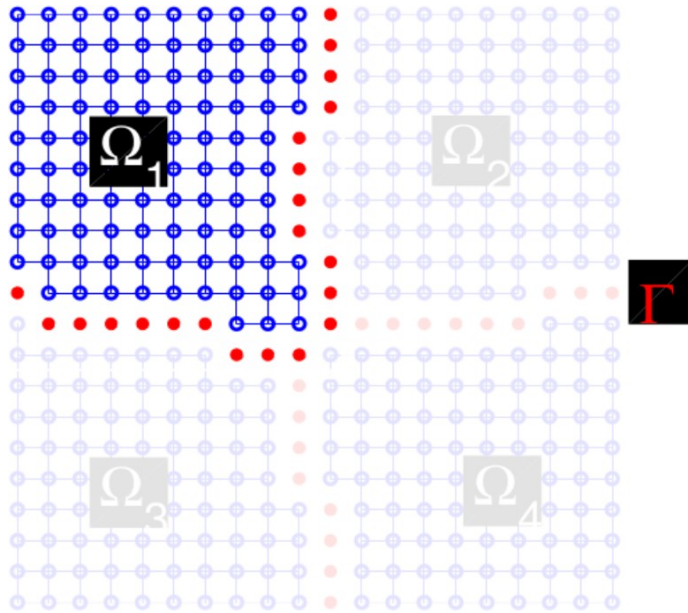
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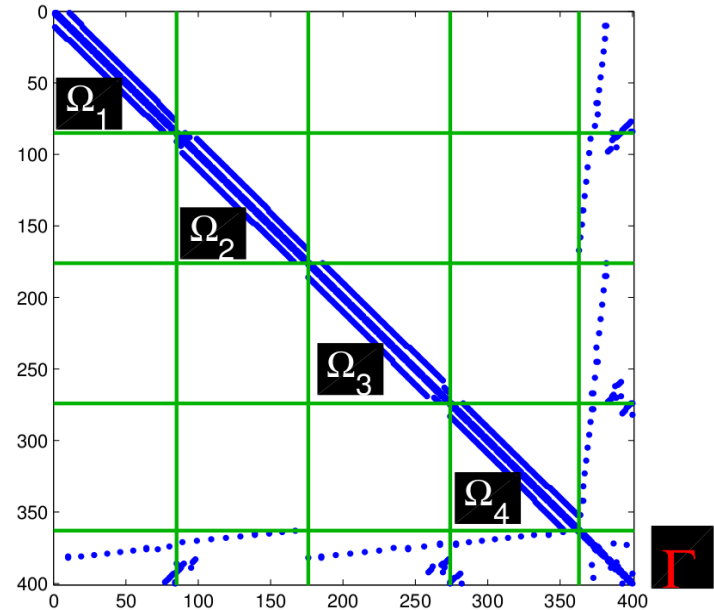
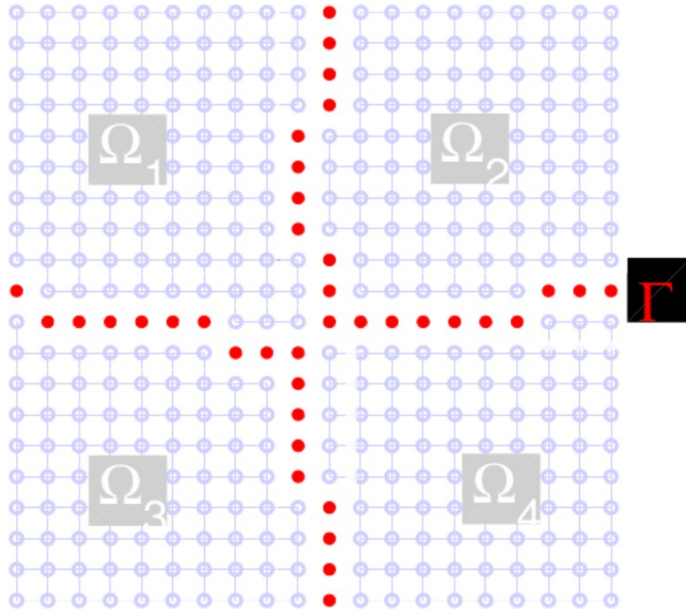
1 Context: load balancing in hybrid solvers



- Both domain interior and domain interface must be balanced
- factorize subdomains
 - build local Schur complement
 - apply local part of preconditioner.

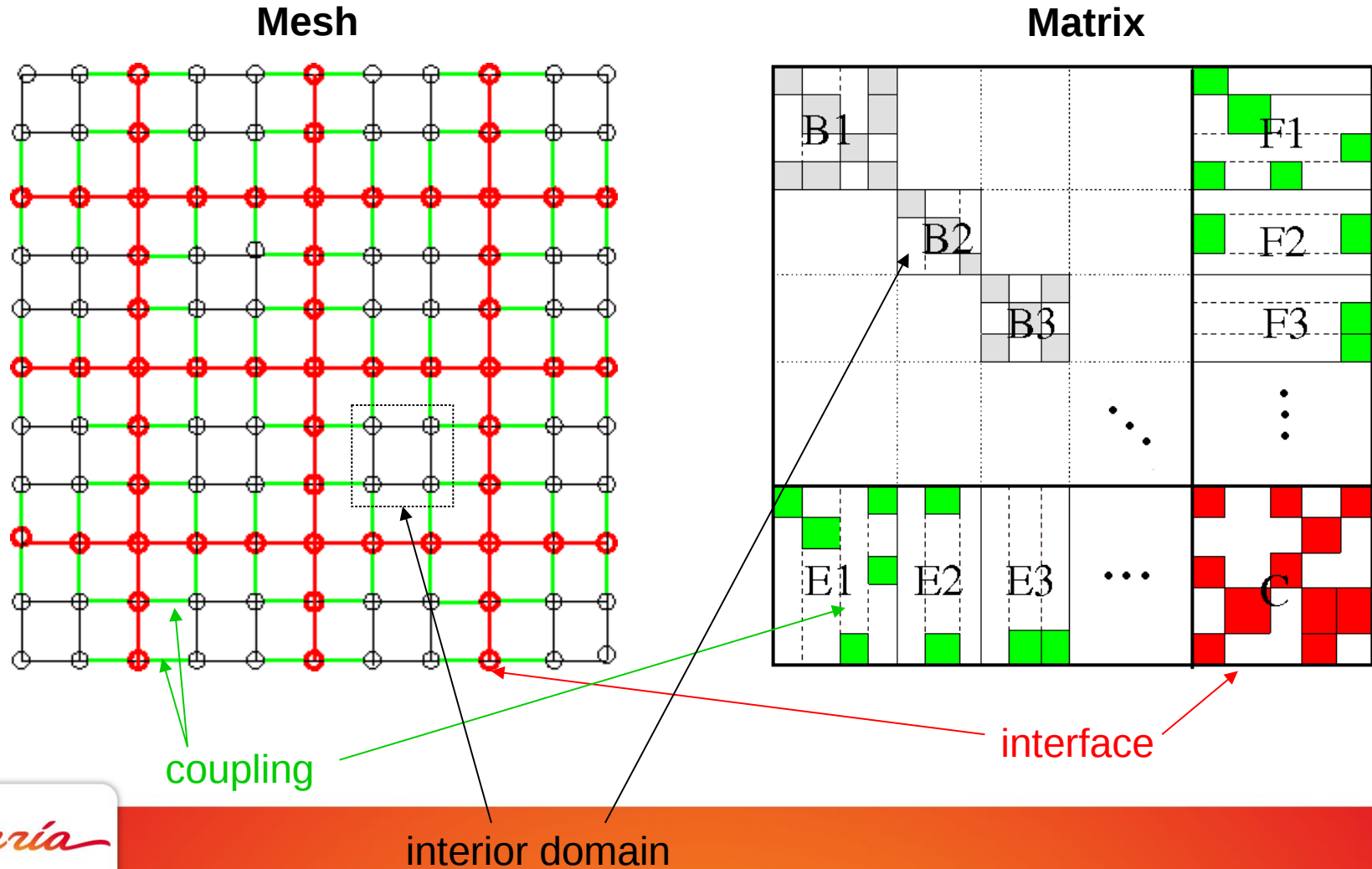
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1 Context: load balancing in hybrid solvers



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Hybrid method (MaPHYS, HIPS, PDSLIN, SHYLU, ...)

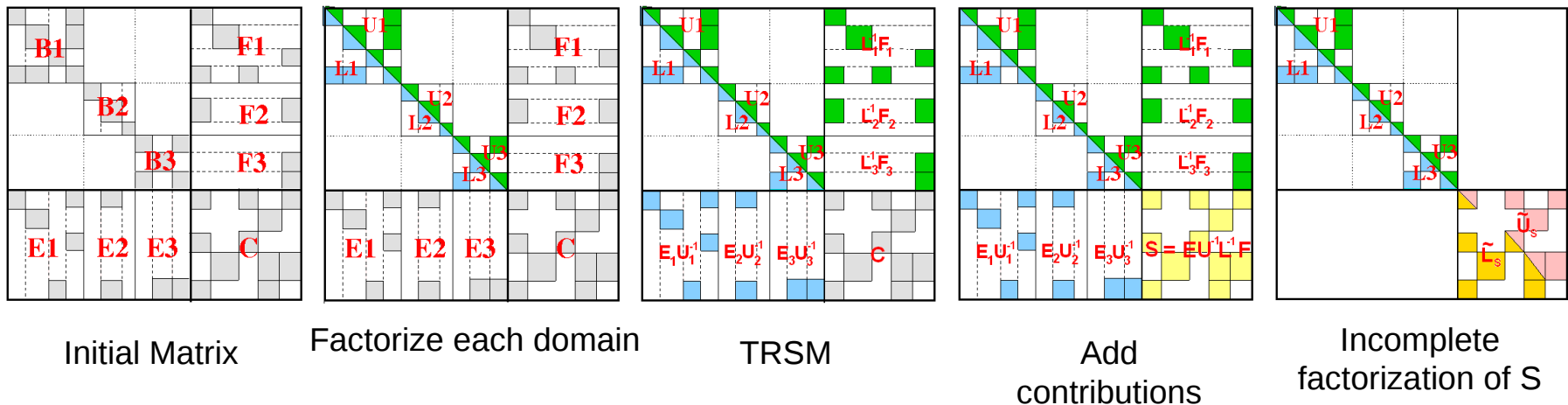


Hybrid method (MaPHYS, HIPS, PDSLIN, SHYLU, ...)

Step 1 :

Build an approximate factorization :

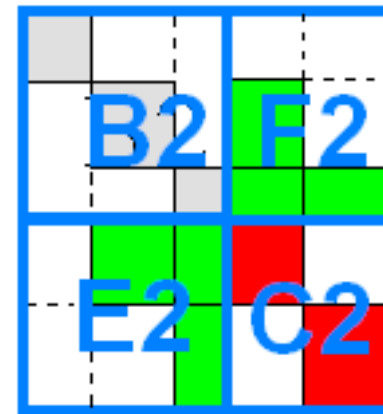
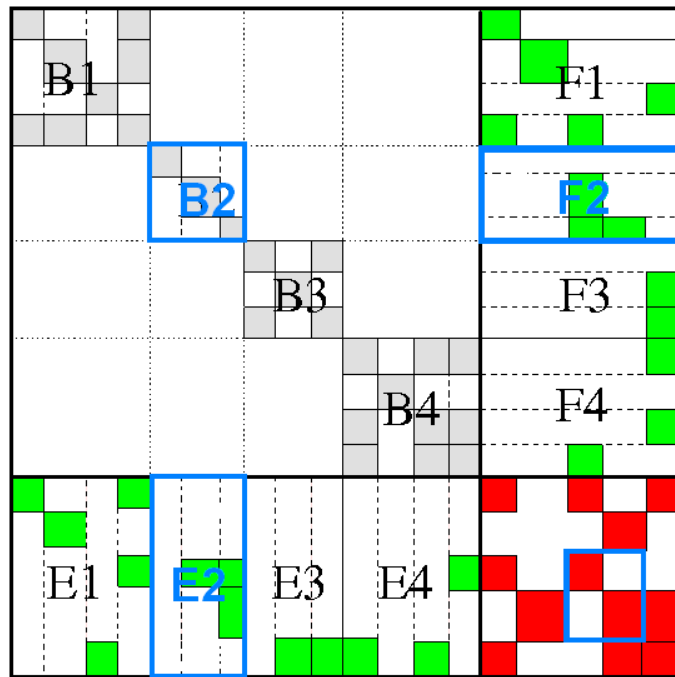
$$A \approx \tilde{L}\tilde{U} = \begin{pmatrix} L_B U_B & \\ & \tilde{L}_S \tilde{U}_S \end{pmatrix}$$



Step 2 :

Iterative method to solve $Ax = b$ using \tilde{L} & \tilde{U} as preconditioner

Hybrid method (MaPHYS, HIPS, PDSLIN, SHYLU, ...)



Local matrix for subdomain 2

2 levels of parallelism :

- parallelism between subdomains
- parallel direct solver to factorize each subdomain

HIPS : hybrid direct-iterative solver

Based on a domain decomposition

$$\begin{pmatrix} A_B & F \\ E & A_C \end{pmatrix}$$



B : Interior nodes of subdomains (direct factorization).

C : Interface nodes.

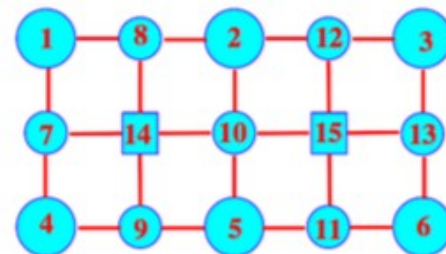
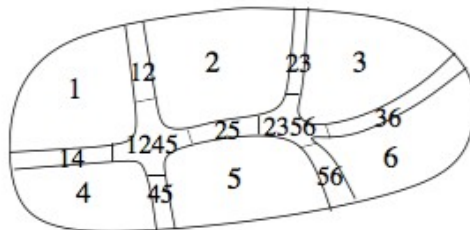
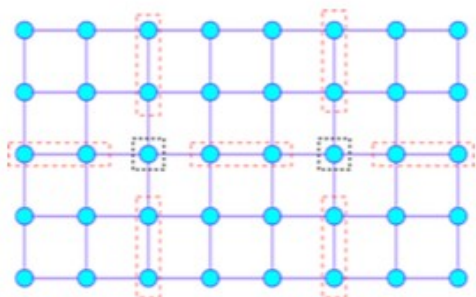
Special decomposition and ordering of the subset **C** :

Goal : Building a **global** Schur complement preconditioner (ILU) from the **local** domain matrices only.

HIPS: domain interface based fill-in policy

Special decomposition and ordering of the subset C :

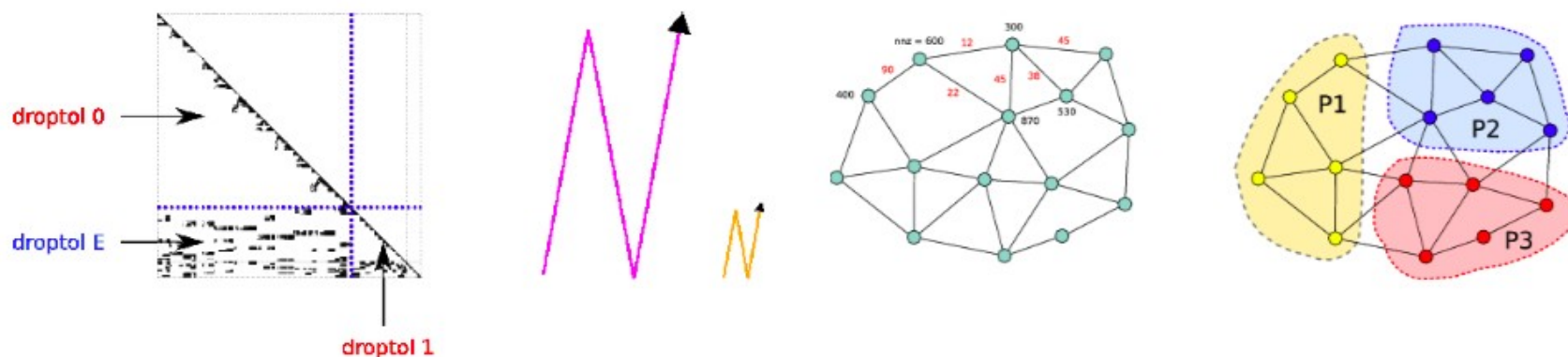
Hierarchical interface decomposition into **connectors** :



Rules :

- ▶ No creation of edge (fill-in) outside the local domain matrices.
 - ▶ Allow edges between connectors adjacent to the same subdomain.
- ⇒ keep the parallelism (communication only between adjacent subdomains).

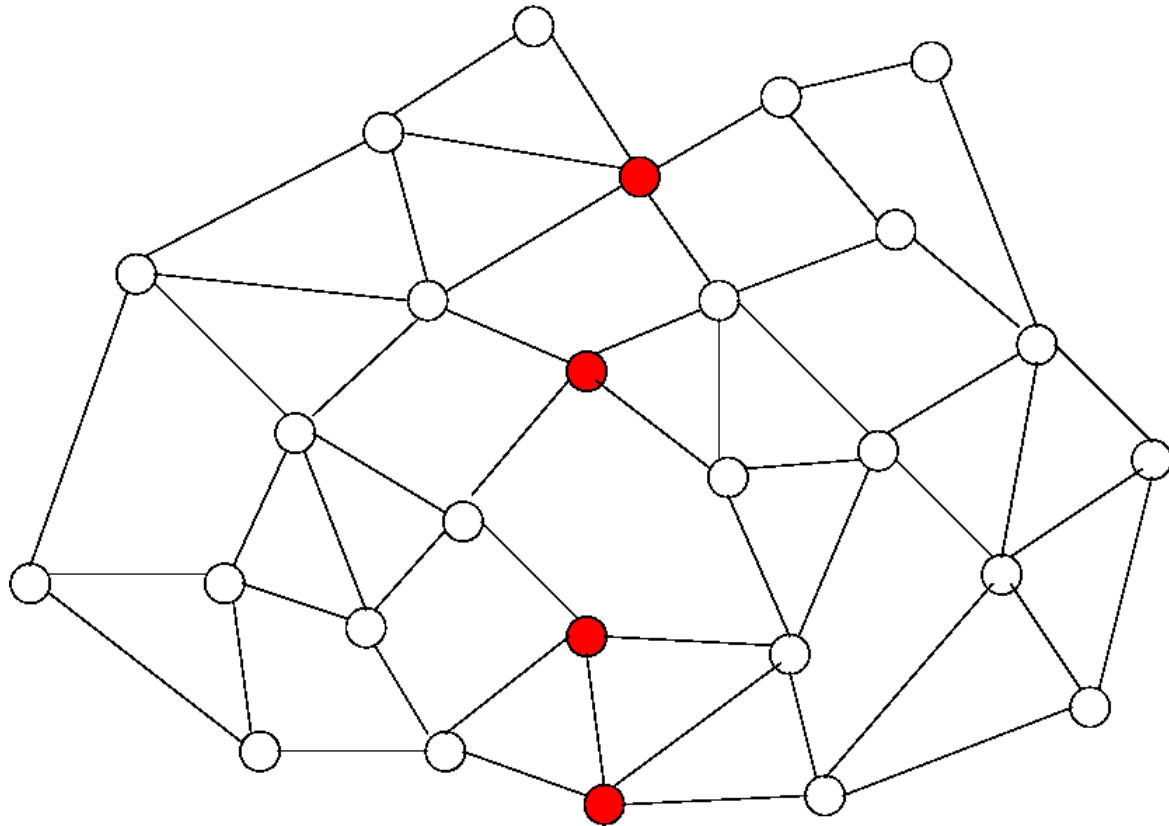
HIPS: preconditioners



Main features

- ▶ Iterative or “hybrid” direct/iterative method are implemented.
- ▶ Mix direct supernodal (BLAS-3) and sparse ILUT factorization in a seamless manner.
- ▶ Memory/Load balancing : distribute the domains on the processors (domains $>$ processors).

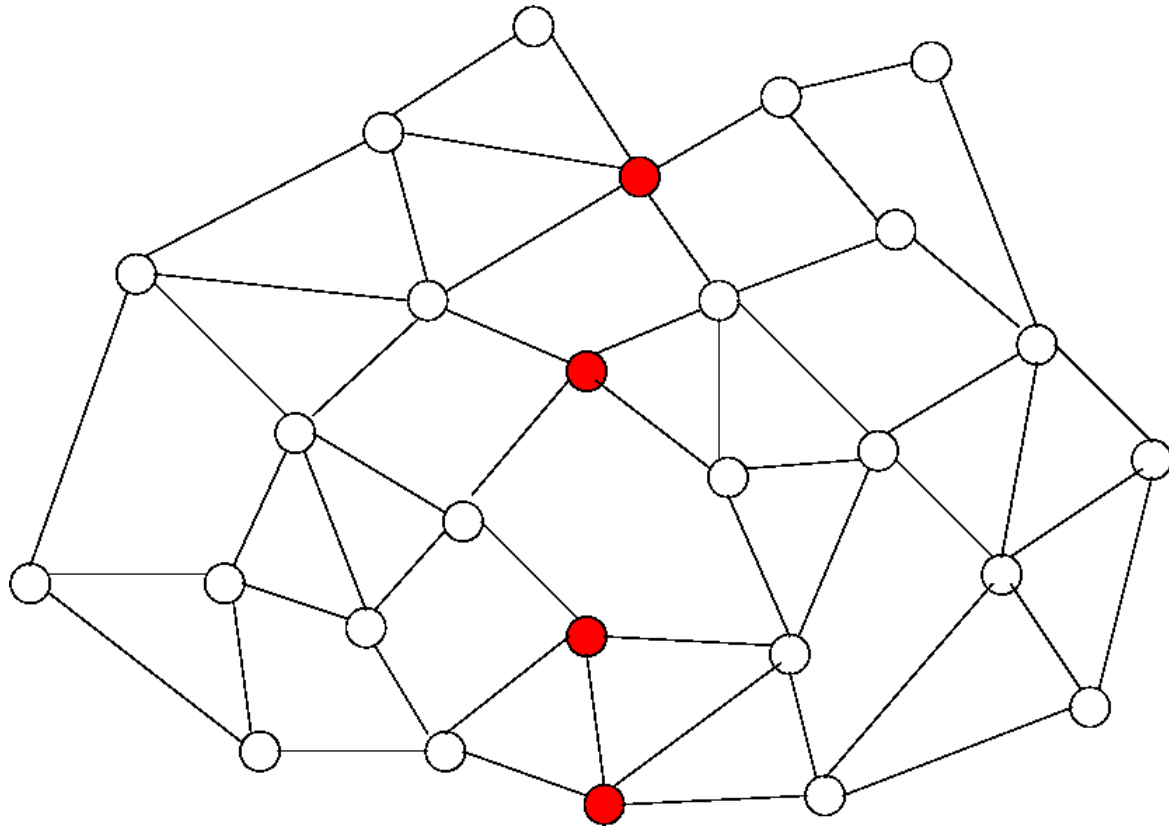
2 Nested dissection



When separating a subgraph, ensure that :

- Parts are balanced
- Separator size is minimized

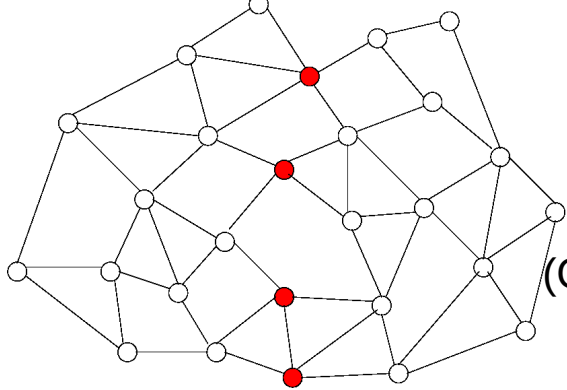
2 Nested dissection



When separating a subgraph, ensure that :

- Parts are balanced
- Separator size is minimized
- **NEW:** Halo is balanced

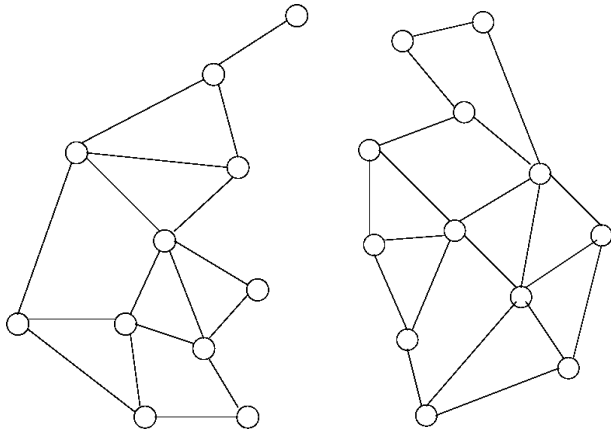
$$Y = P_0 \cup S \cup P_1$$



Classical nested dissection

Do ND on P_0 and P_1

(George)

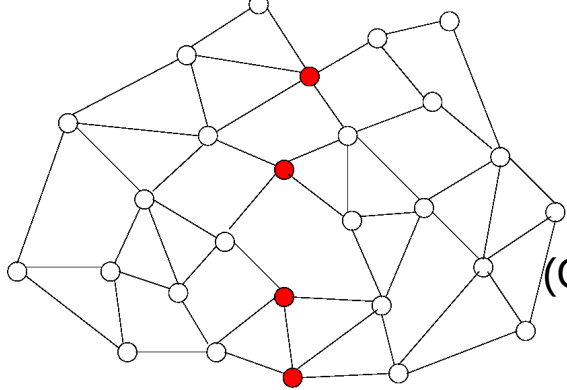


ND Keeping track of halo vertices

Do ND on $P_0 \cup S$ and $P_1 \cup S$

(Generalized ND, Lipton, Rose, Tarjan)

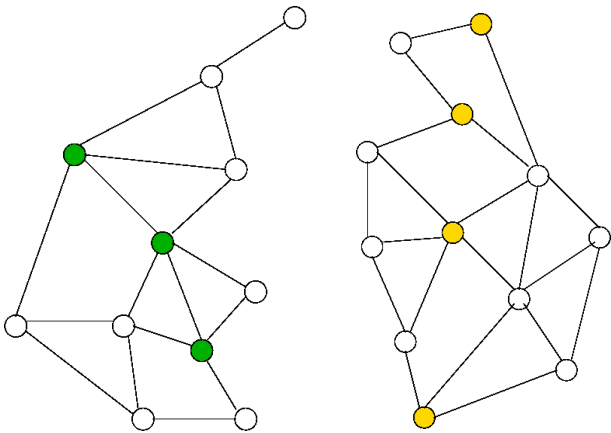
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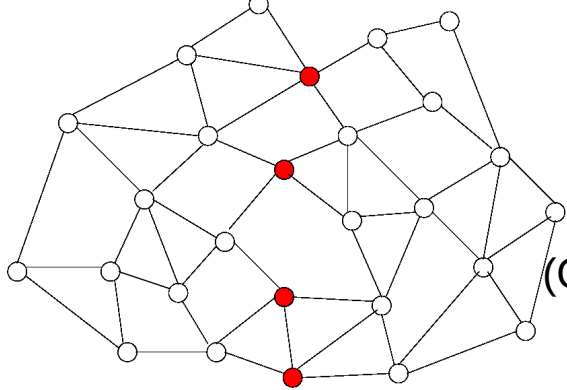


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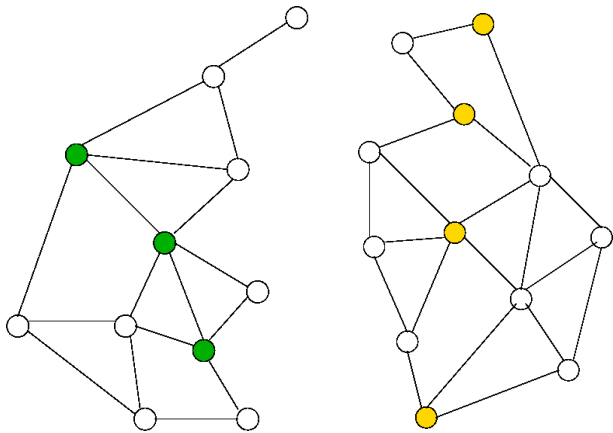
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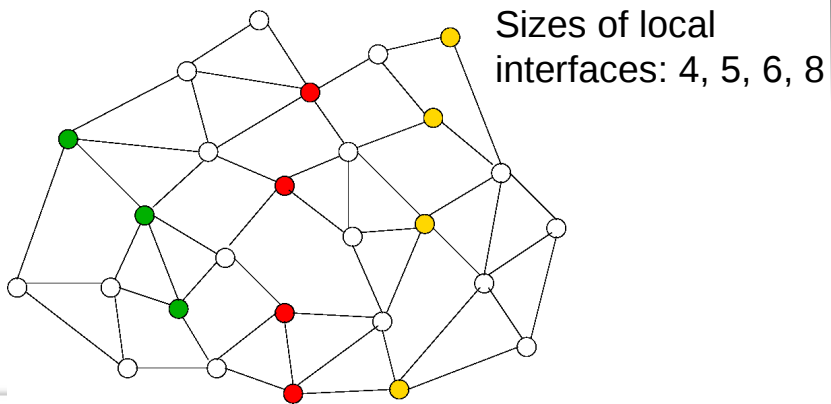
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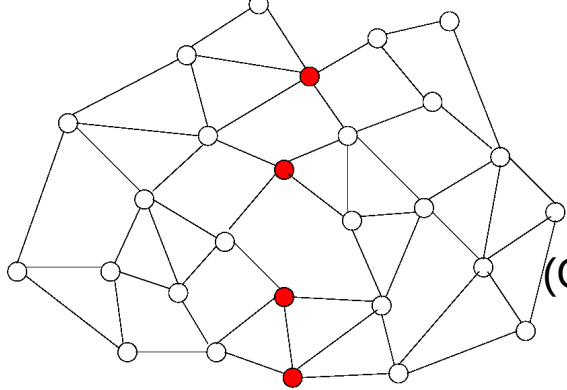


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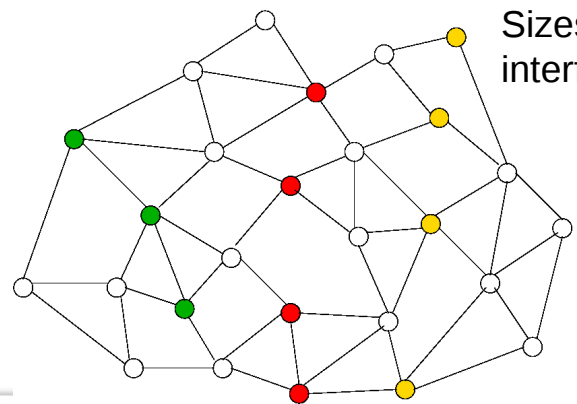
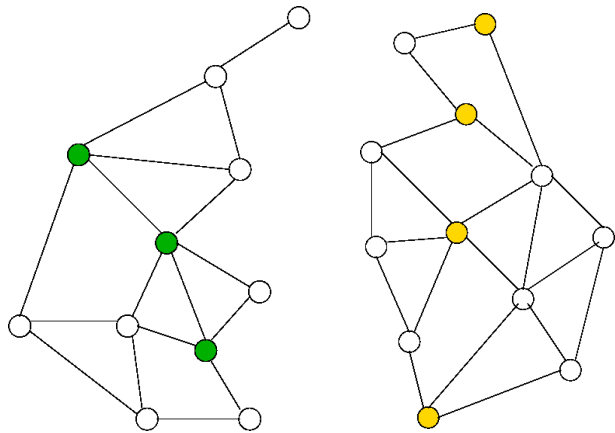


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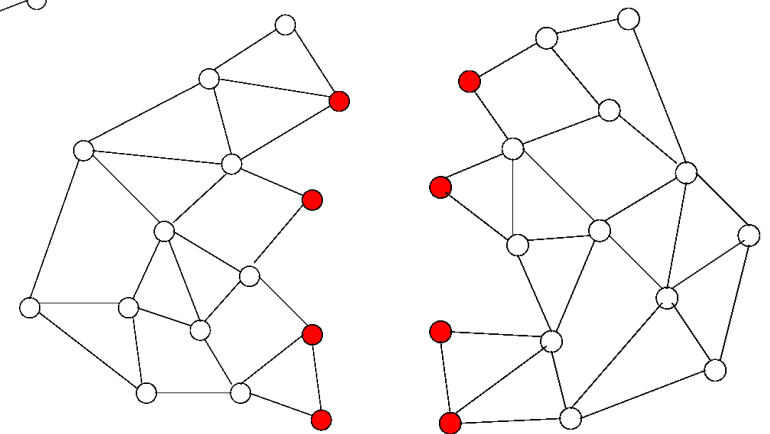
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Sizes of local interfaces: 4, 5, 6, 8

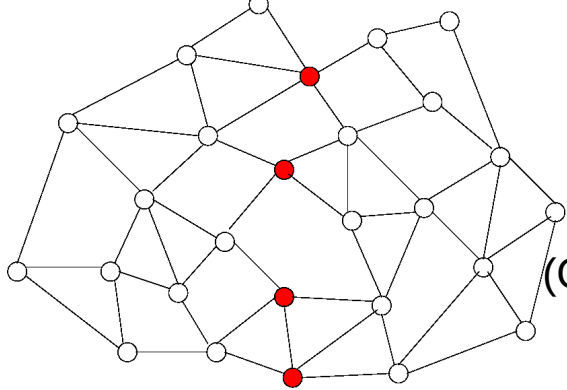
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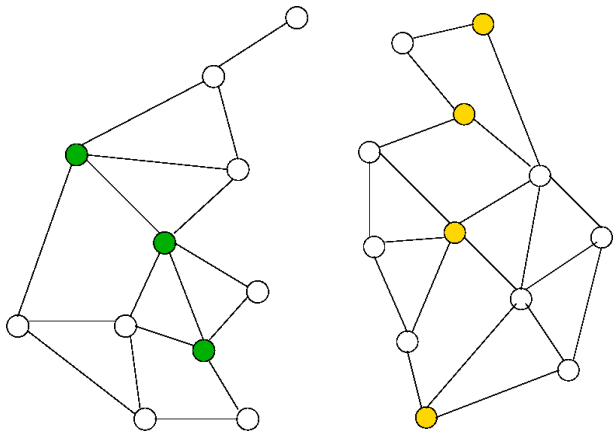
Halo: vertices of old separators adjacent to subgraph

$$Y = P_0 \cup S \cup P_1$$



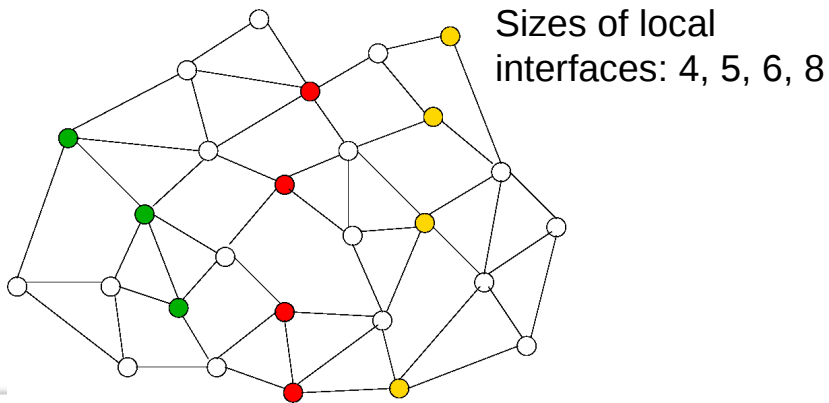
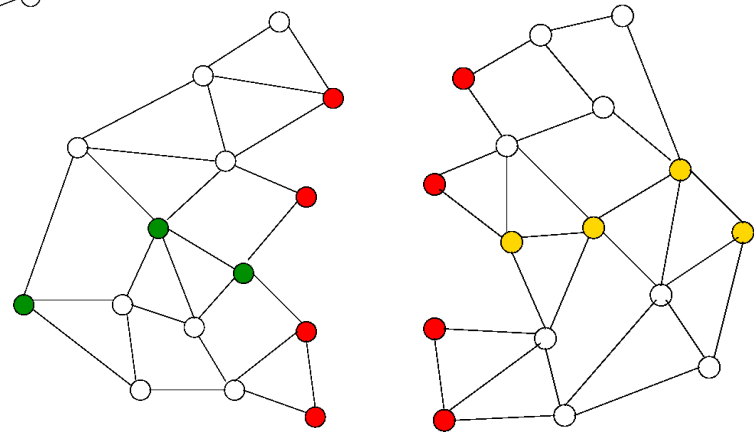
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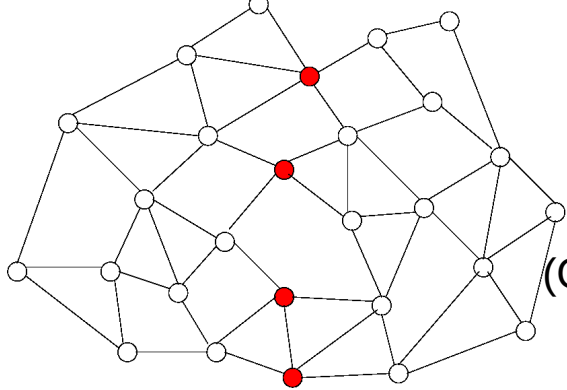
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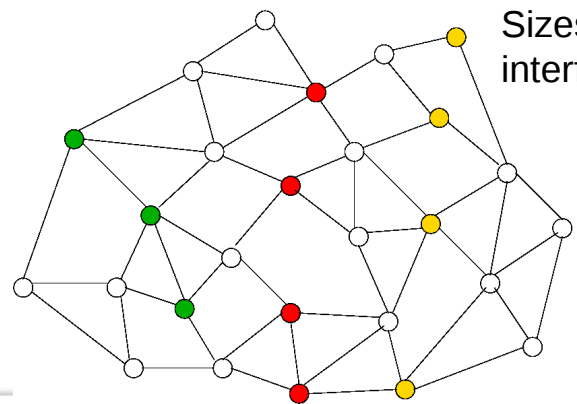
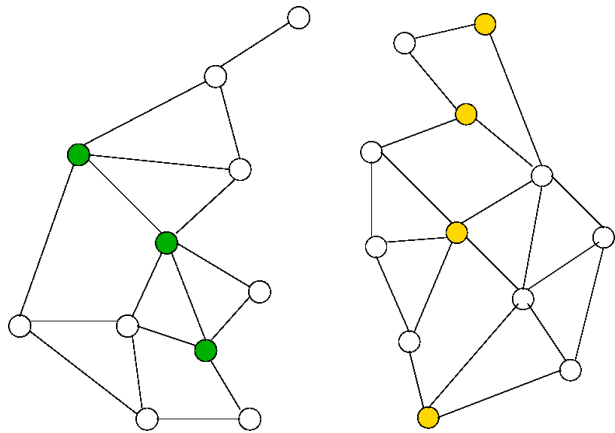
Sizes of local interfaces: 4, 5, 6, 8

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Classical nested dissection

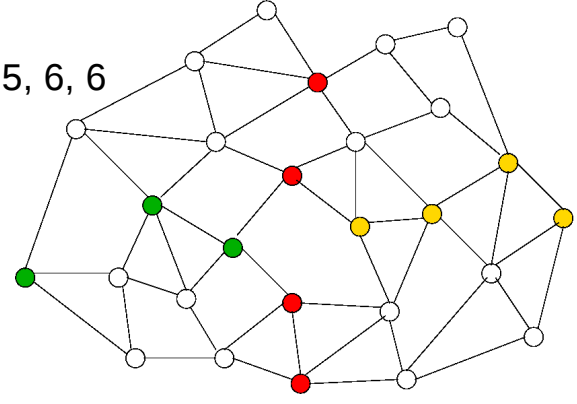
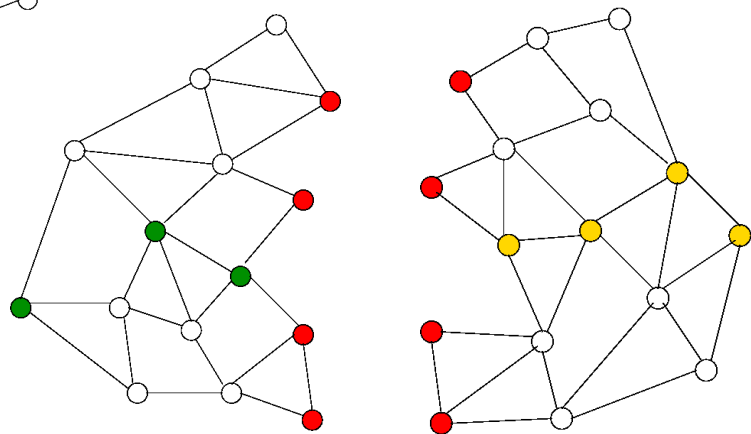
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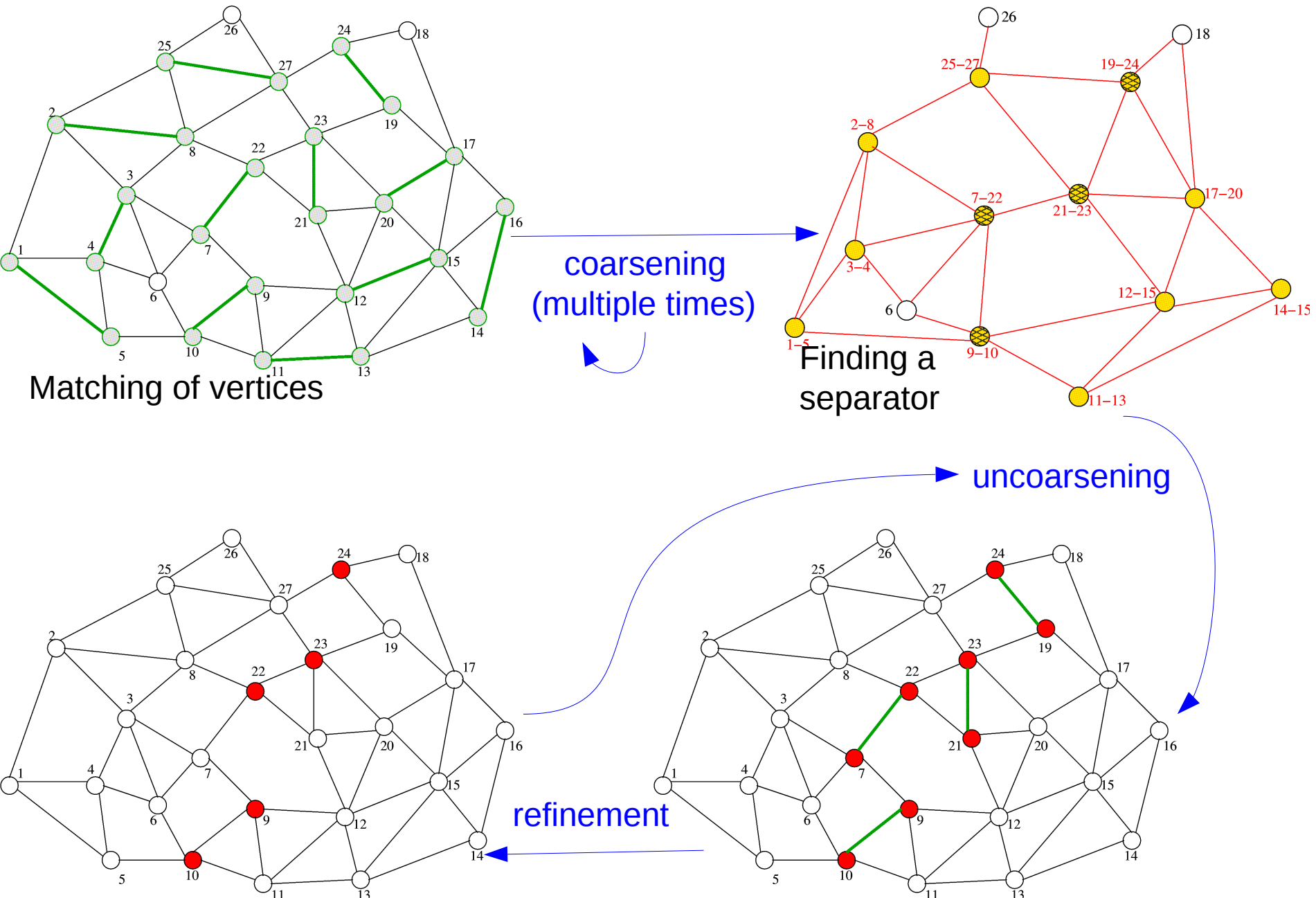
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Sizes of local interfaces: 5, 5, 6, 6

3 The multilevel framework



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```
 $G_1 \leftarrow G;$   
 $i \leftarrow 1;$   
while  $G_i$  can be coarsened do  
   $G_{i+1} \leftarrow \text{coarsenGraph}(G_i);$   
   $i++;$   
 $n \leftarrow i;$   
 $S_n \leftarrow \text{findSeparator}(G_n);$   
for  $i$  from  $n - 1$  to 1 do  
   $S_i \leftarrow \text{uncoarsenSeparator}(G_{i+1}, S_{i+1});$   
   $S_i \leftarrow \text{refineSeparator}(G_i, S_i);$ 
```

Greedy graph growing



Fiduccia-Mattheyses algorithm



4 Fiduccia-Mattheyses algorithm

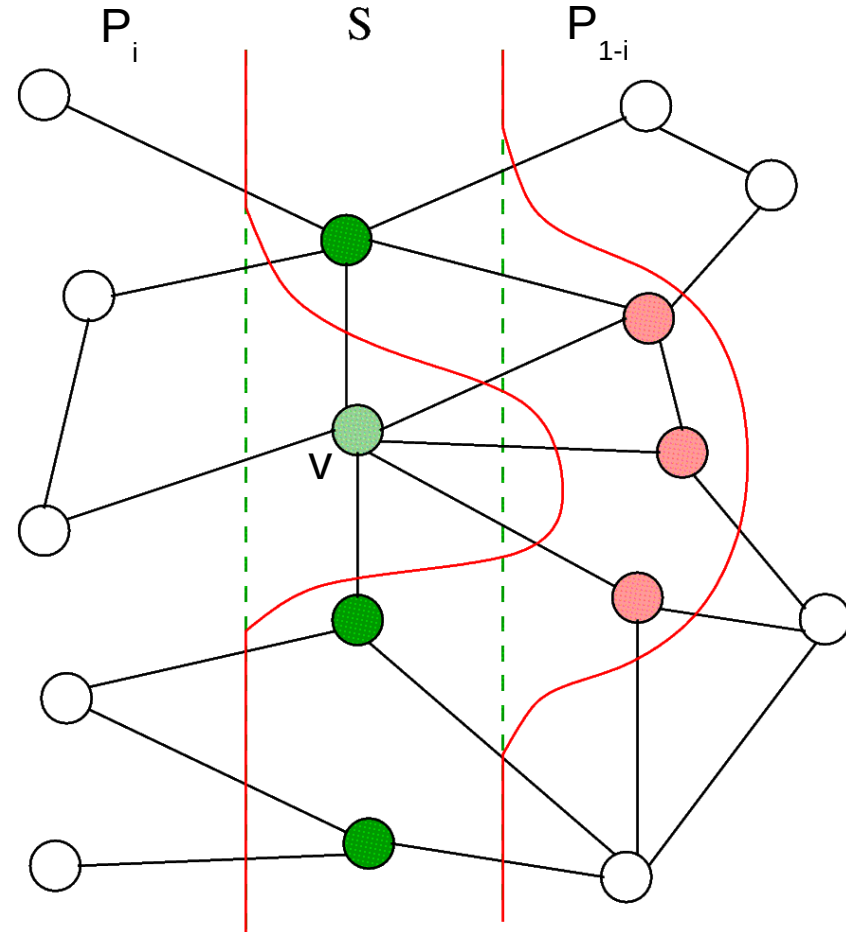
Original version

Main action of FM:

moving of vertex v from S to a part P_i

Choice based on:

- if $||P_0| - |P_1|| > \delta$, part balance
- separator minimization



4 Fiduccia-Mattheyses algorithm

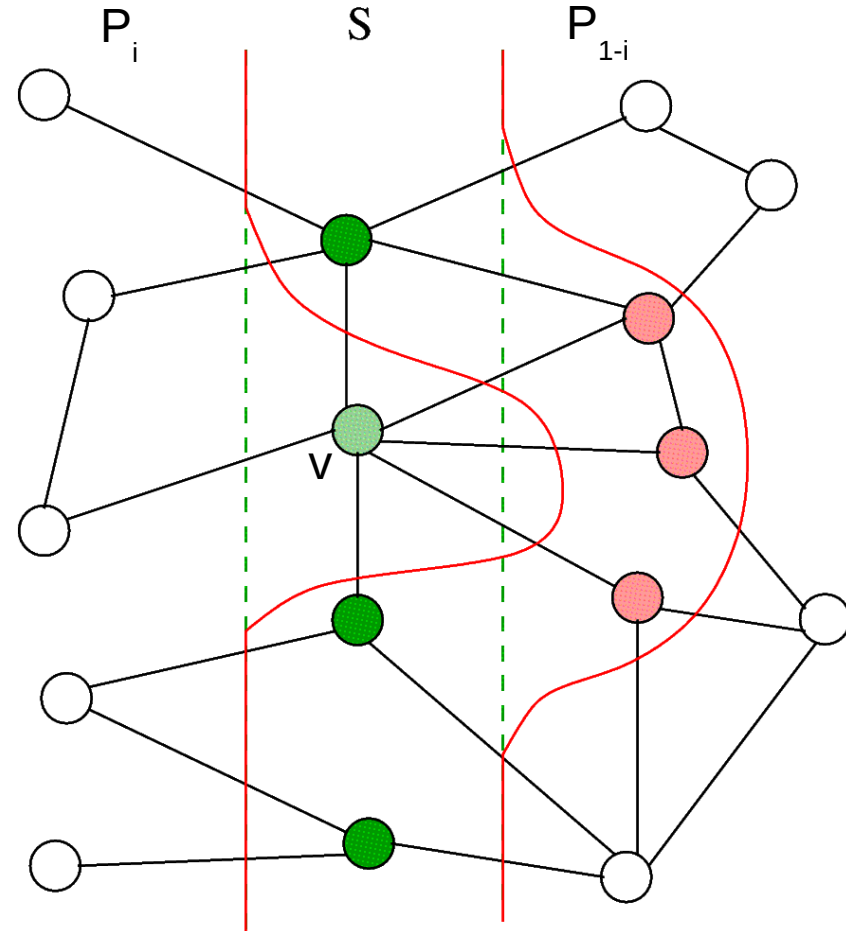
Modified version

Main action of FM:

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Choice based on:

- if $||P_0 \cap V_h| - |P_1 \cap V_h|| > \delta_{halo}$, halo balance
- if $||P_0| - |P_1|| > \delta$, part balance
- separator minimization



4 Fiduccia-Mattheyses algorithm

Modified version

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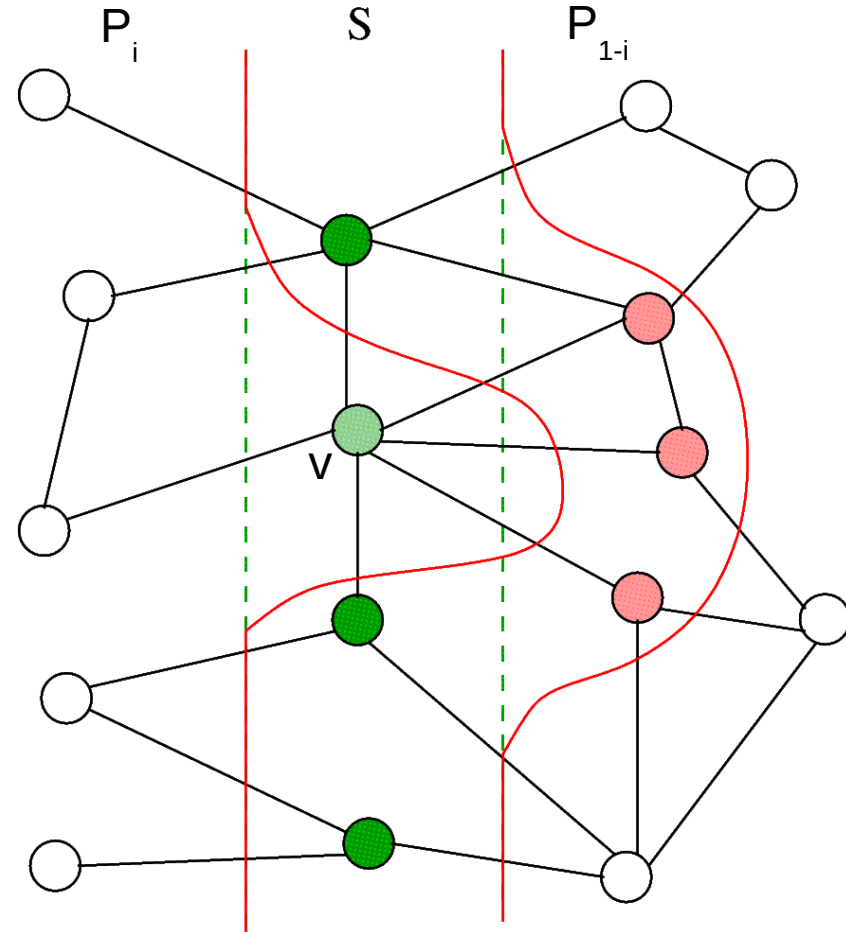
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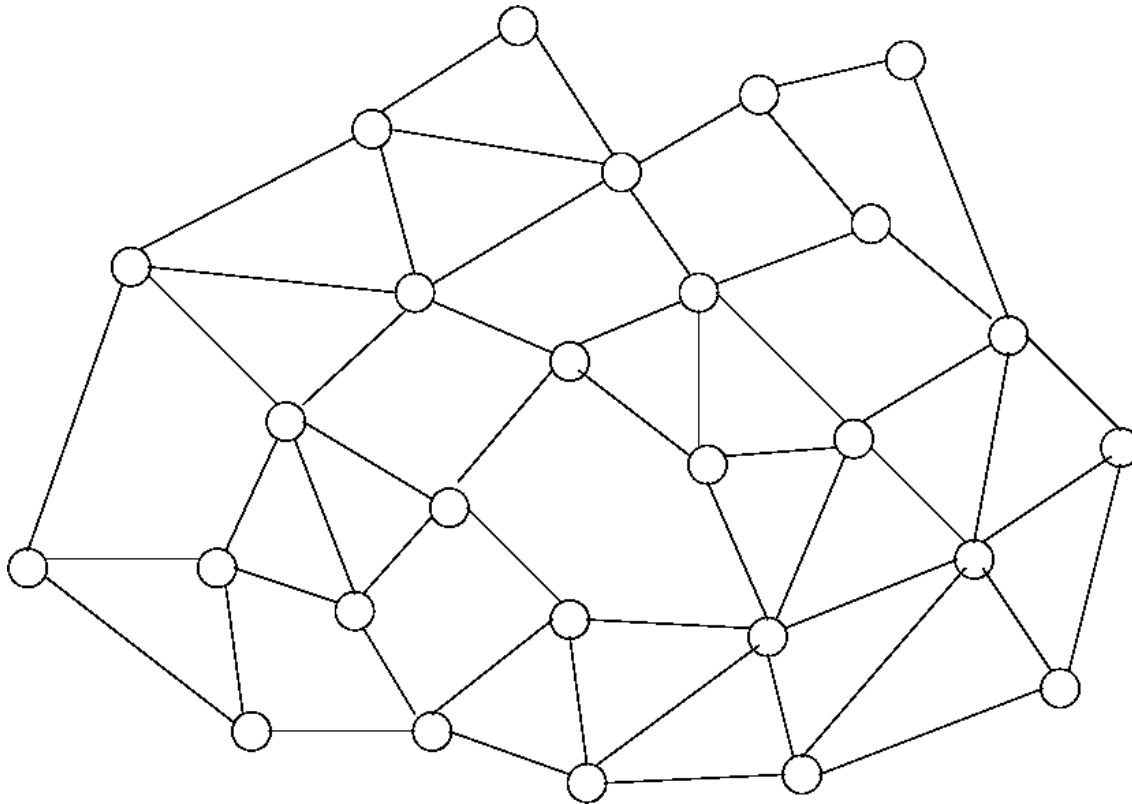
To select best separator, choice based on:

- reasonable part balance
- reasonable halo balance
- separator minimization
- halo balance
- part balance



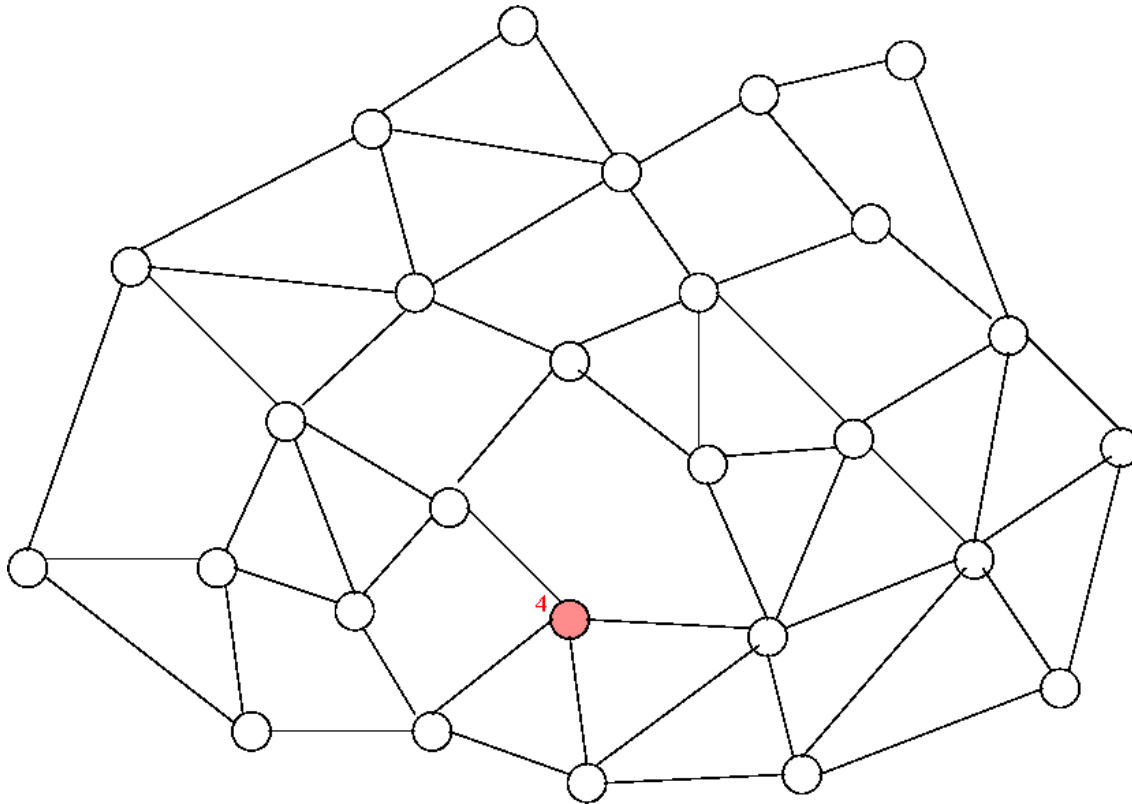
5 Greedy Graph Growing

- **Initialization** : $w \leftarrow \text{randomVertexSeed}()$, $P_0 \leftarrow V \setminus \{w\}$, $P_1 \leftarrow \emptyset$, $S \leftarrow \{w\}$
- **At each step** : move a vertex v from S to P_1 and update separator (choose v which minimize S)
- **Stop** : whenever $|P_0| \approx |P_1|$



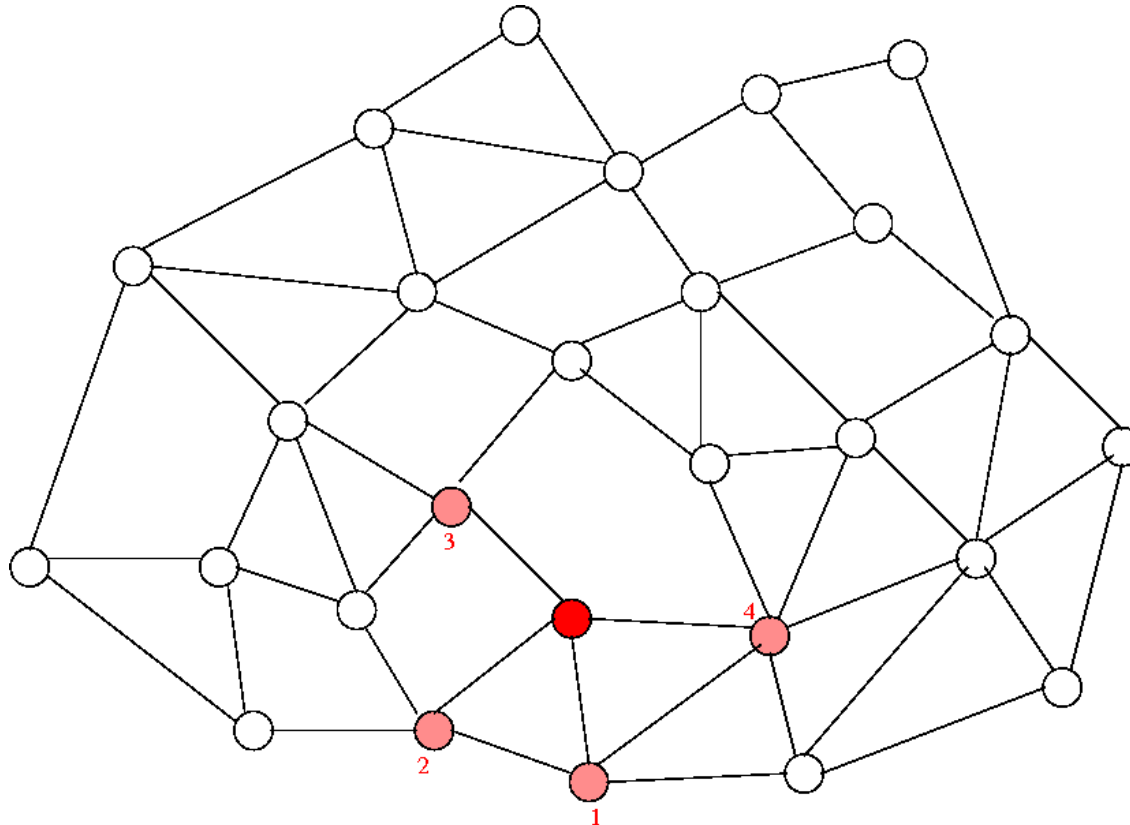
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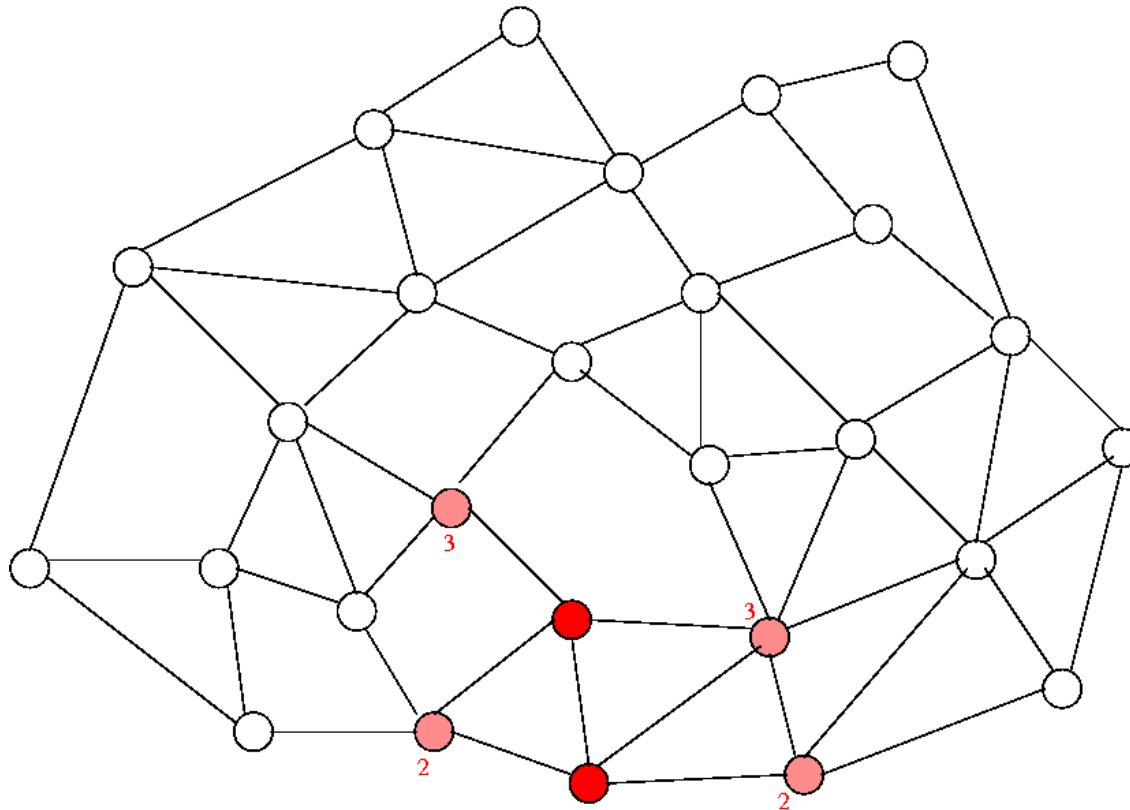
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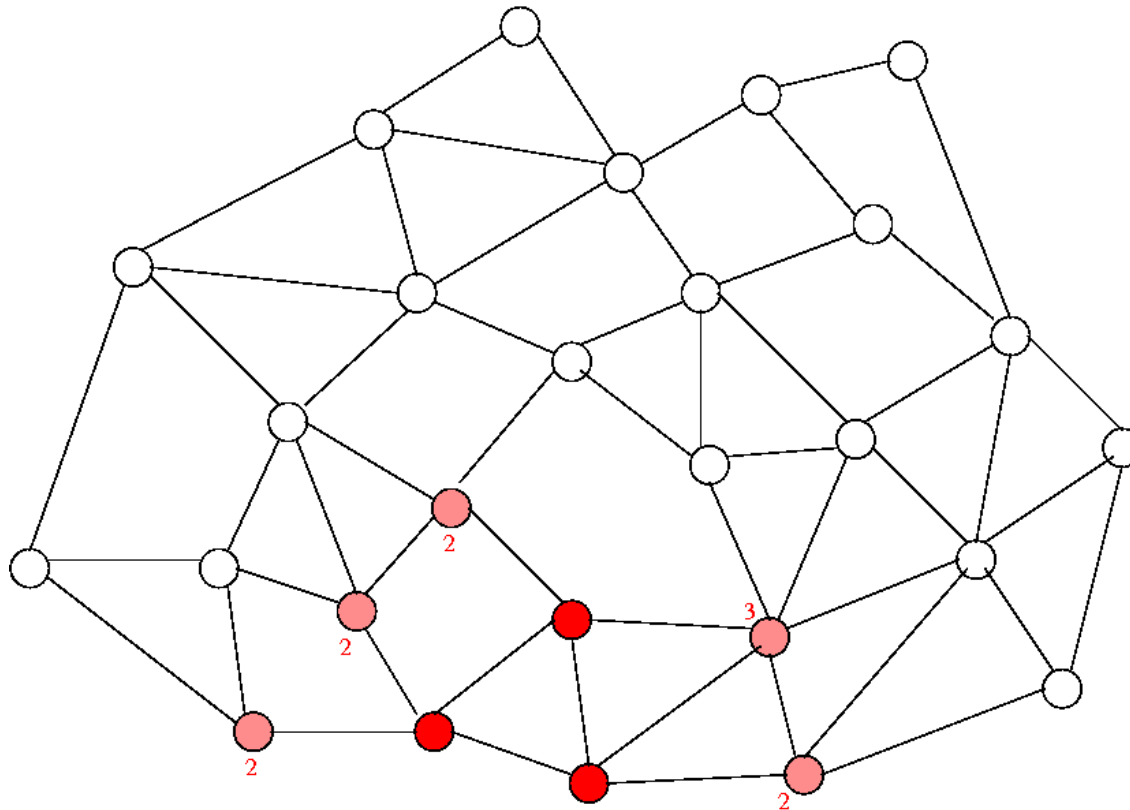
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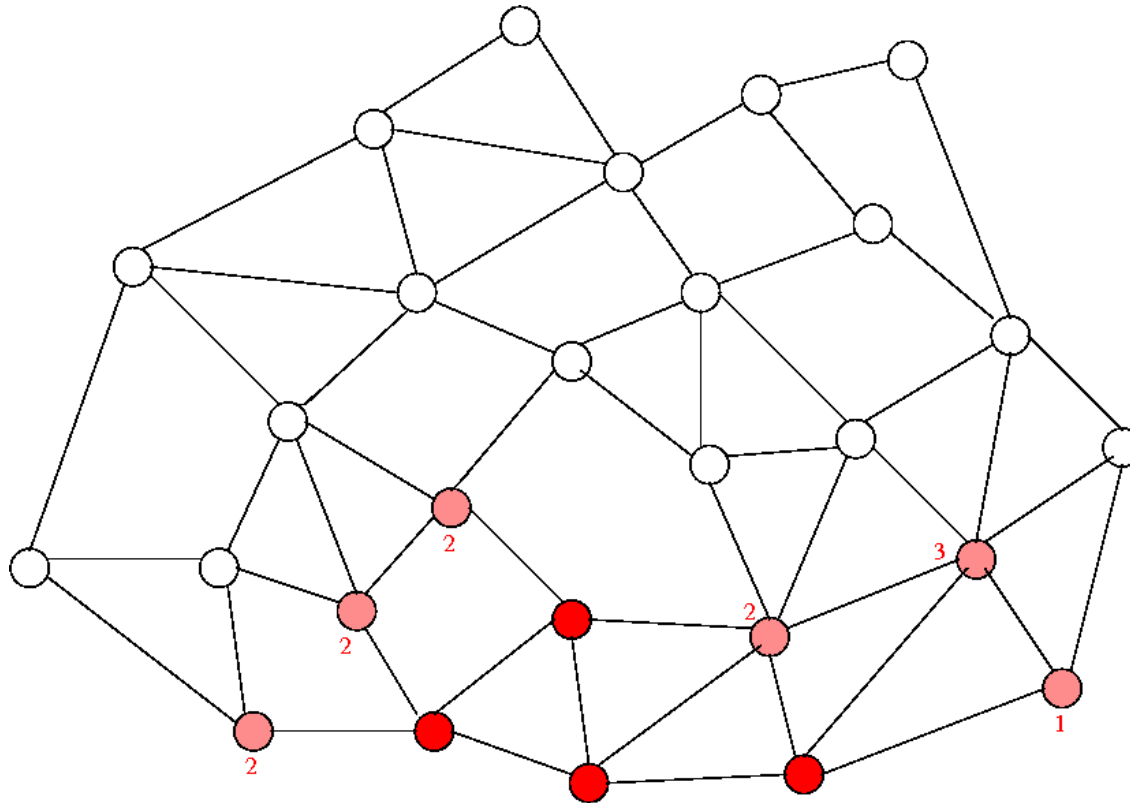
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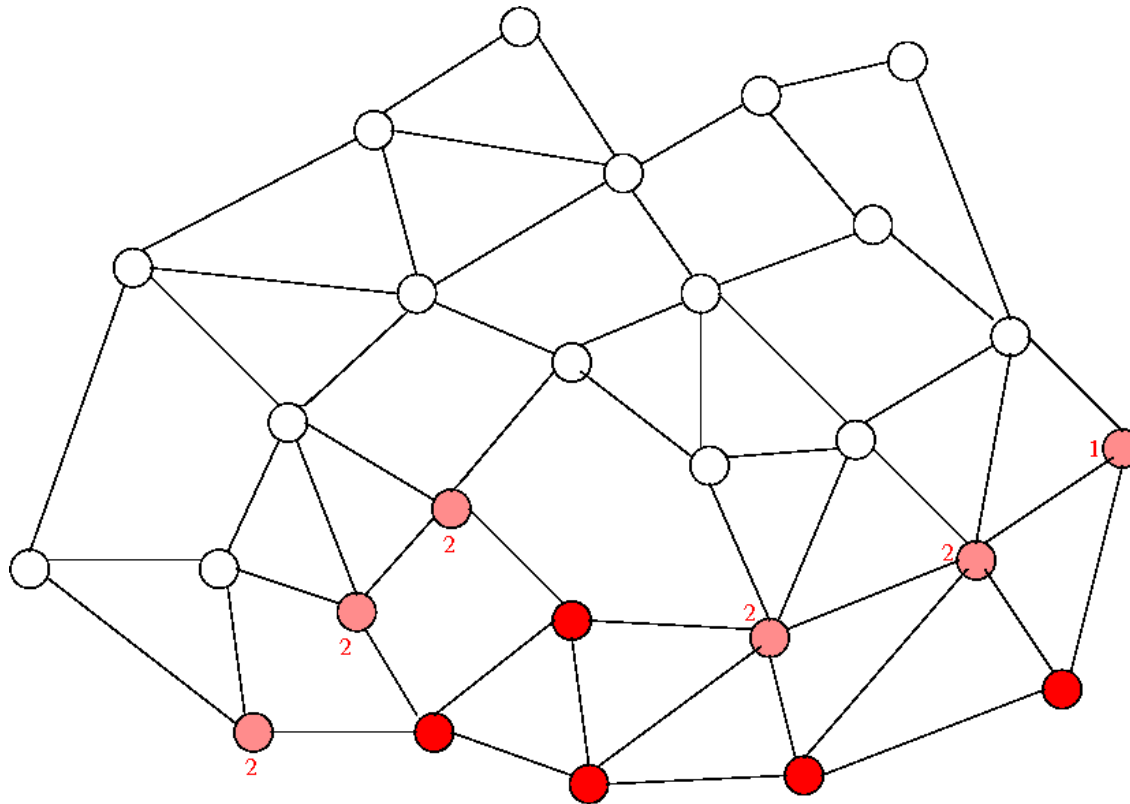
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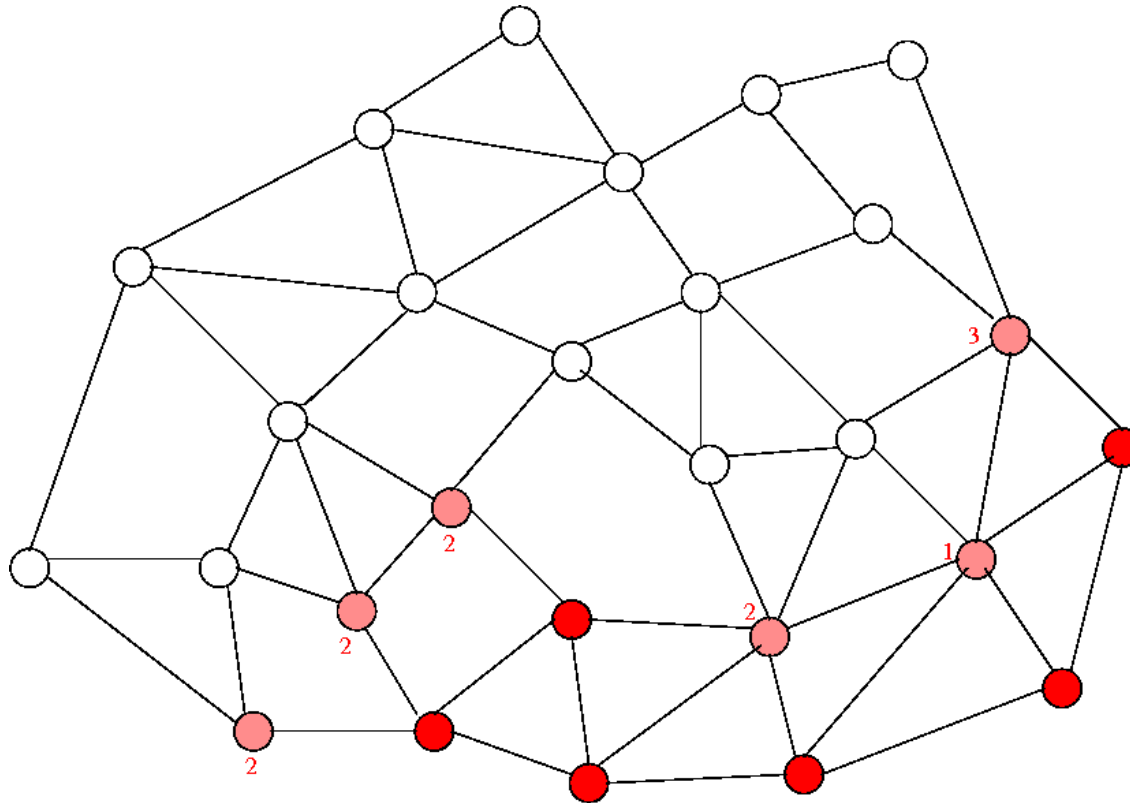
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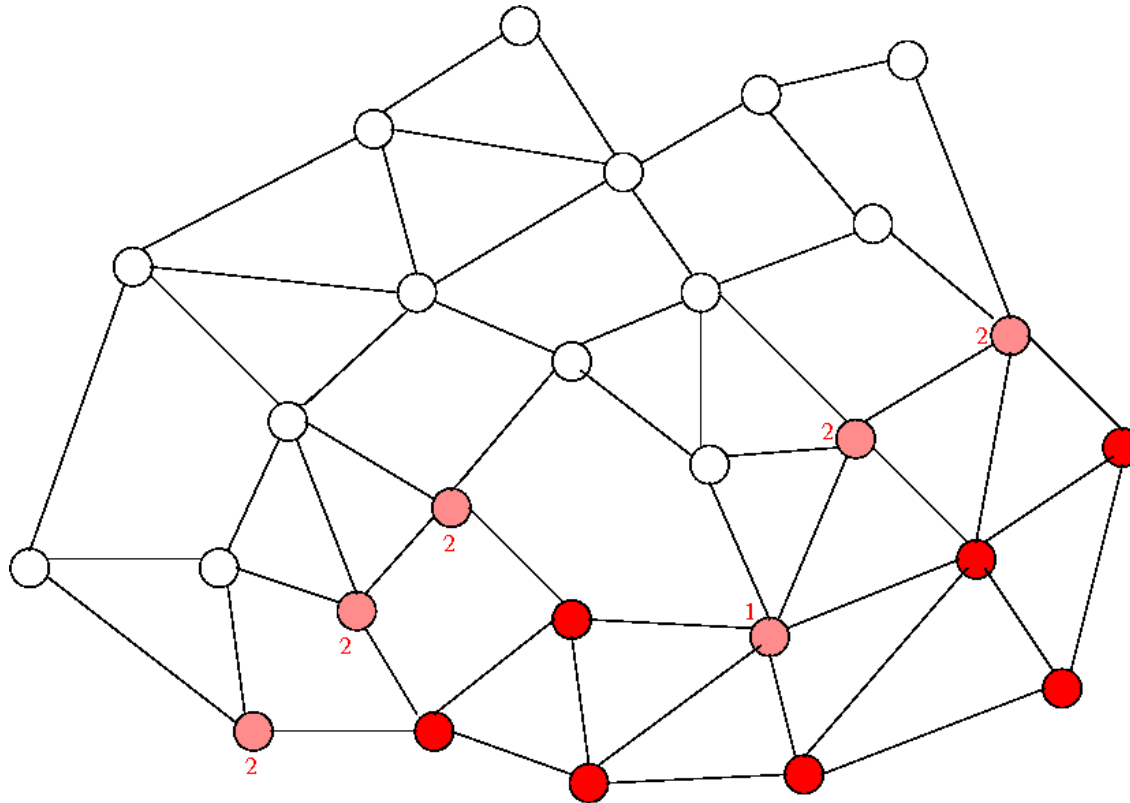
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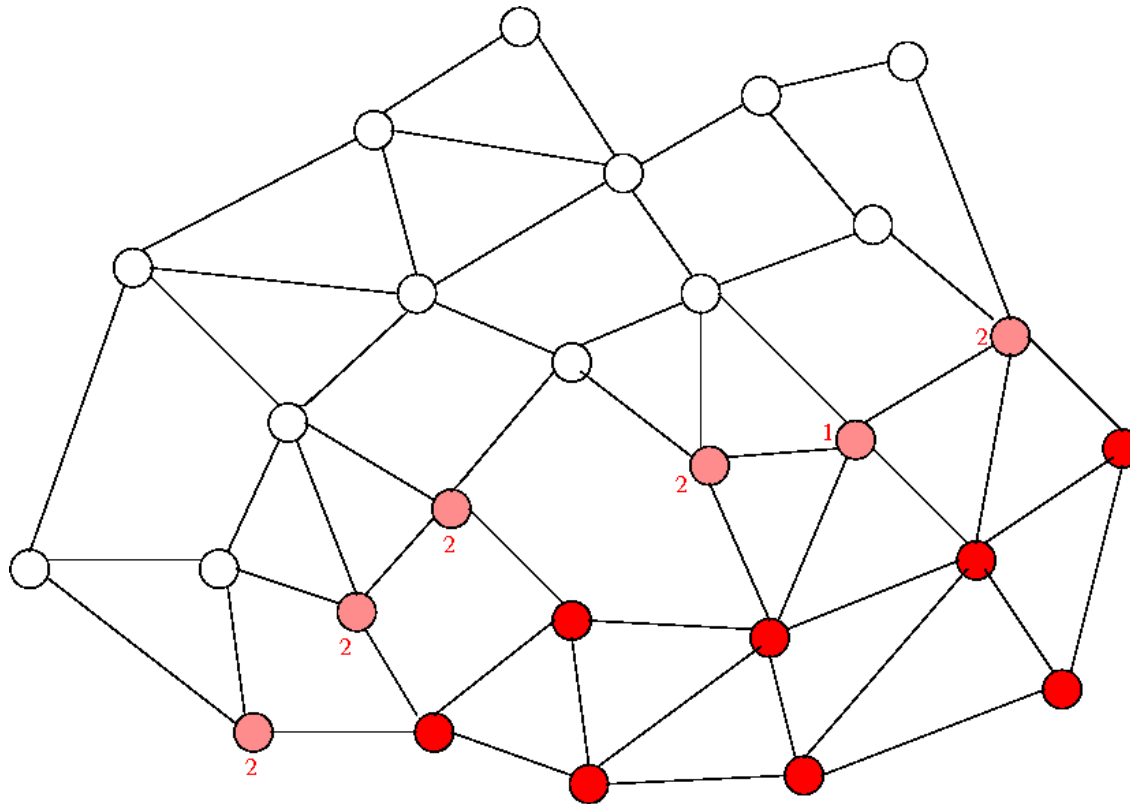
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5 Greedy Graph Growing

Original version

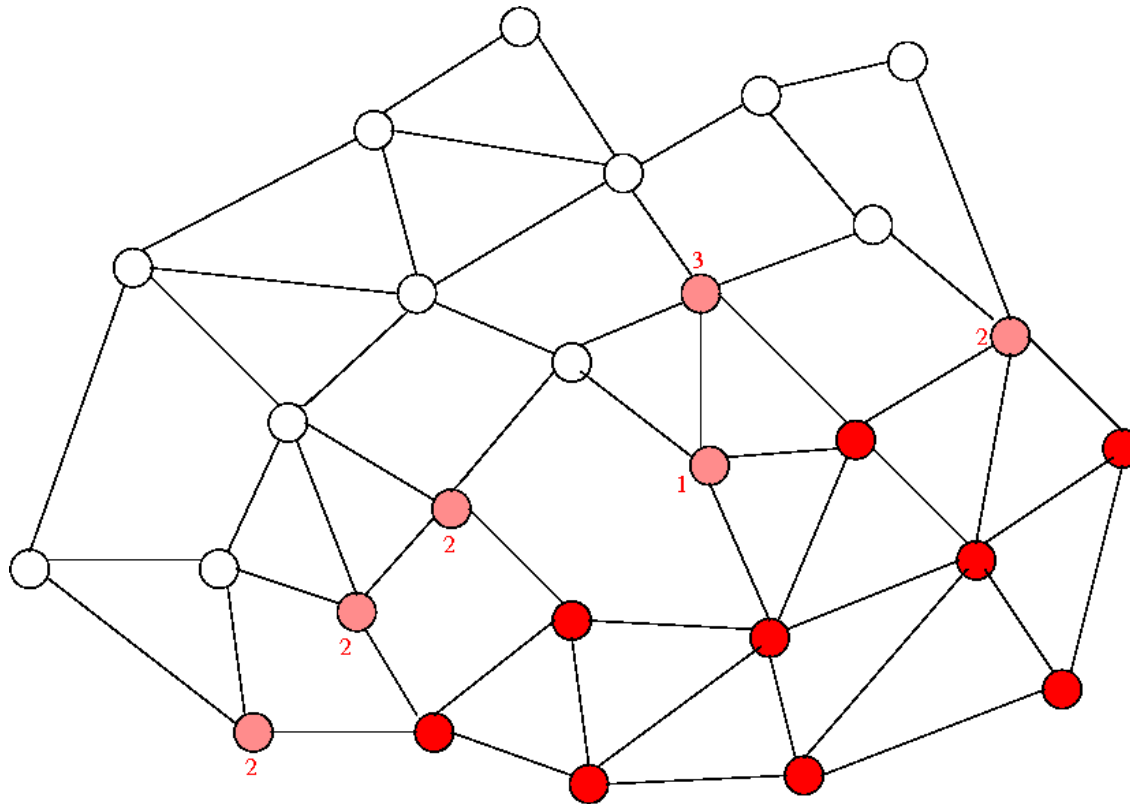
- **Initialization** : $w \leftarrow \text{randomVertexSeed}()$, $P_0 \leftarrow V \setminus \{w\}$, $P_1 \leftarrow \emptyset$, $S \leftarrow \{w\}$
- **At each step** : move a vertex v from S to P_1 and update separator (choose v which minimize S)
- **Stop** : whenever $|P_0| \approx |P_1|$



5 Greedy Graph Growing

Original version

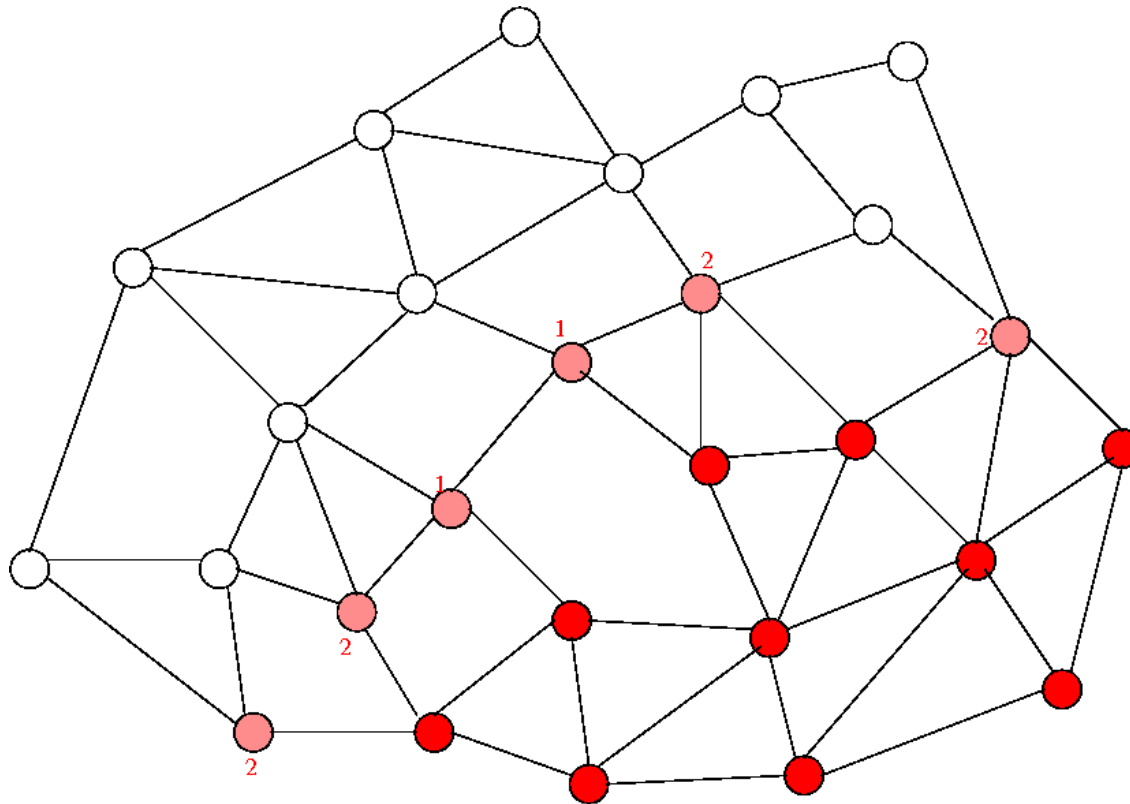
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5 Greedy Graph Growing

Original version

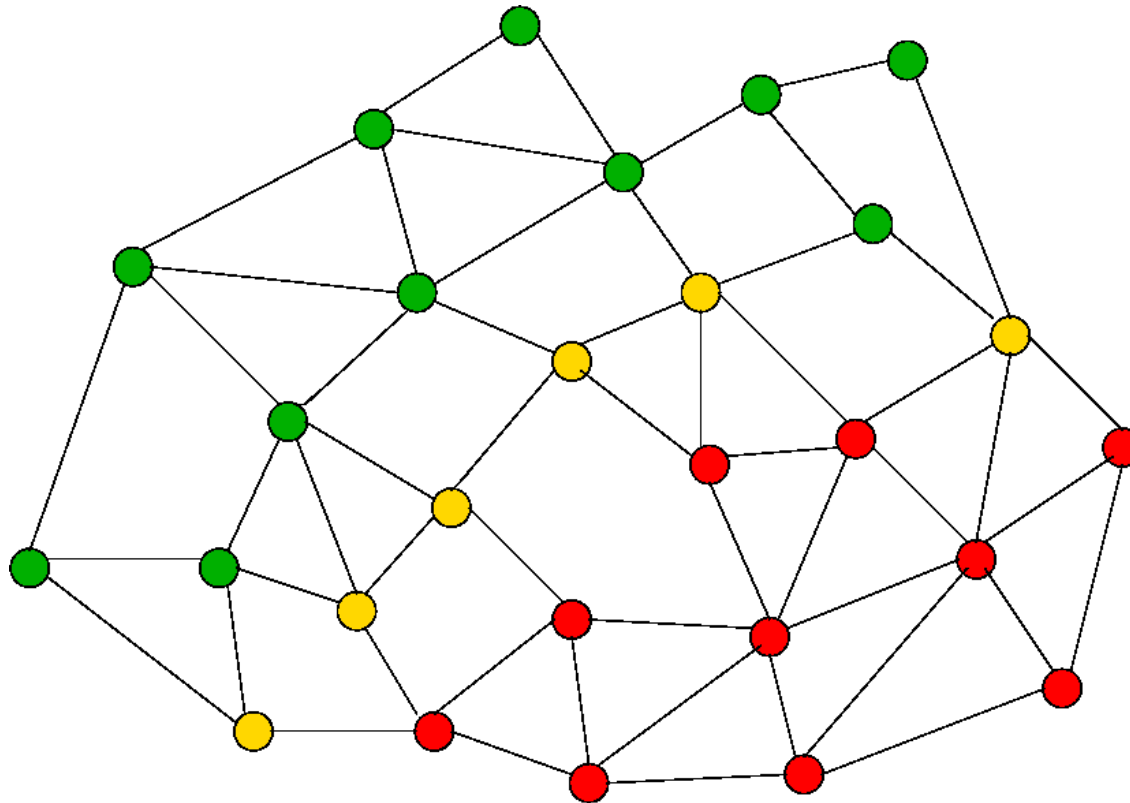
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5 Greedy Graph Growing

Original version

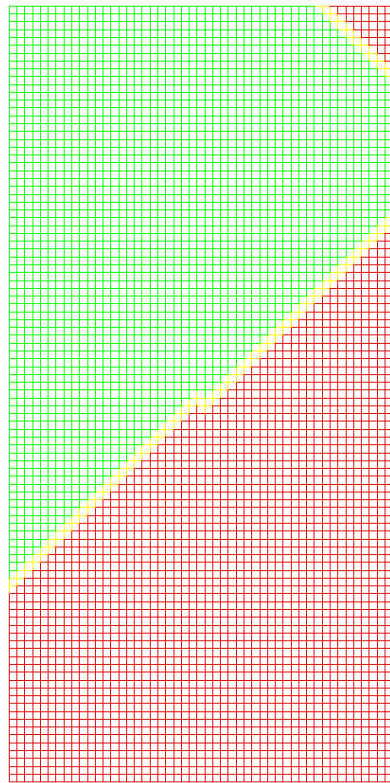
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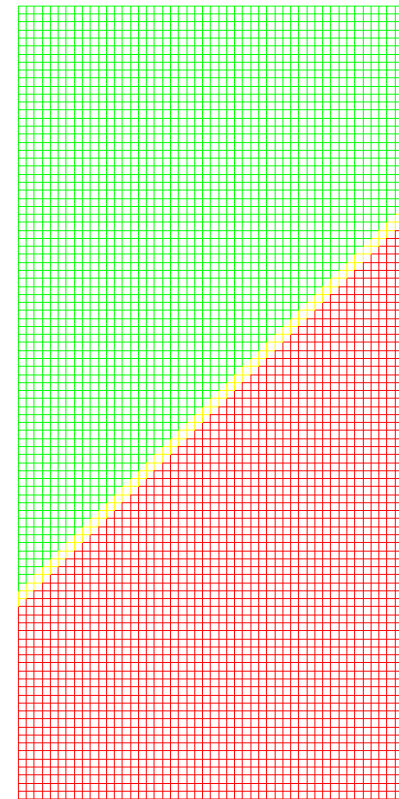
5 Greedy Graph Growing

Original version

- P_1 always connex, but not P_0
- Several passes made with different seeds, smallest separator eventually selected



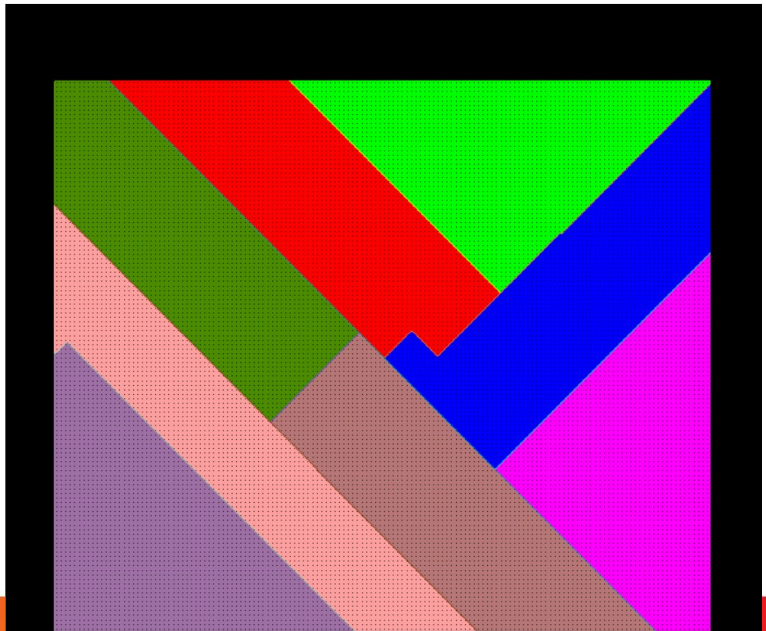
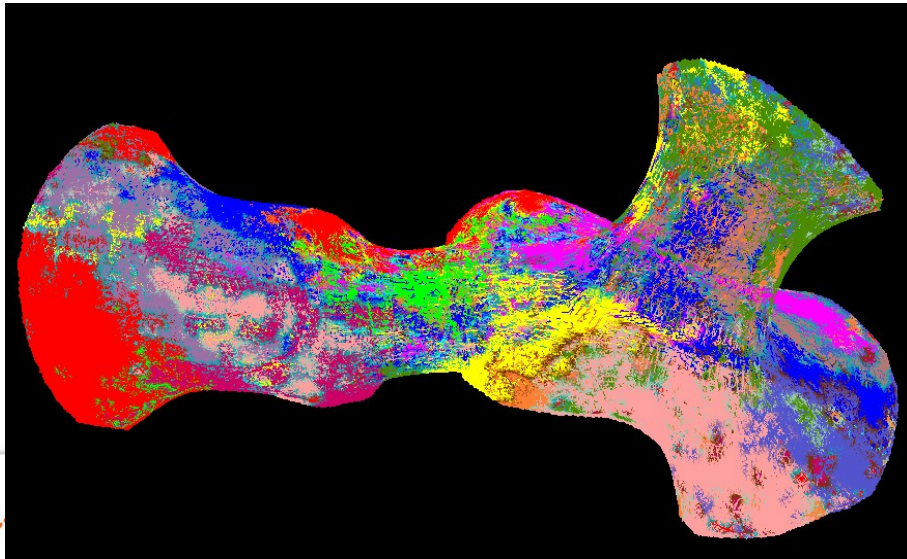
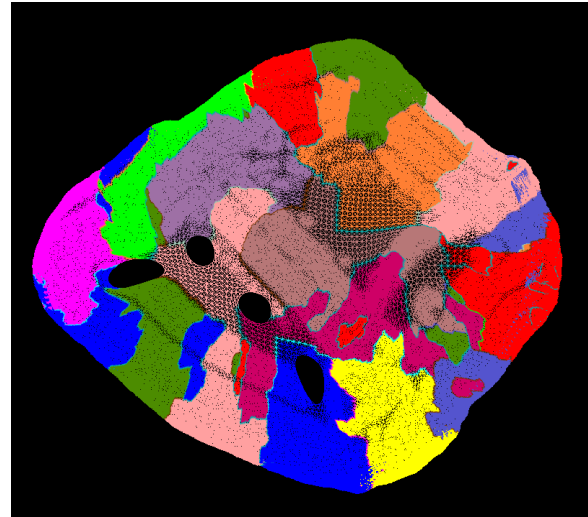
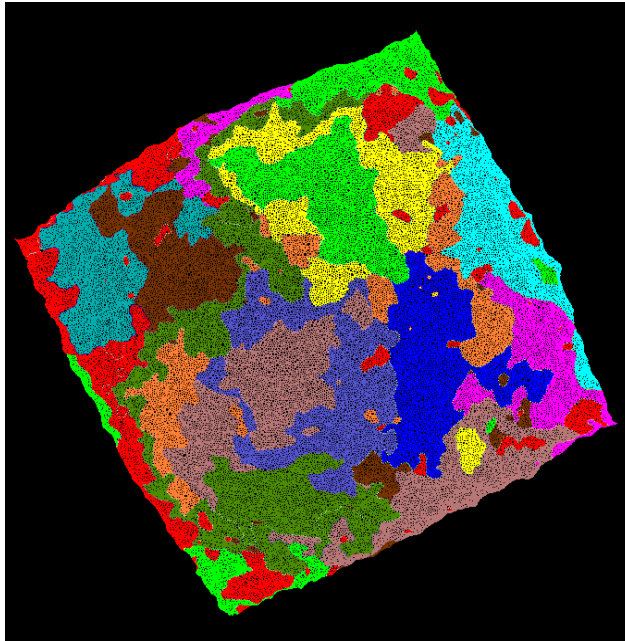
1 passe



10 passes

5 Greedy Graph Growing

Original version



5 Greedy Graph Growing

Modified version

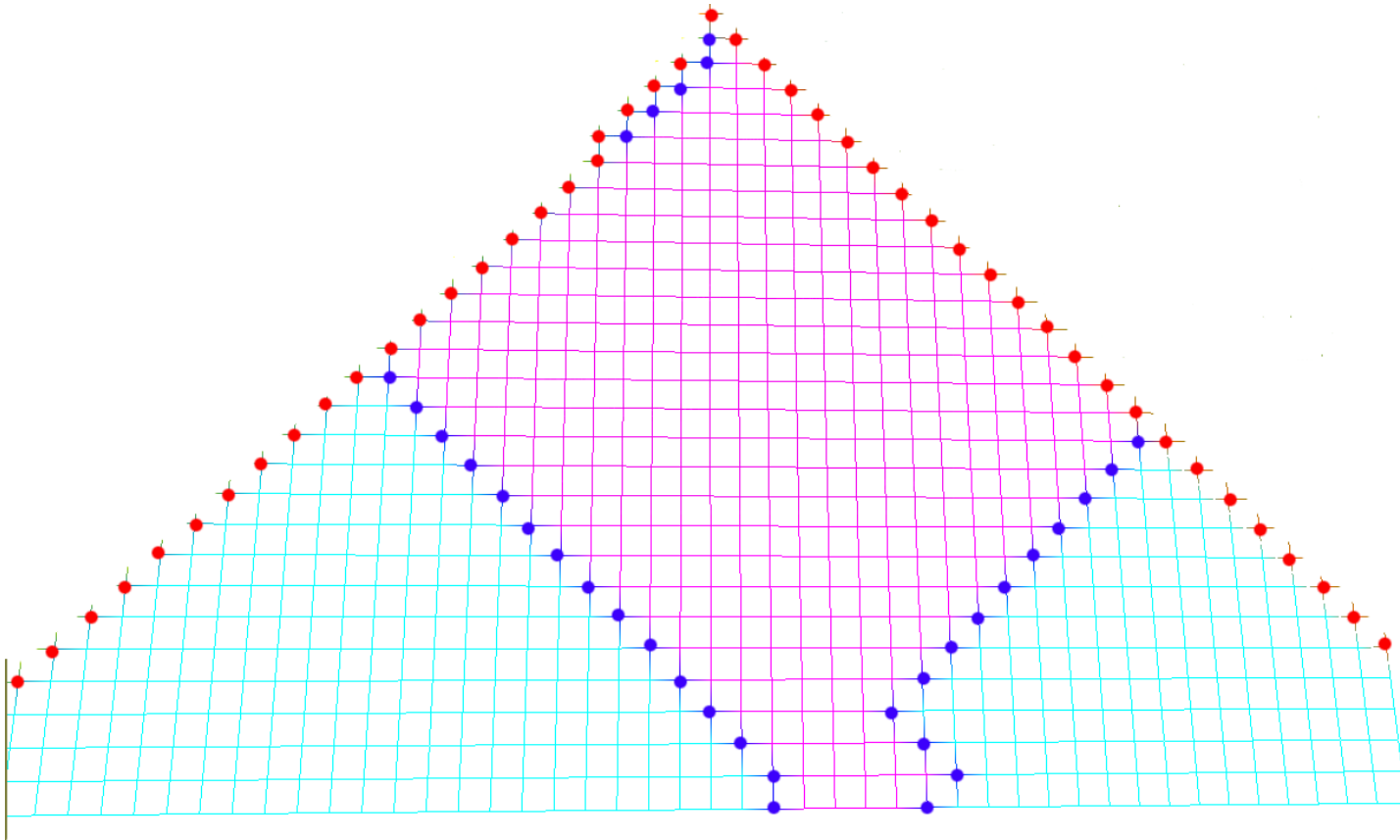
Idea: as P_1 grows, ensure $\frac{|P_0 \cap V_h|}{|P_0|} \simeq \frac{|P_1 \cap V_h|}{|P_1|}$

Changes:

- Choice of vertex v to move from S to P_1 :
 - If $\frac{|P_1 \cap V_h|}{|P_1|} < \frac{|P_0 \cap V_h|}{|P_0|}$ and $S \cap V_h \neq \emptyset \rightarrow$ choose among $S \cap V_h$
 - Minimize separator
- Choice of the seed among halo
- Choice of « best pass » based on separator minimization *and* halo balance

5 Greedy Graph Growing

Modified version



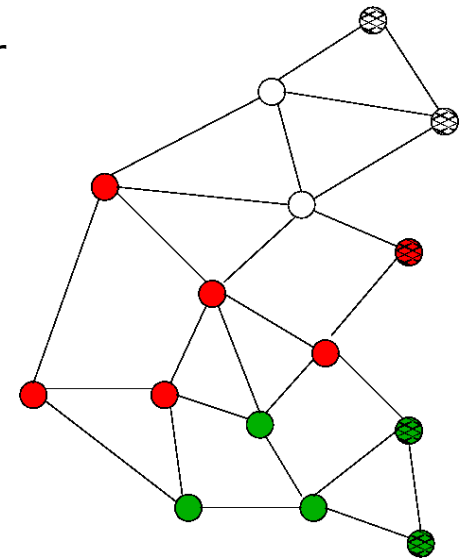
Problems:

- Allowing larger separators often results in non-connected P_0
- Always possible to enhance halo balance by adding a connected component to P_0

6 Double Greedy Graph Growing

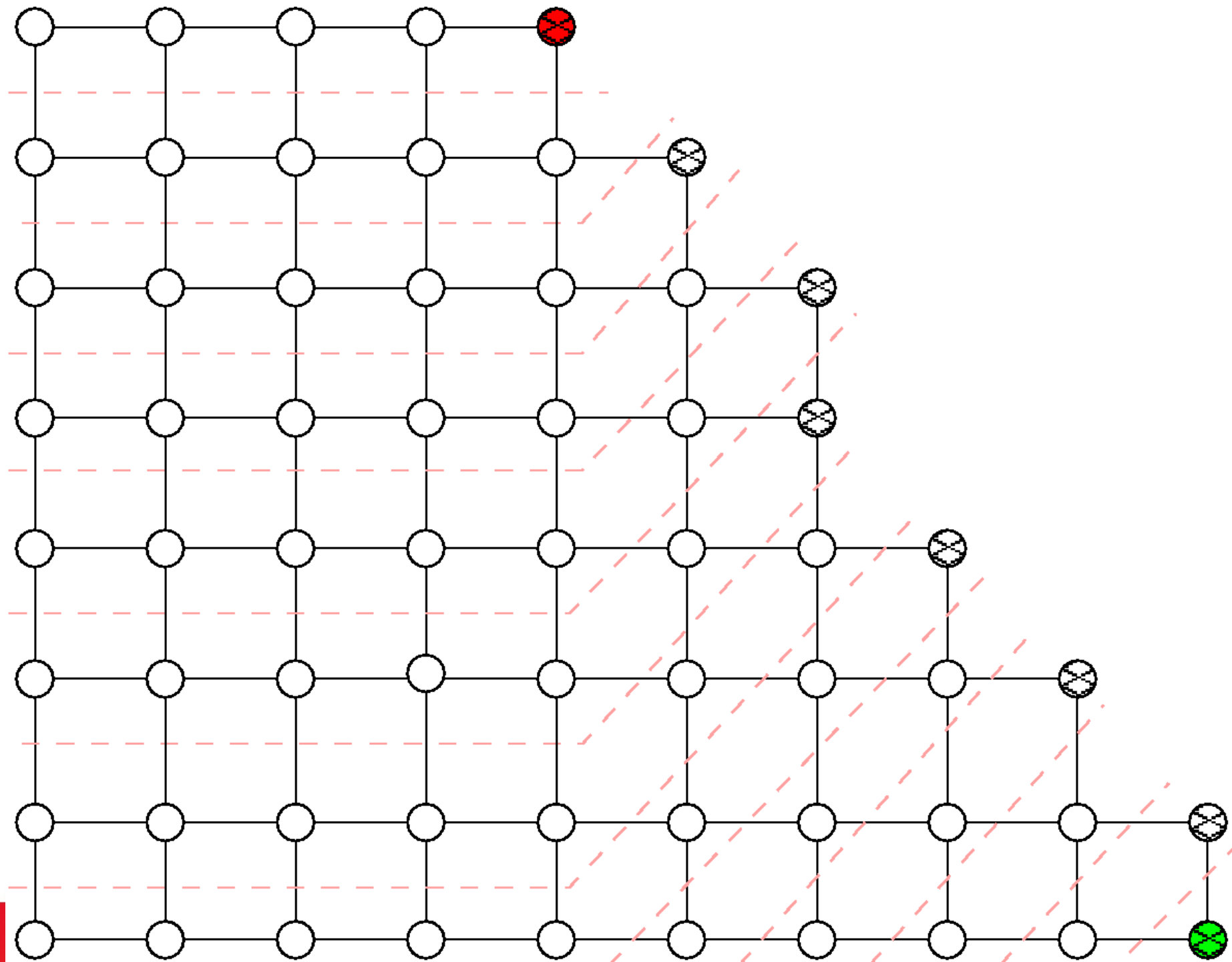
Idea: 2 random seeds, both parts are made grown simultaneously until all vertices are taken

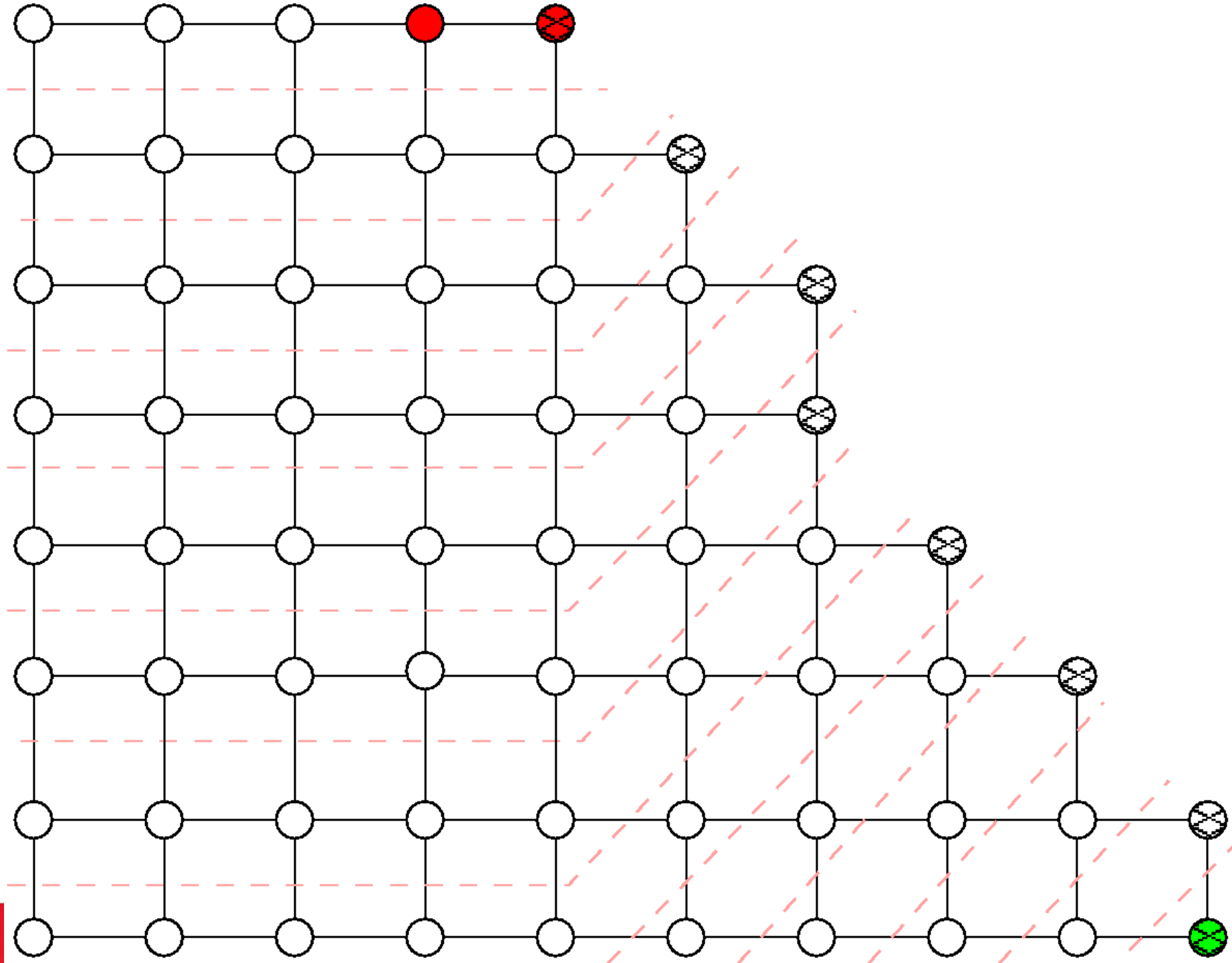
Problem: one part may block the progression of the other

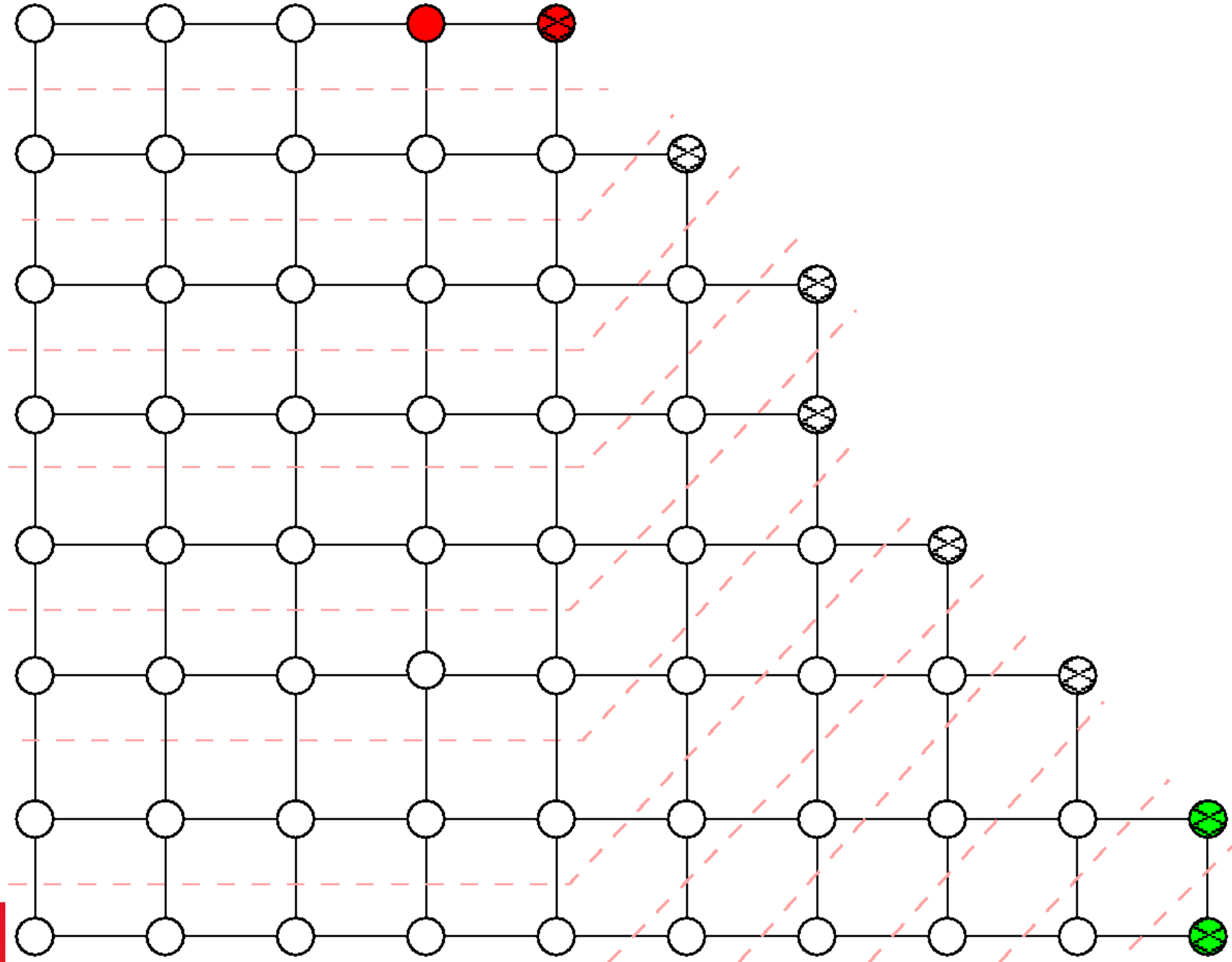


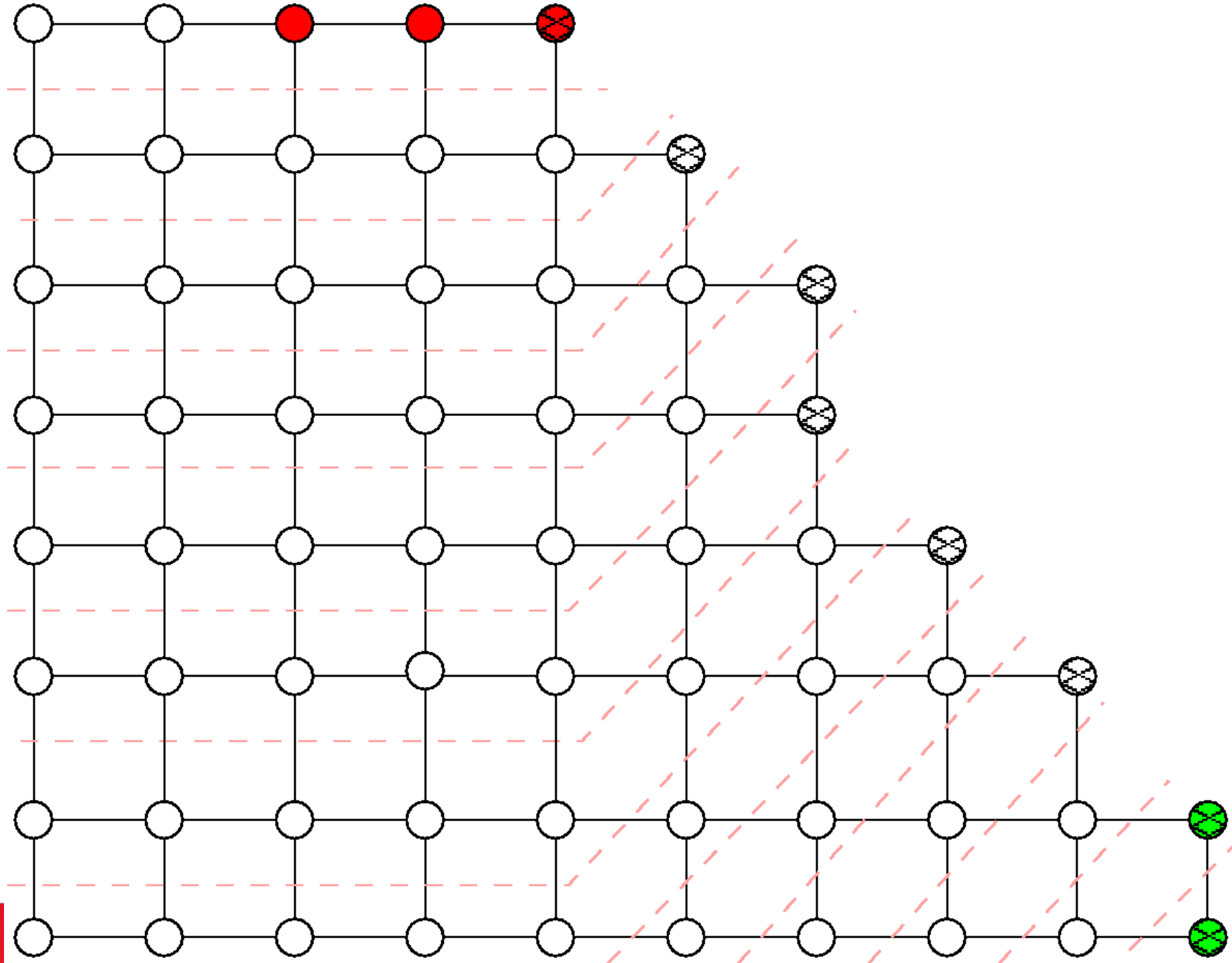
Solutions:

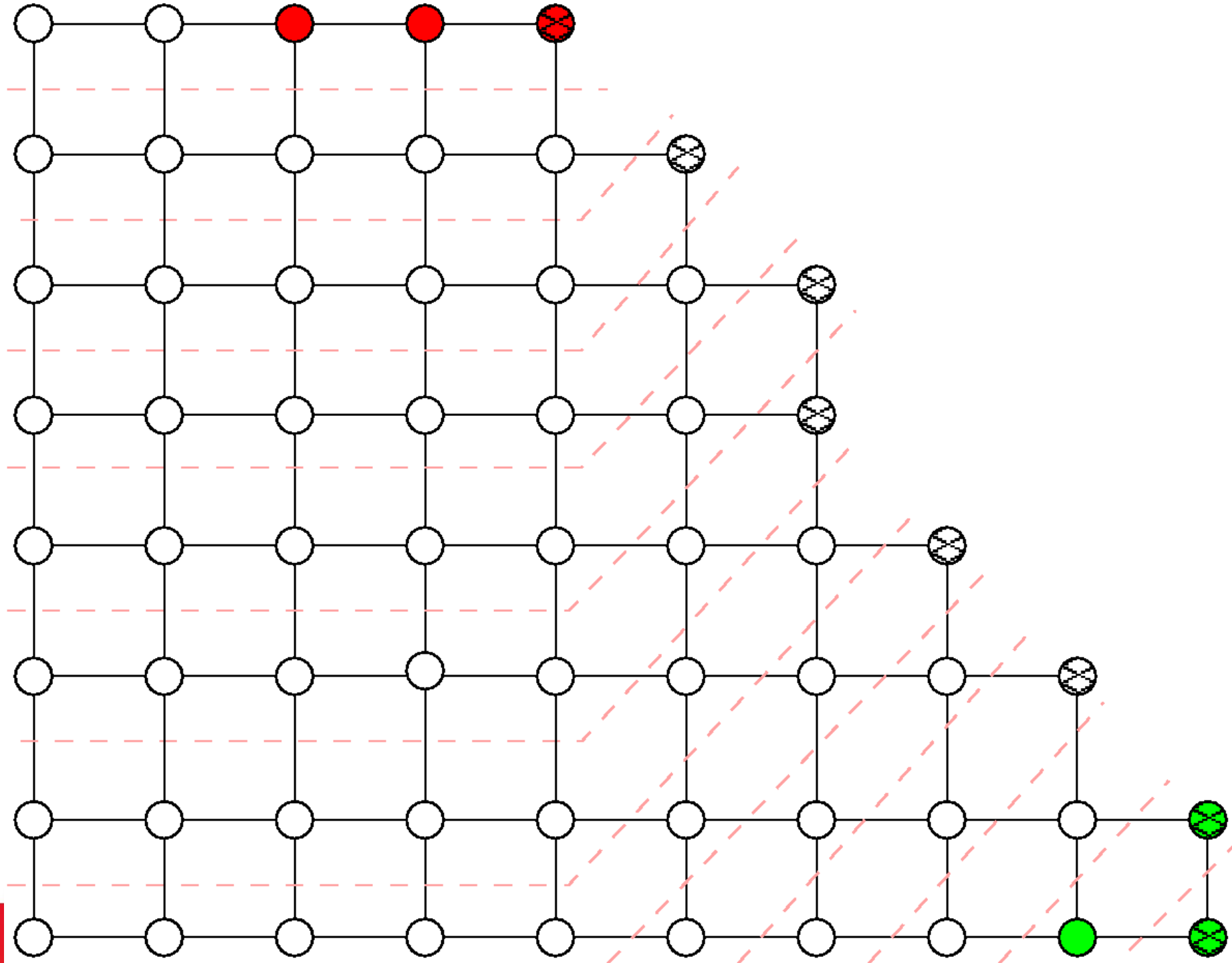
- Seeds s_0 and s_1 as far as possible in halo
- If several choices \rightarrow choose suitable vertex the nearest from s_i / farthest from s_{1-i}
- If stucked with a lot of vertices left \rightarrow make a new pass

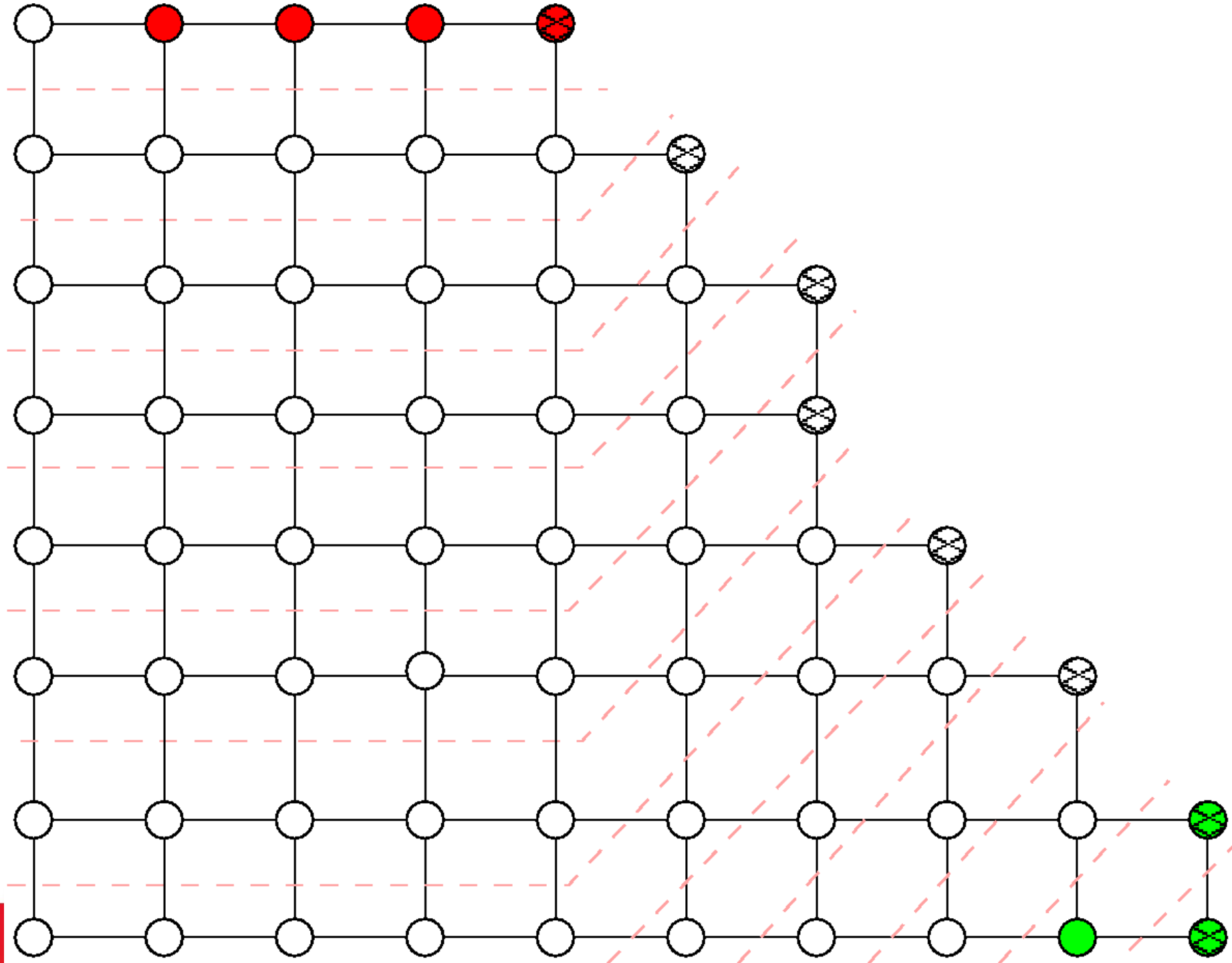


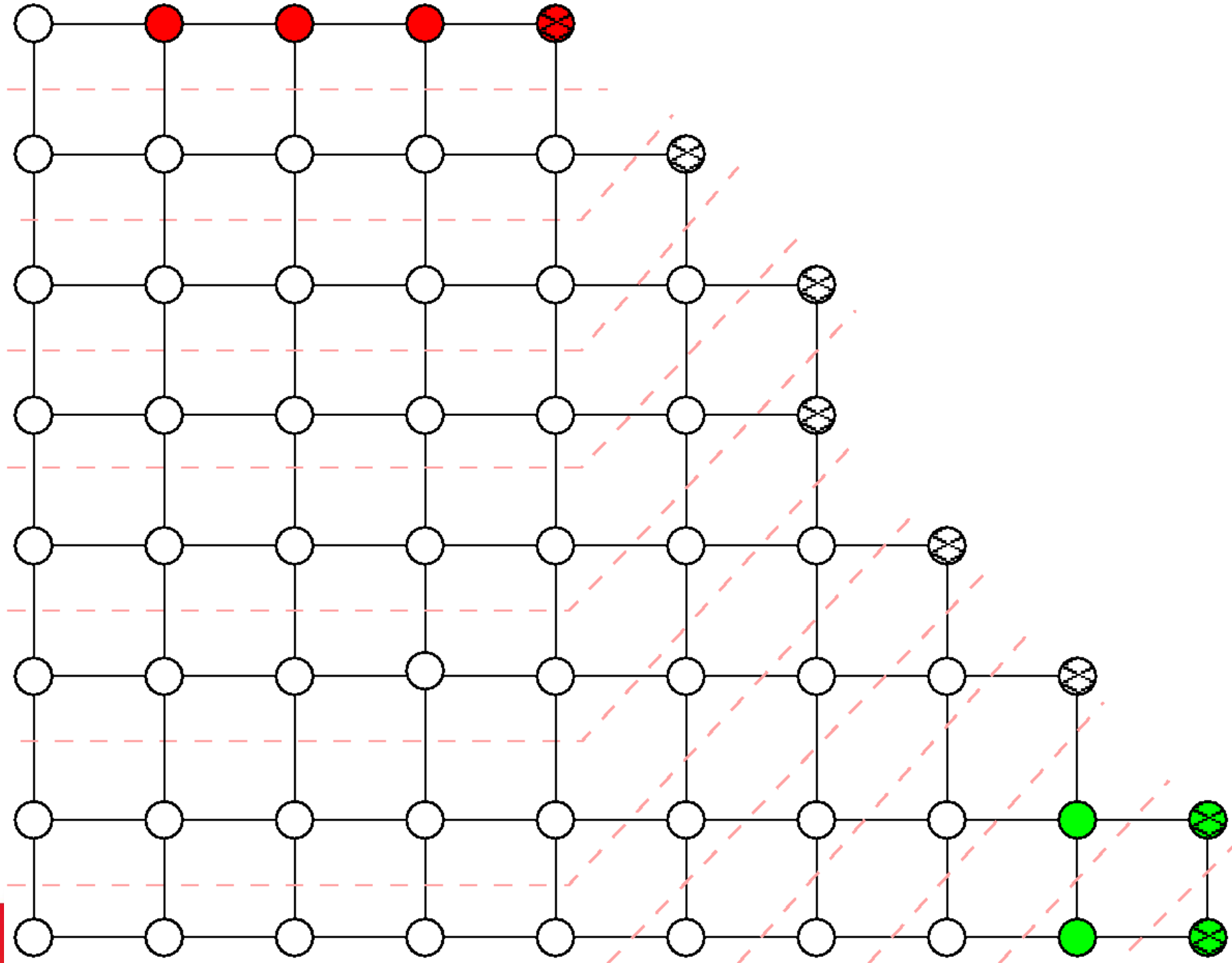


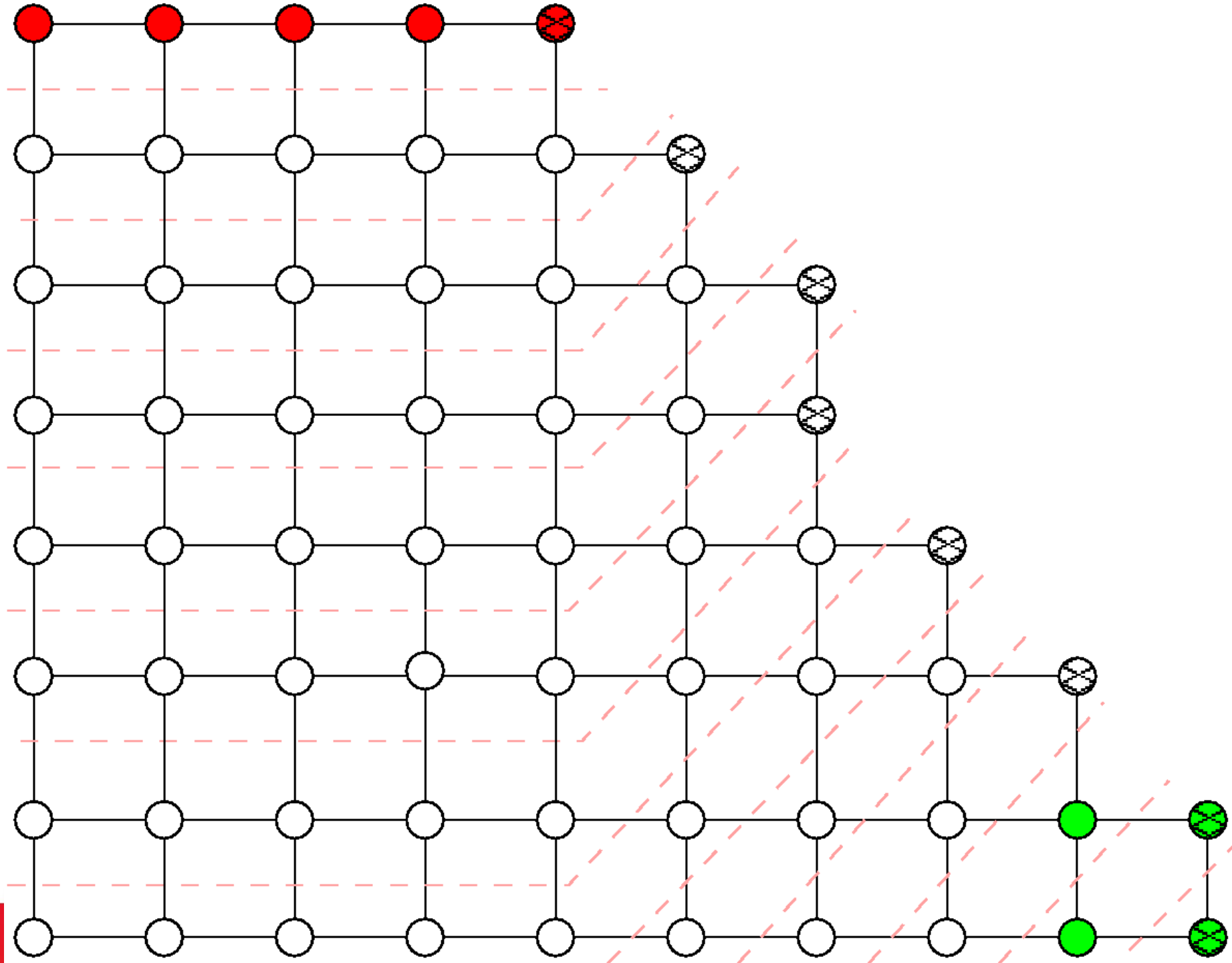


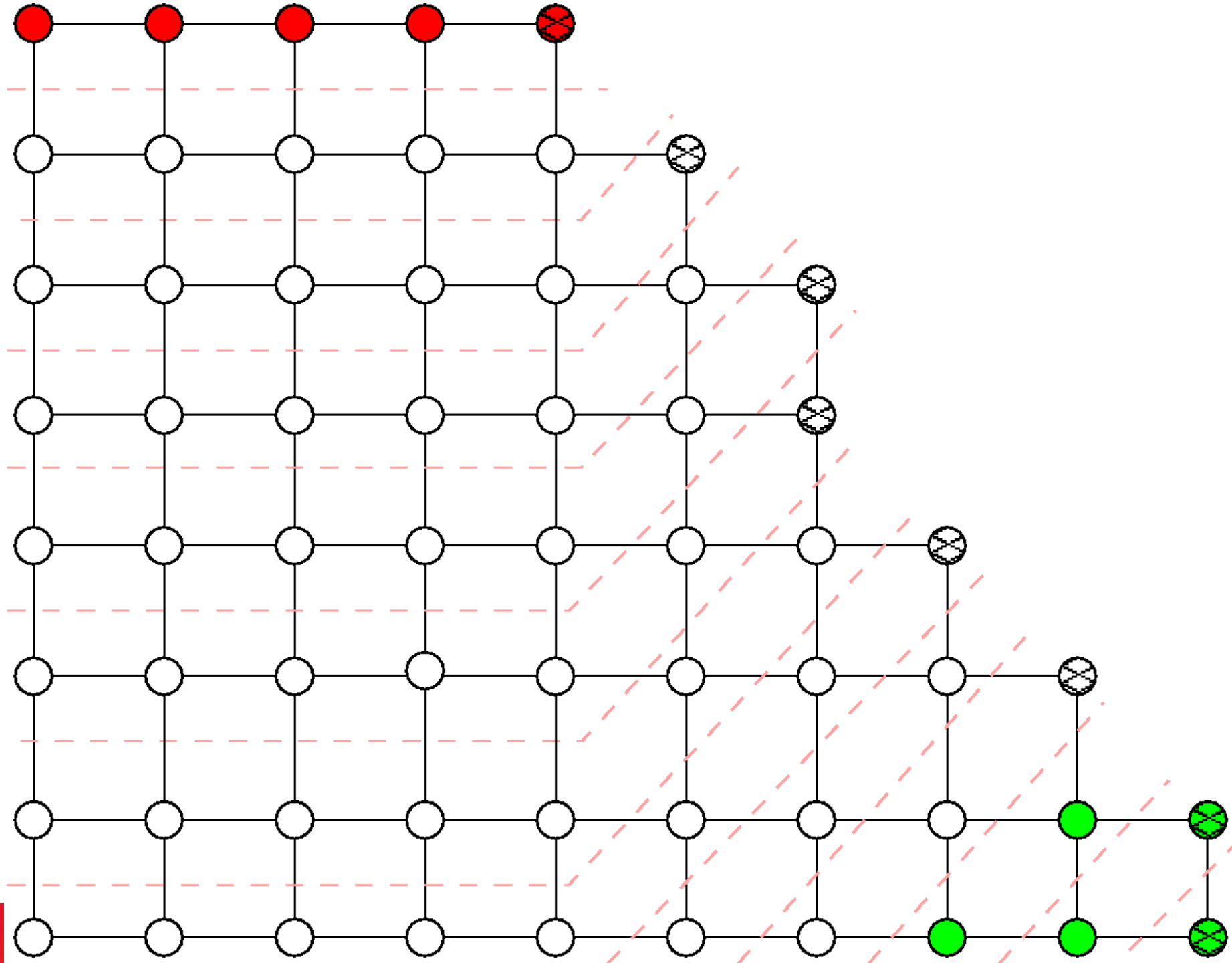


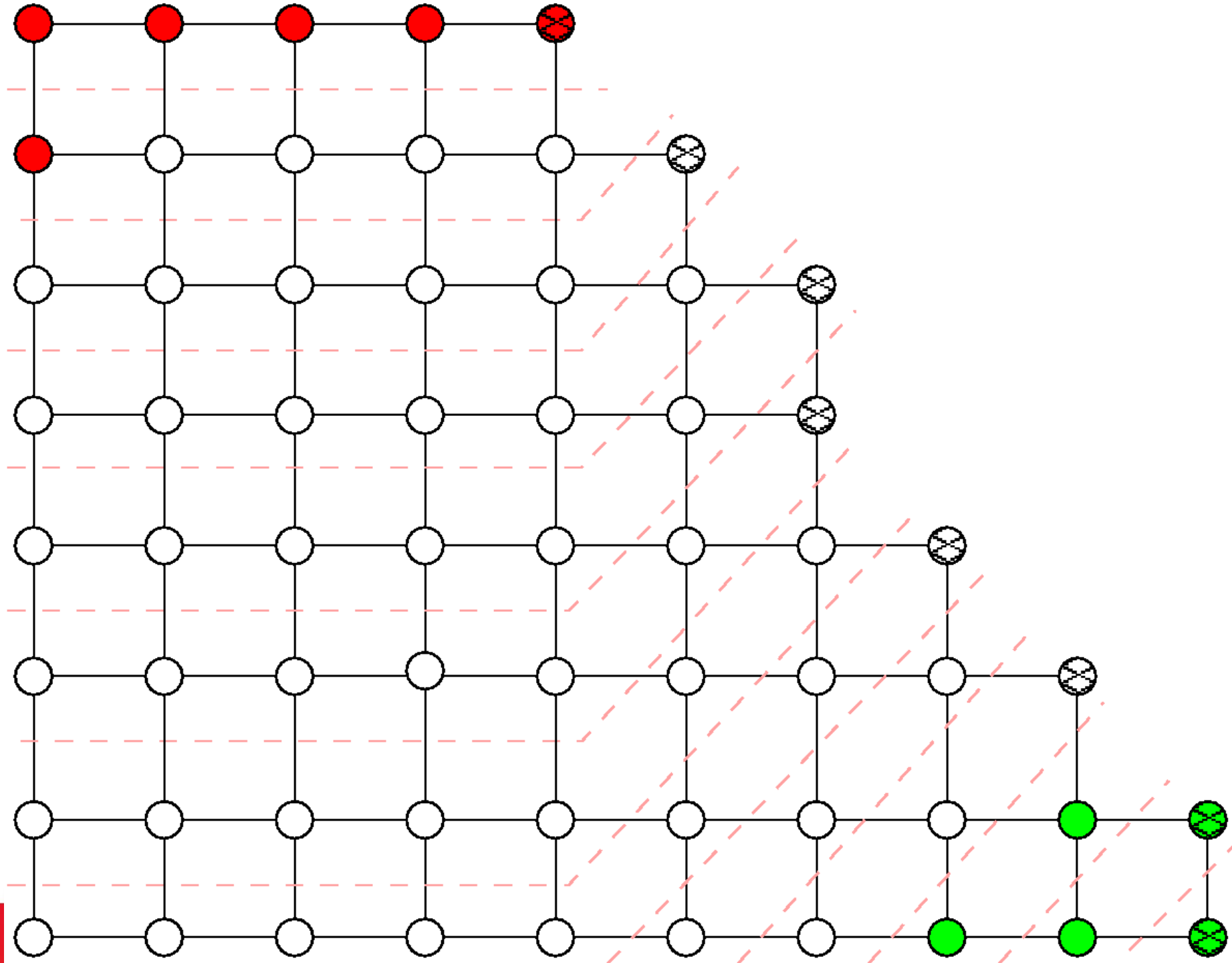


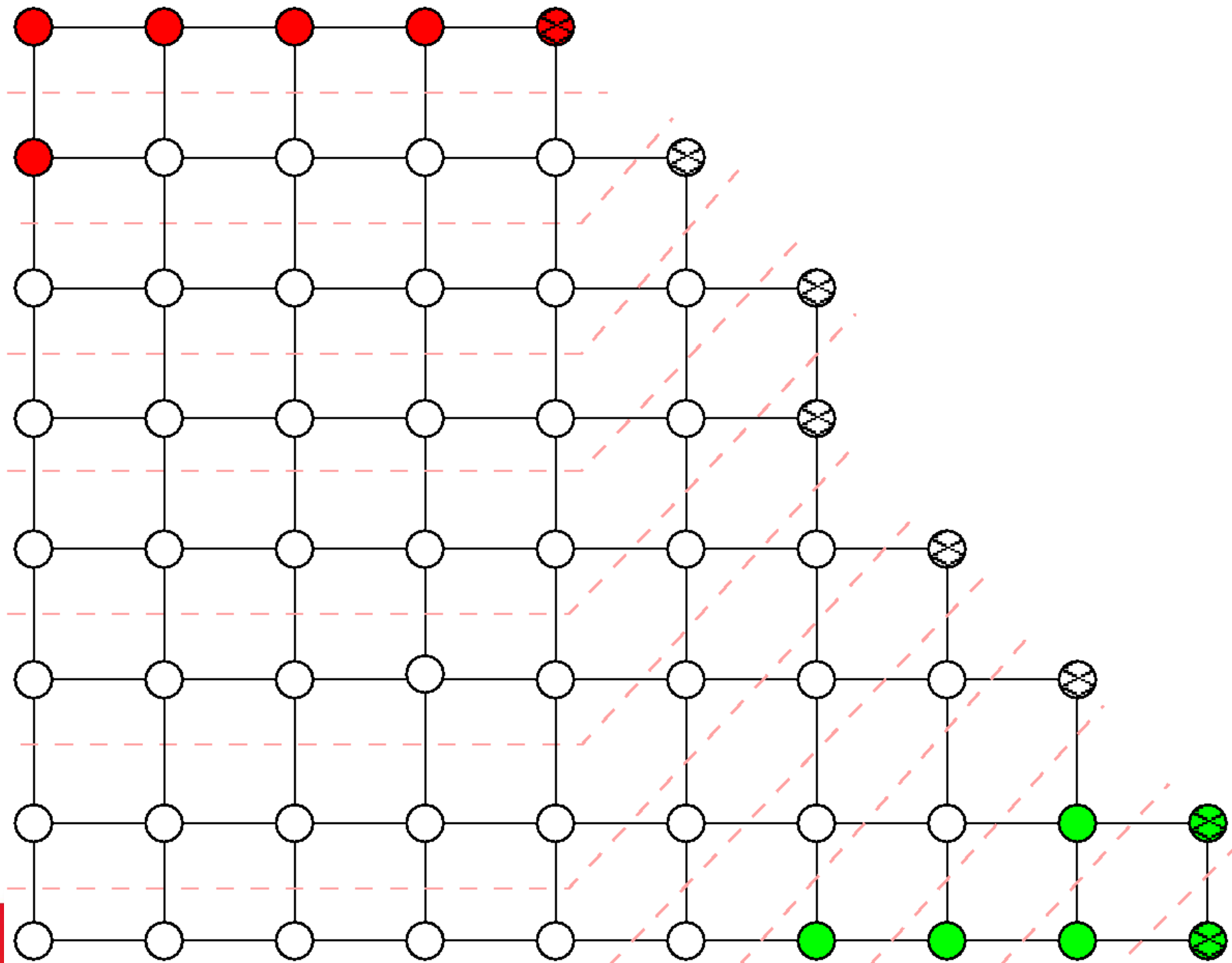


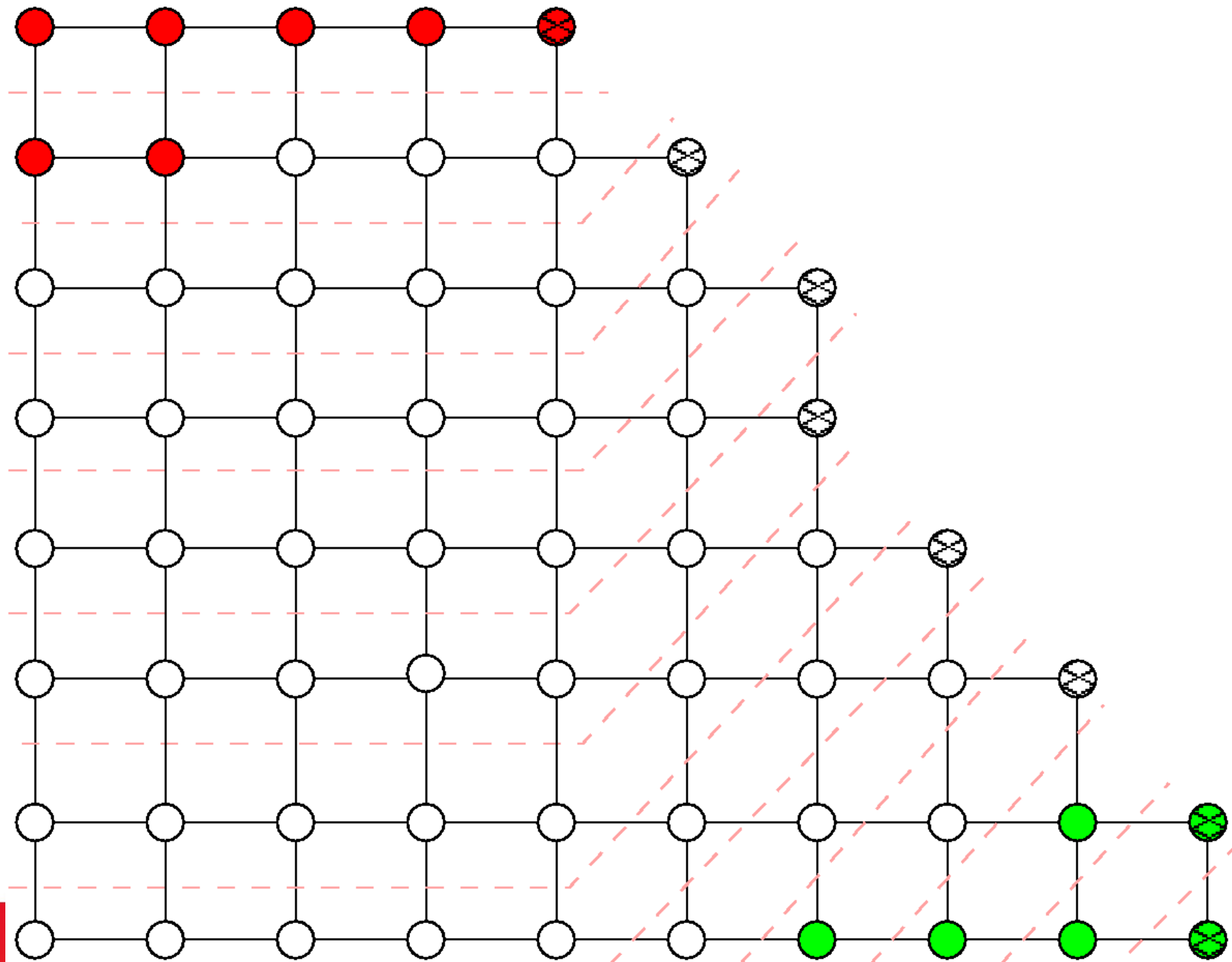


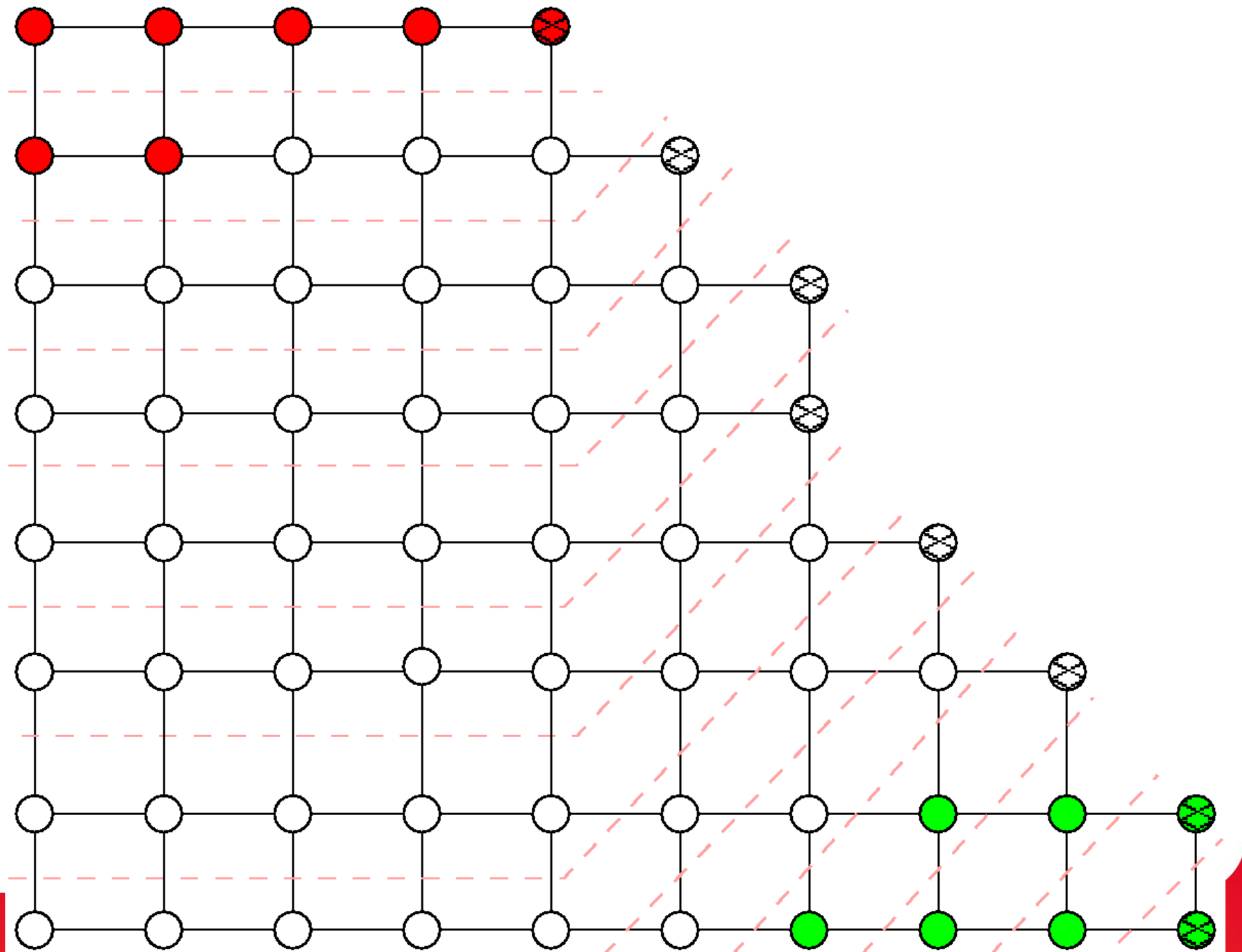


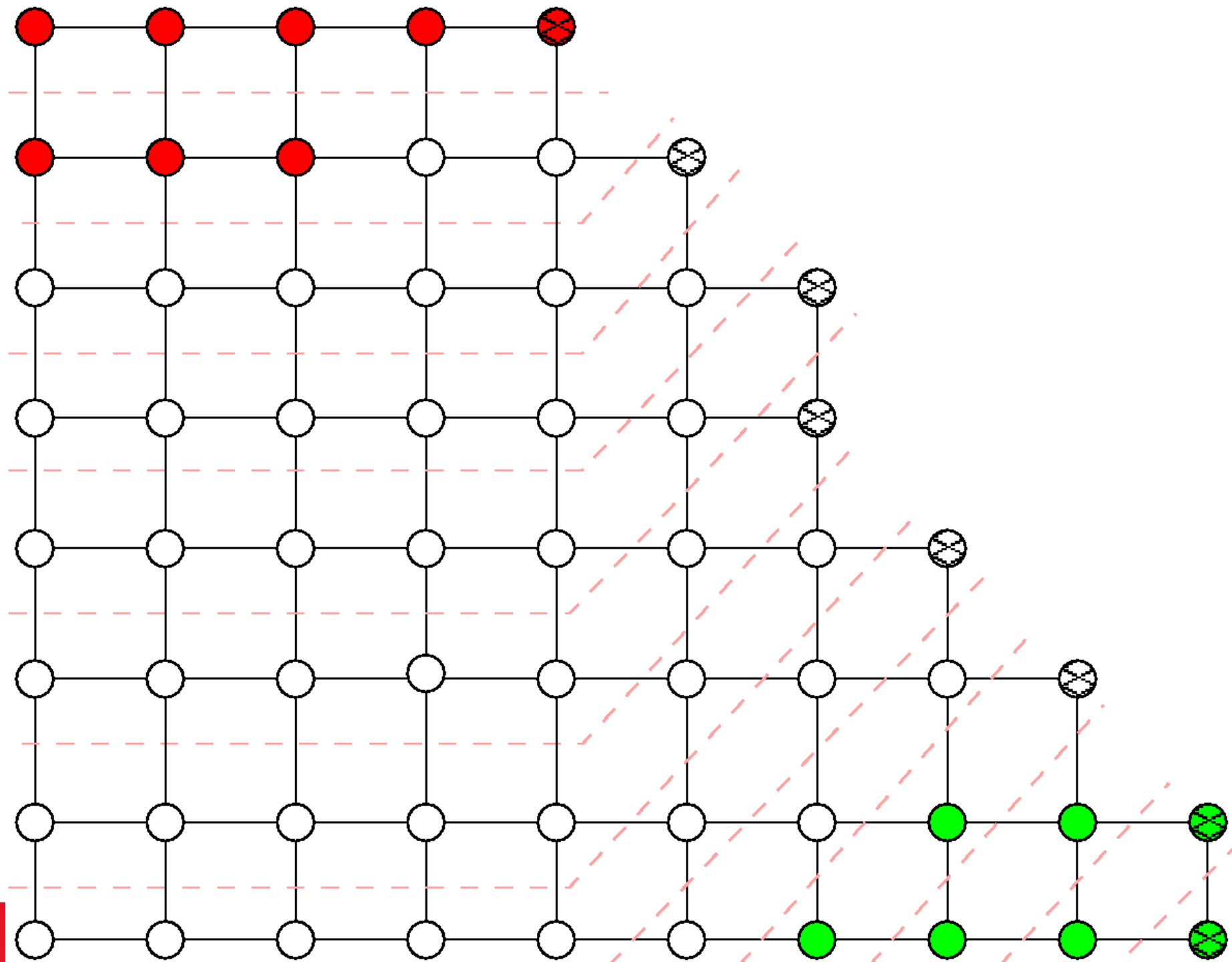


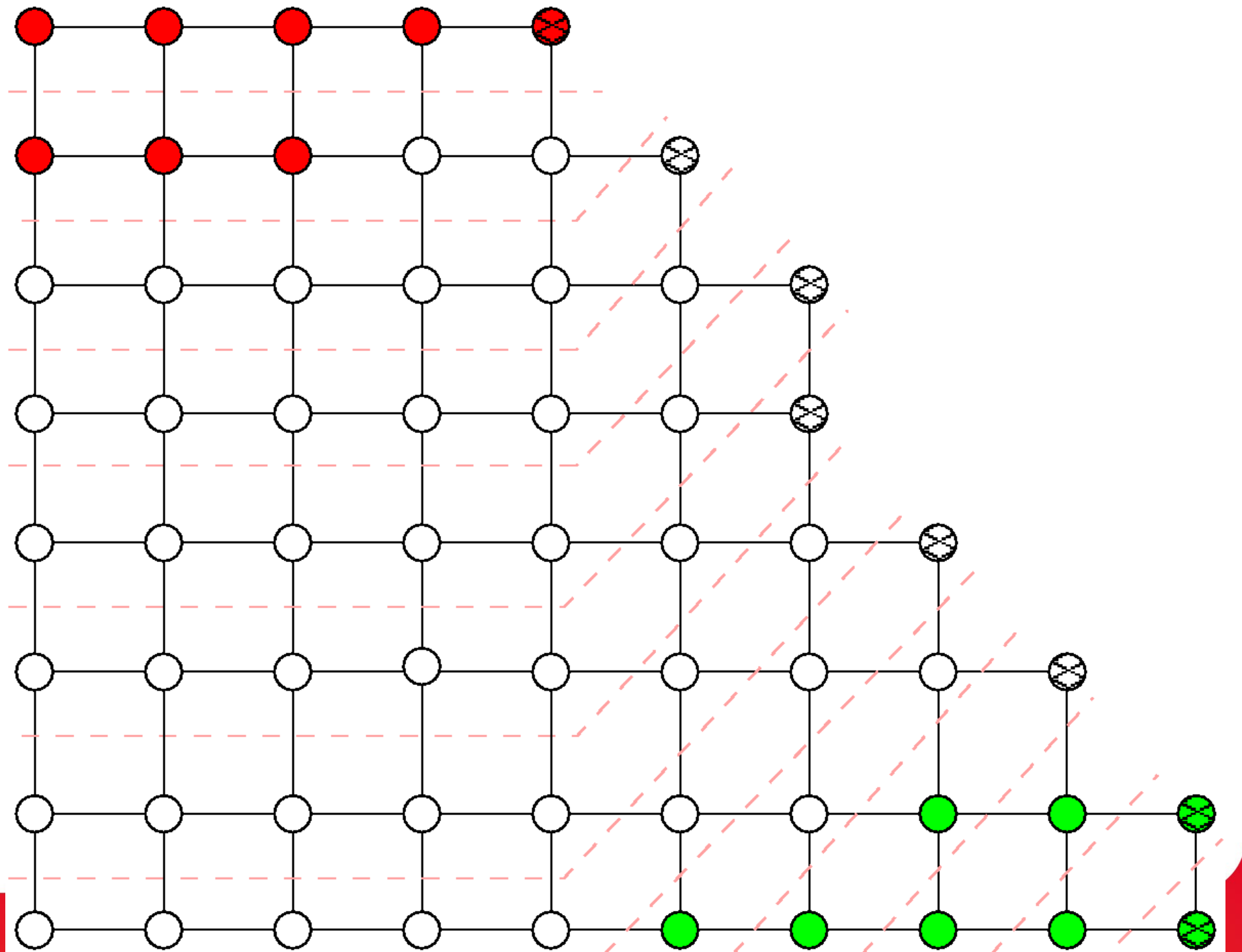


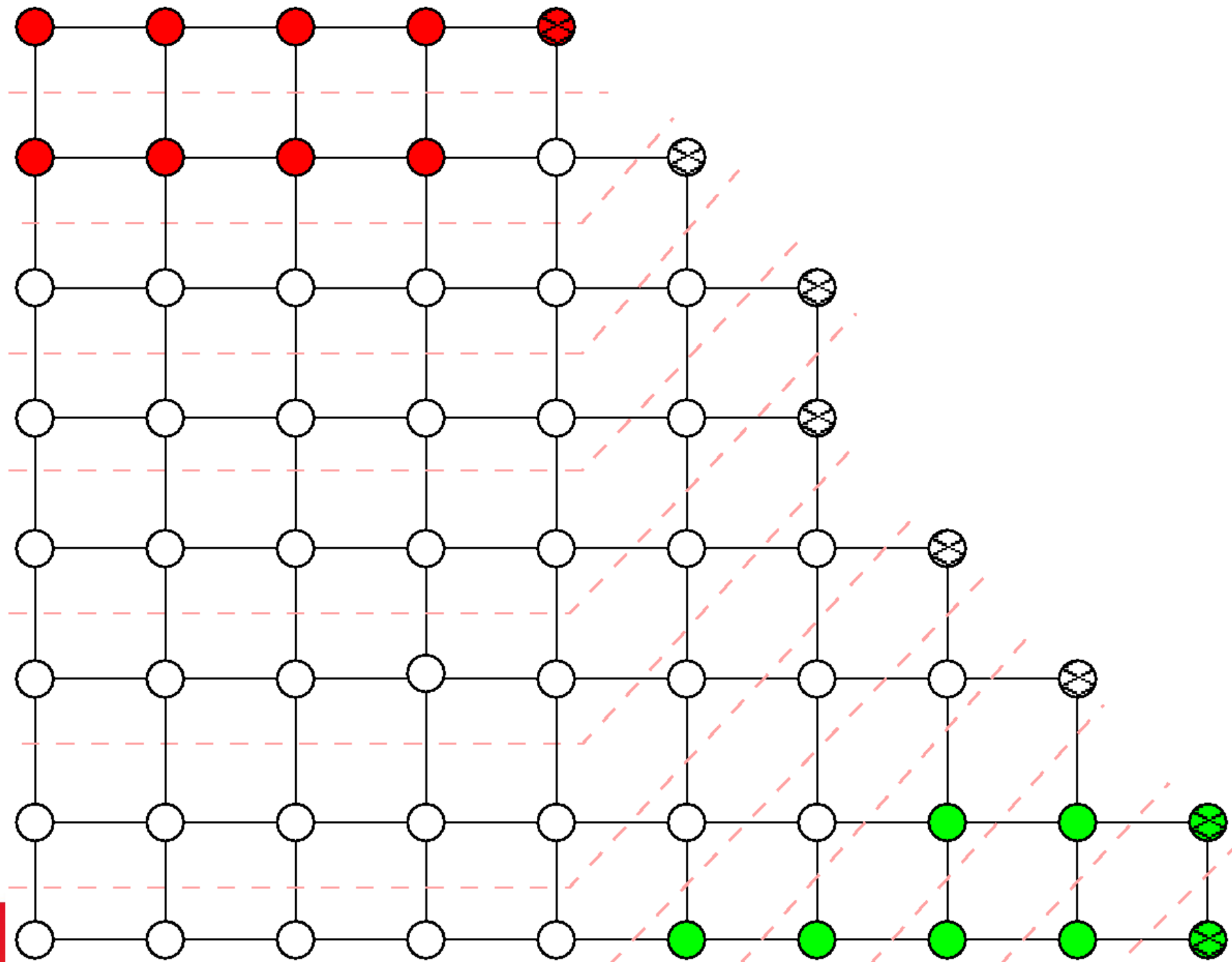


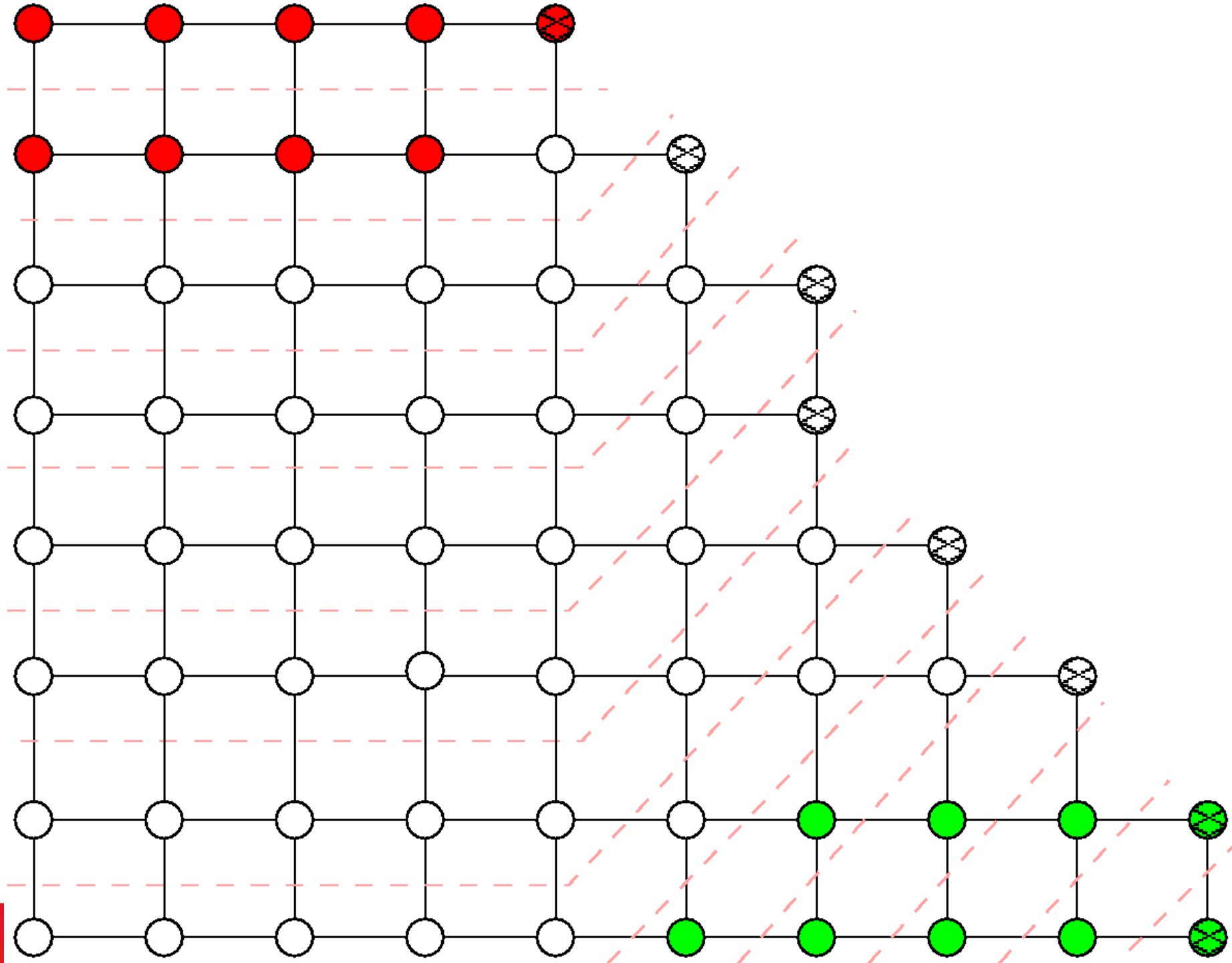


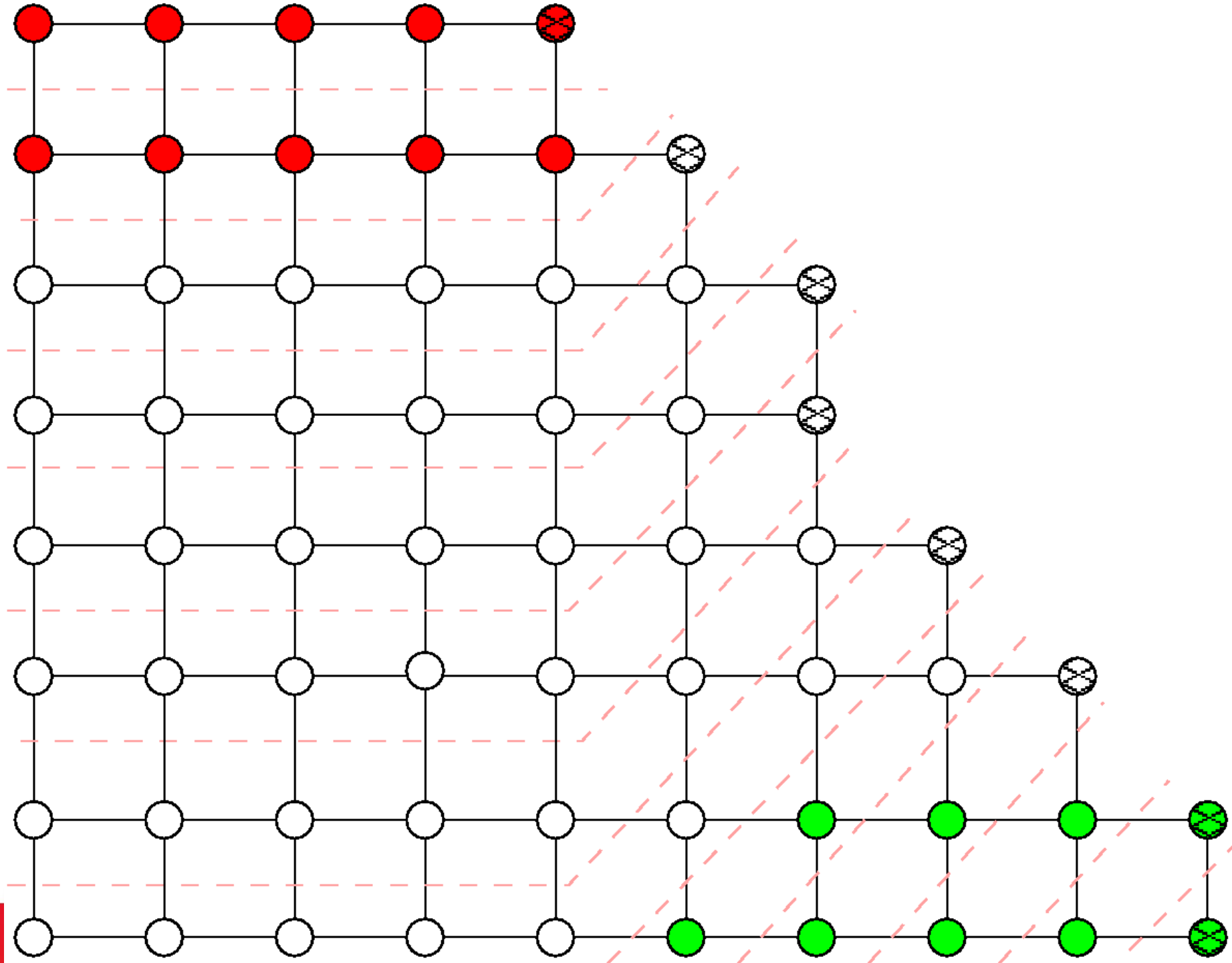


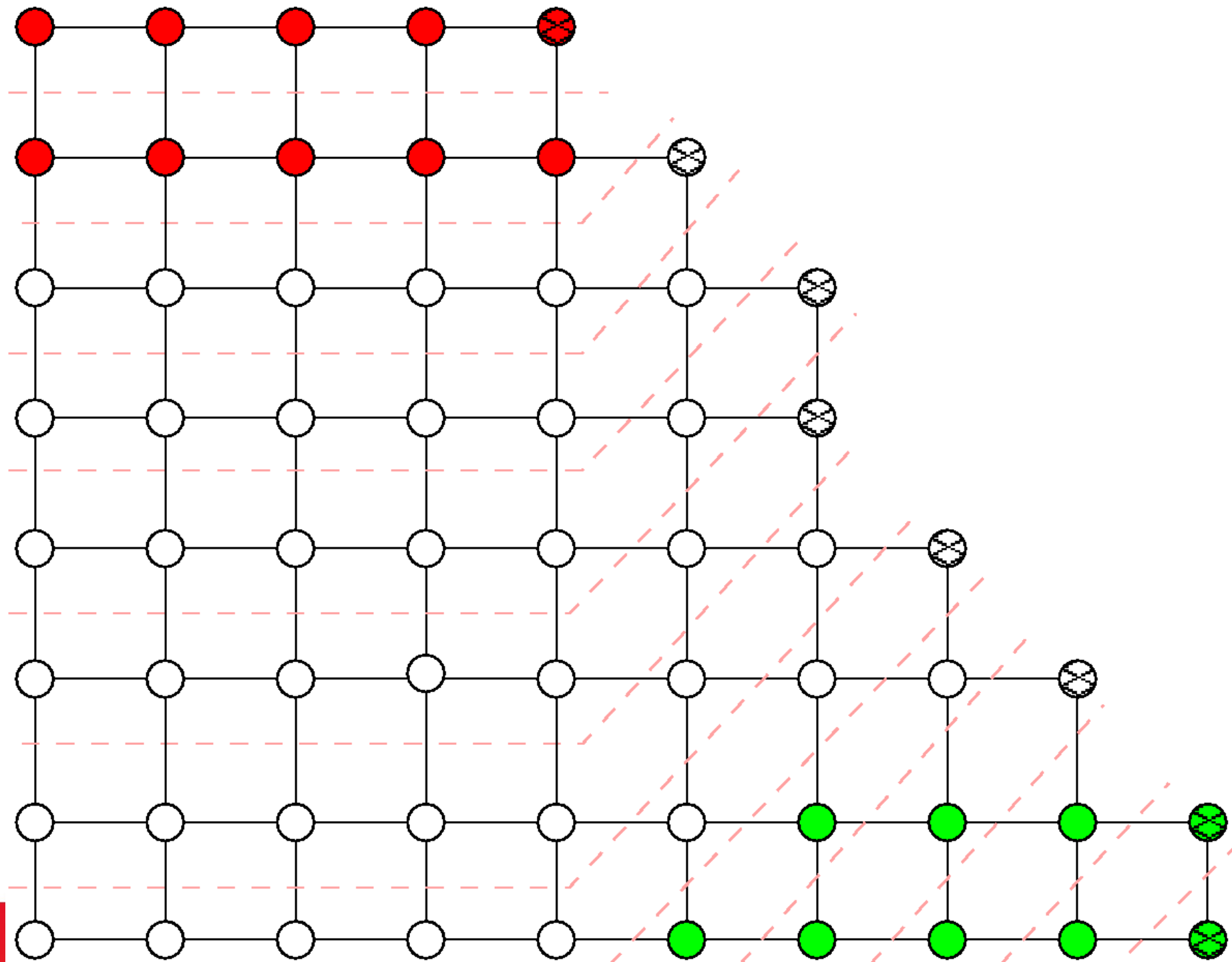


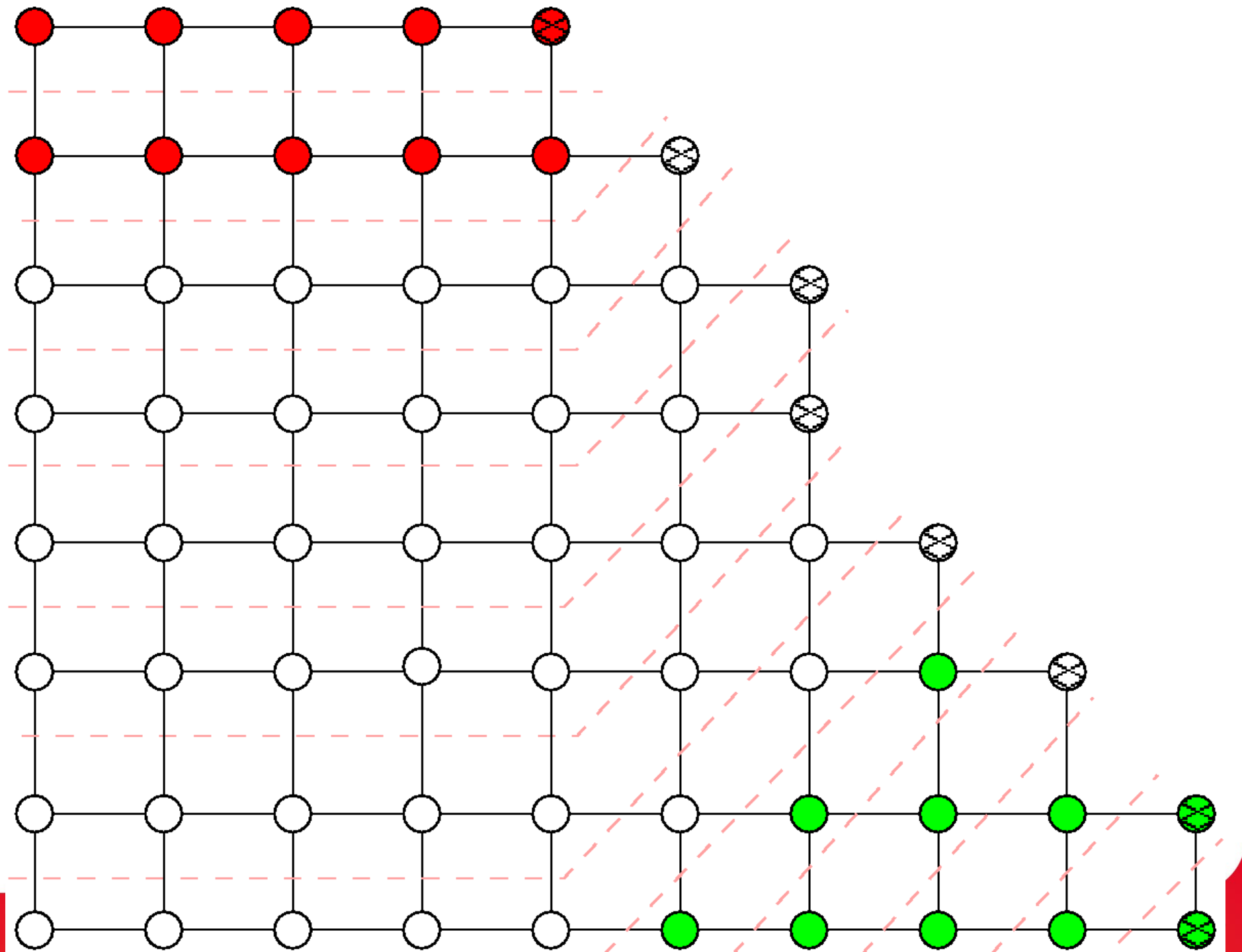


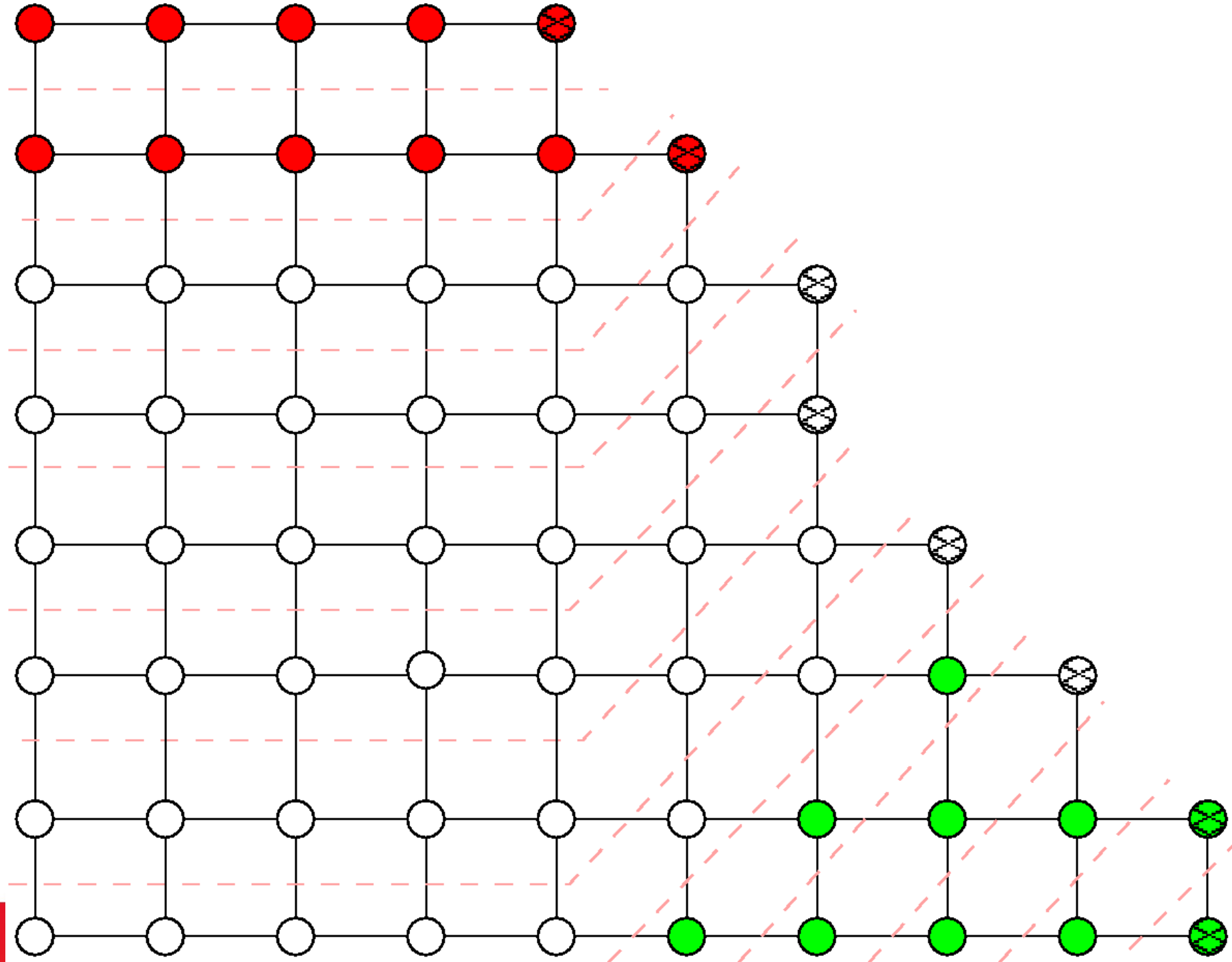


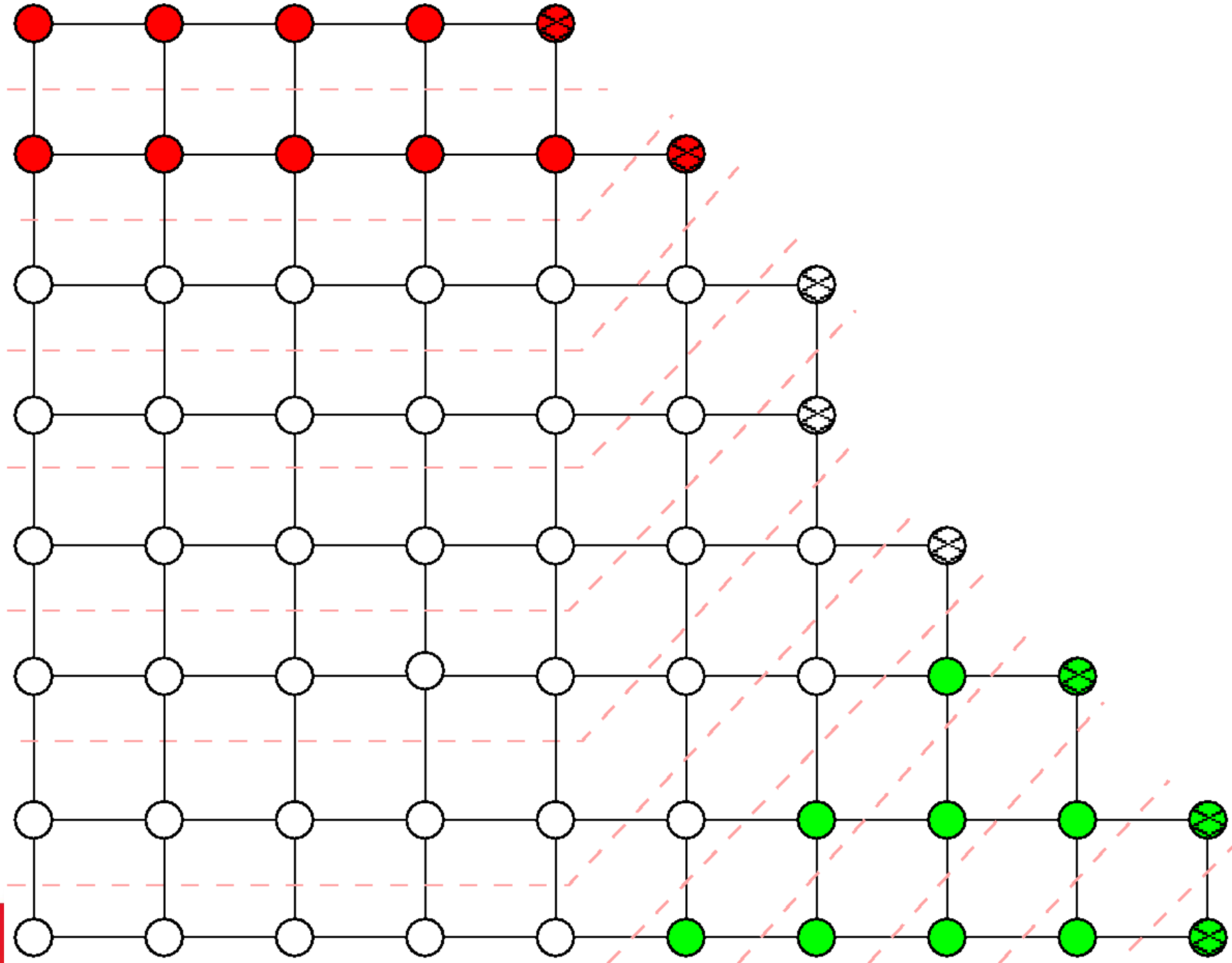


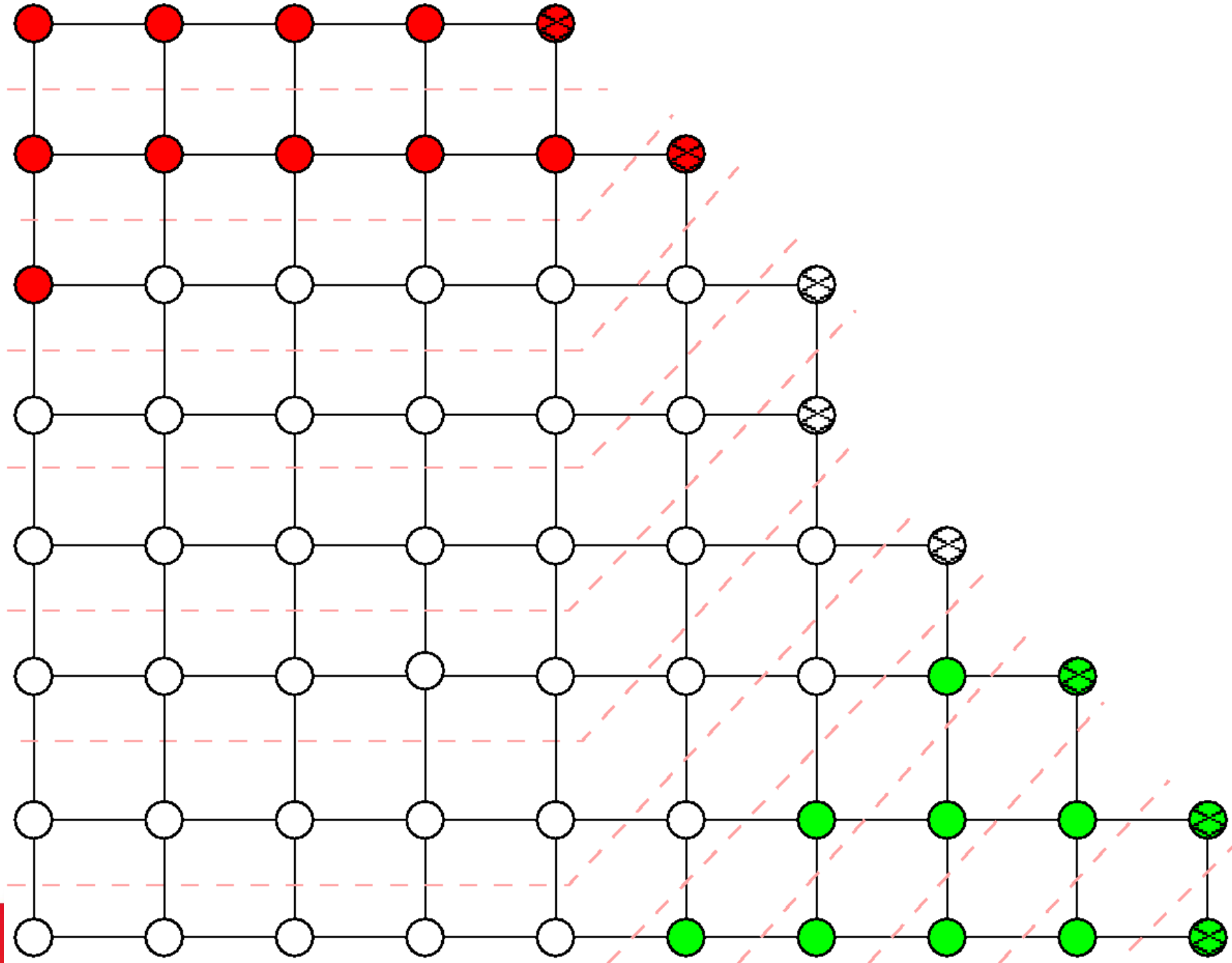


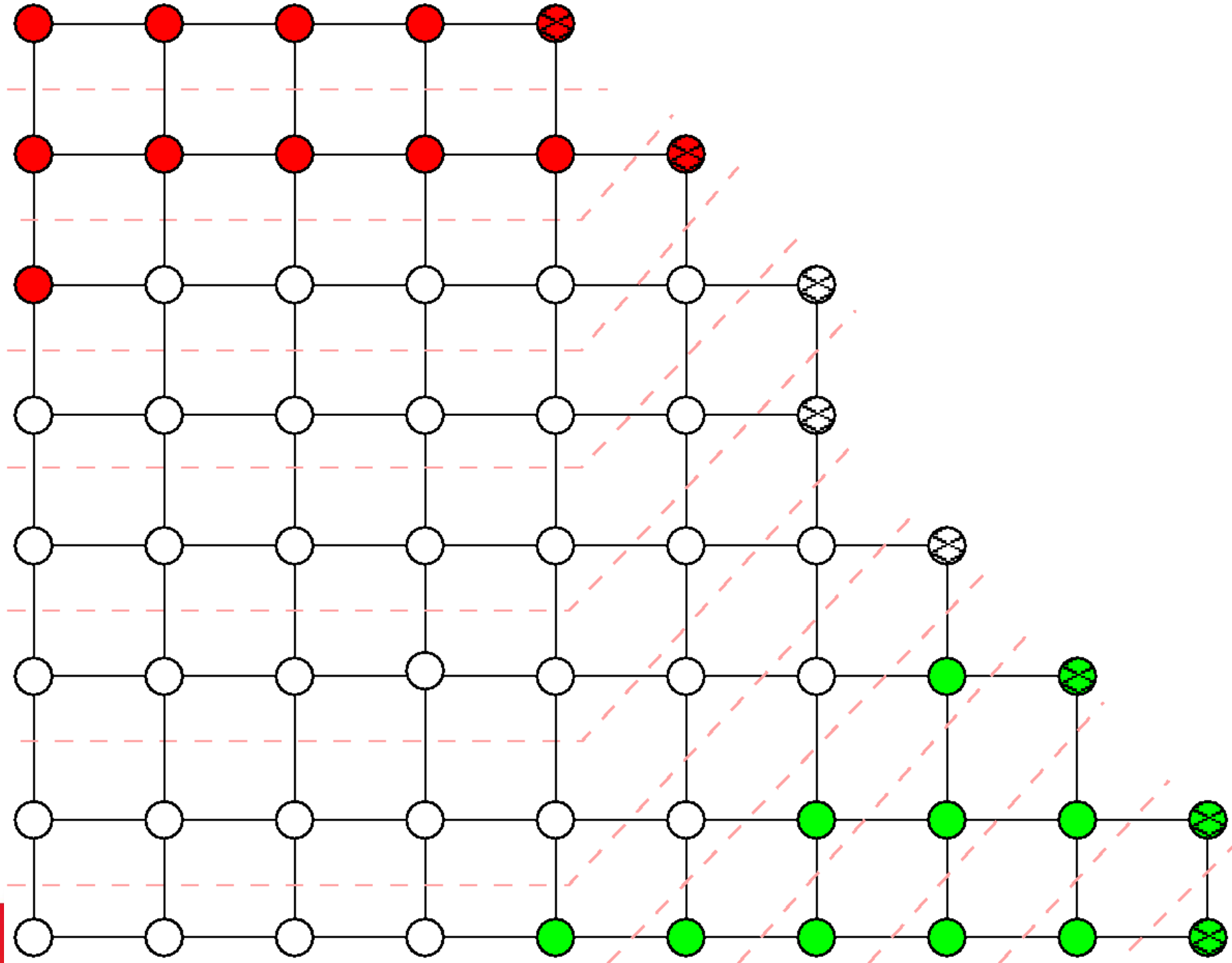


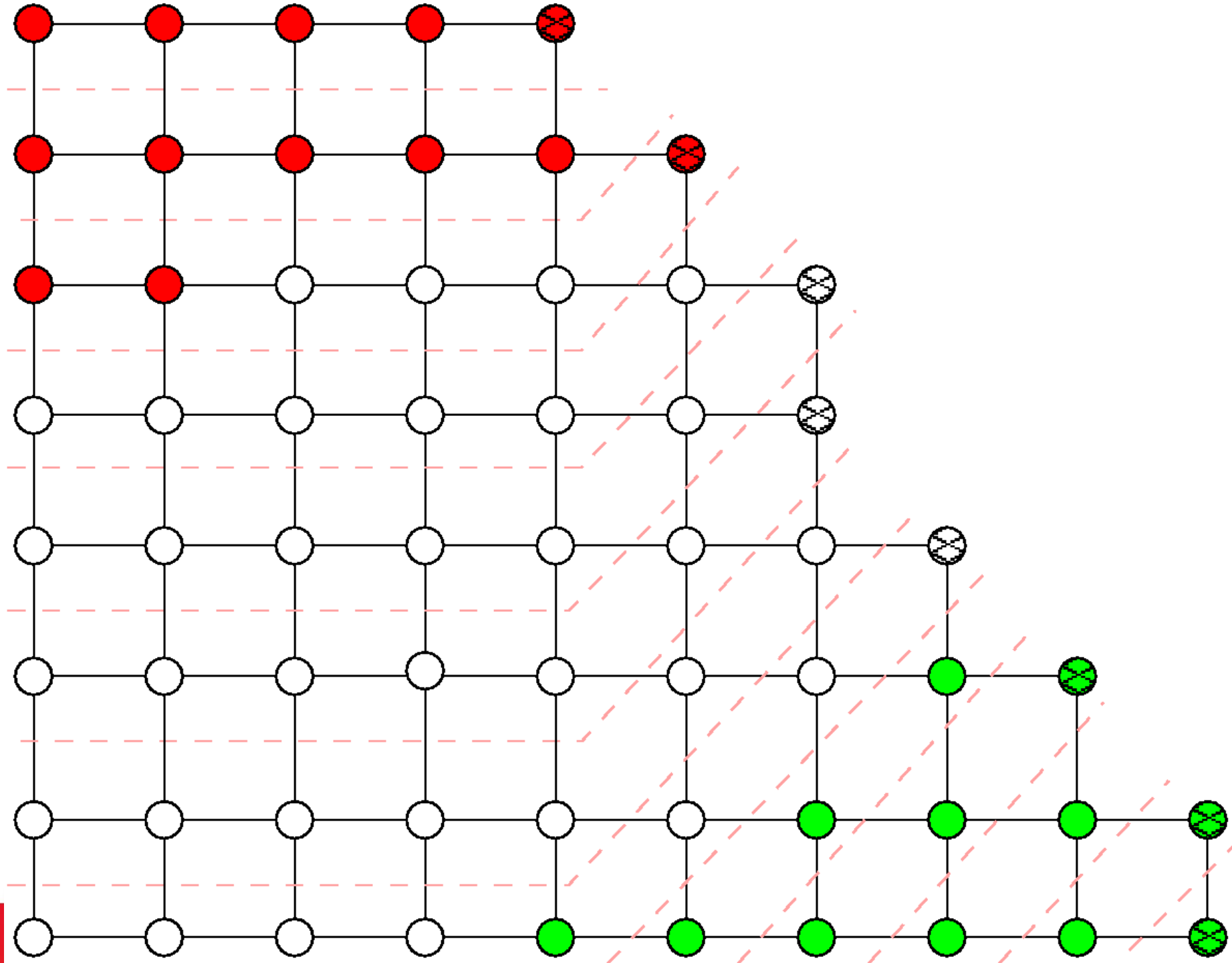


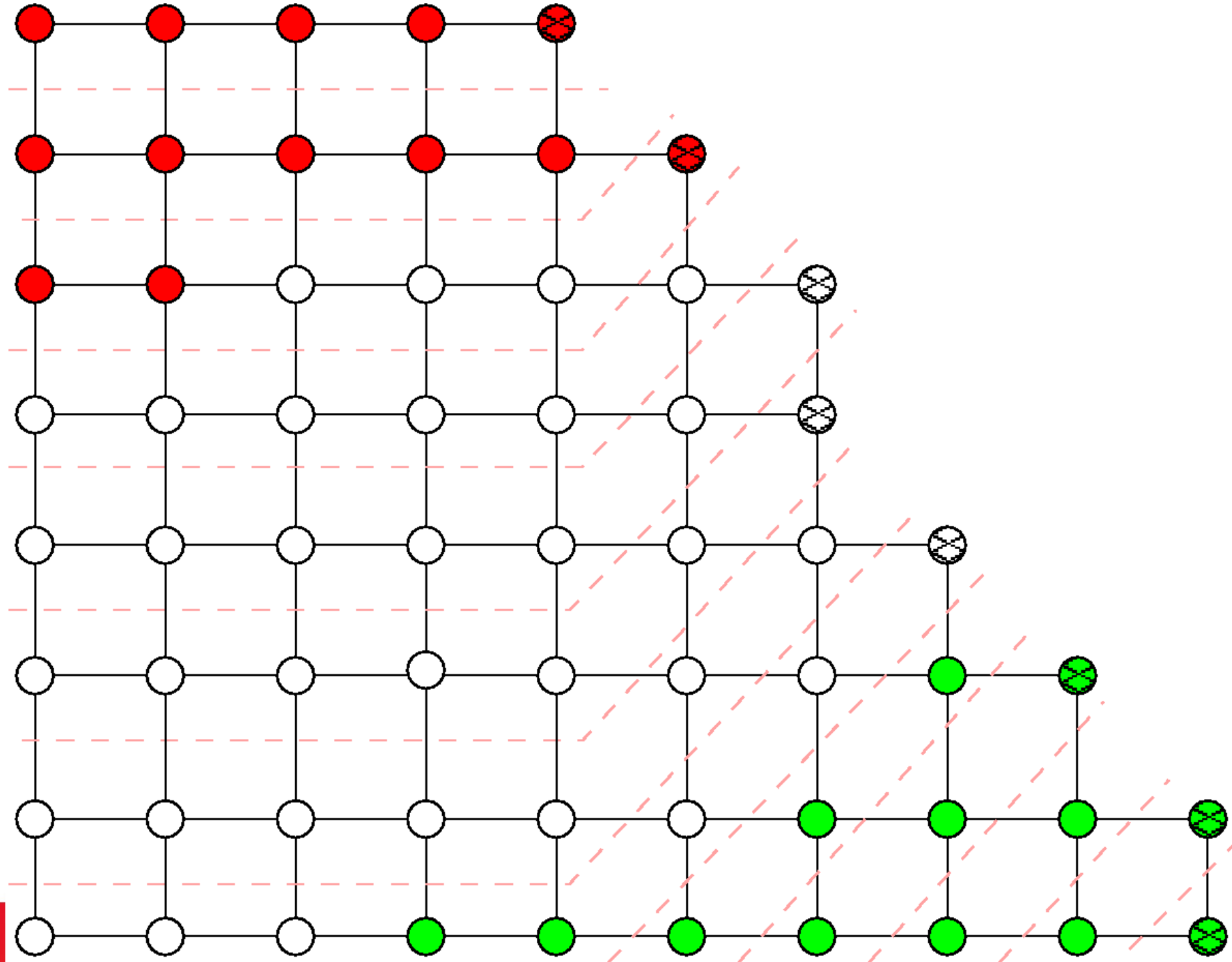


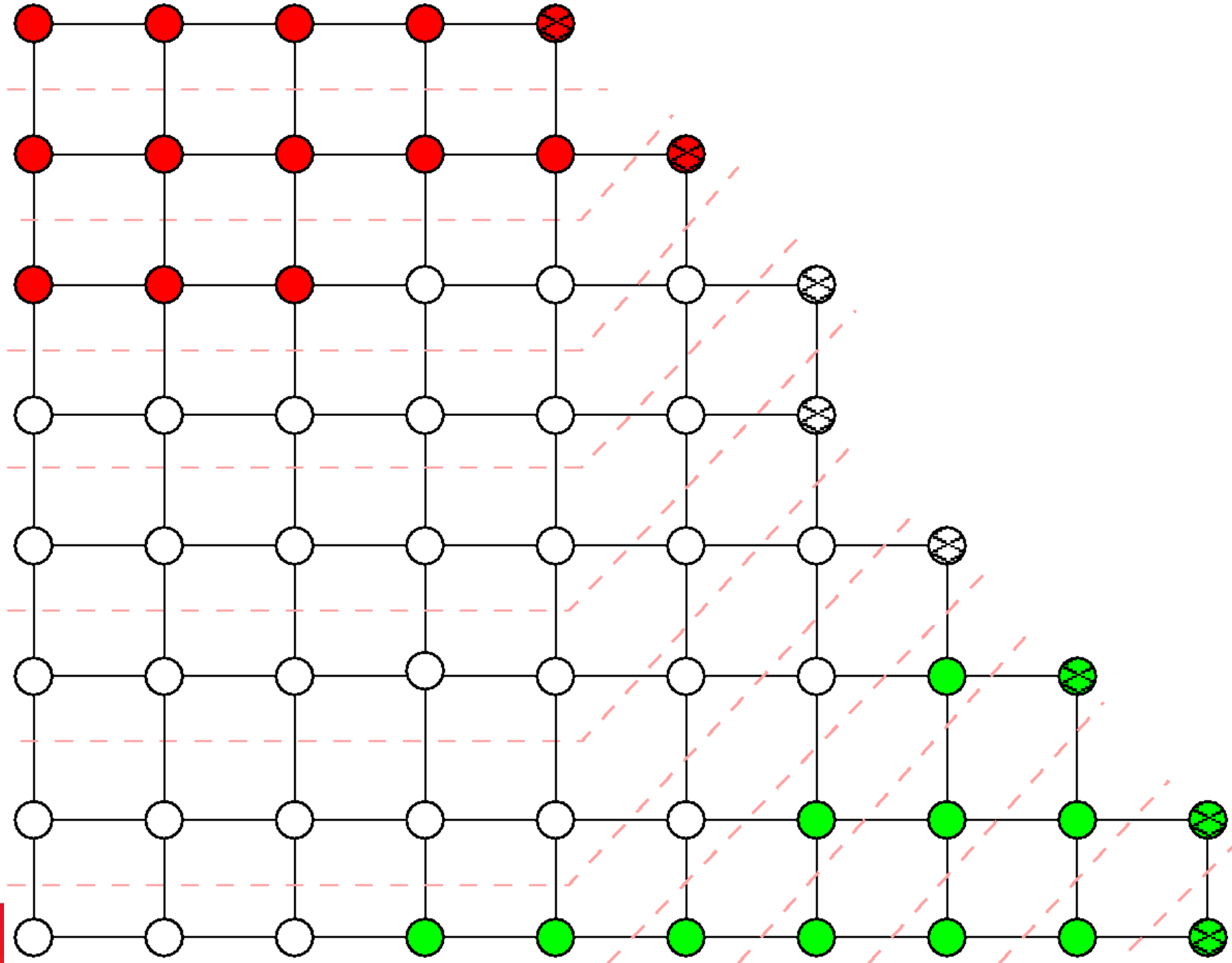


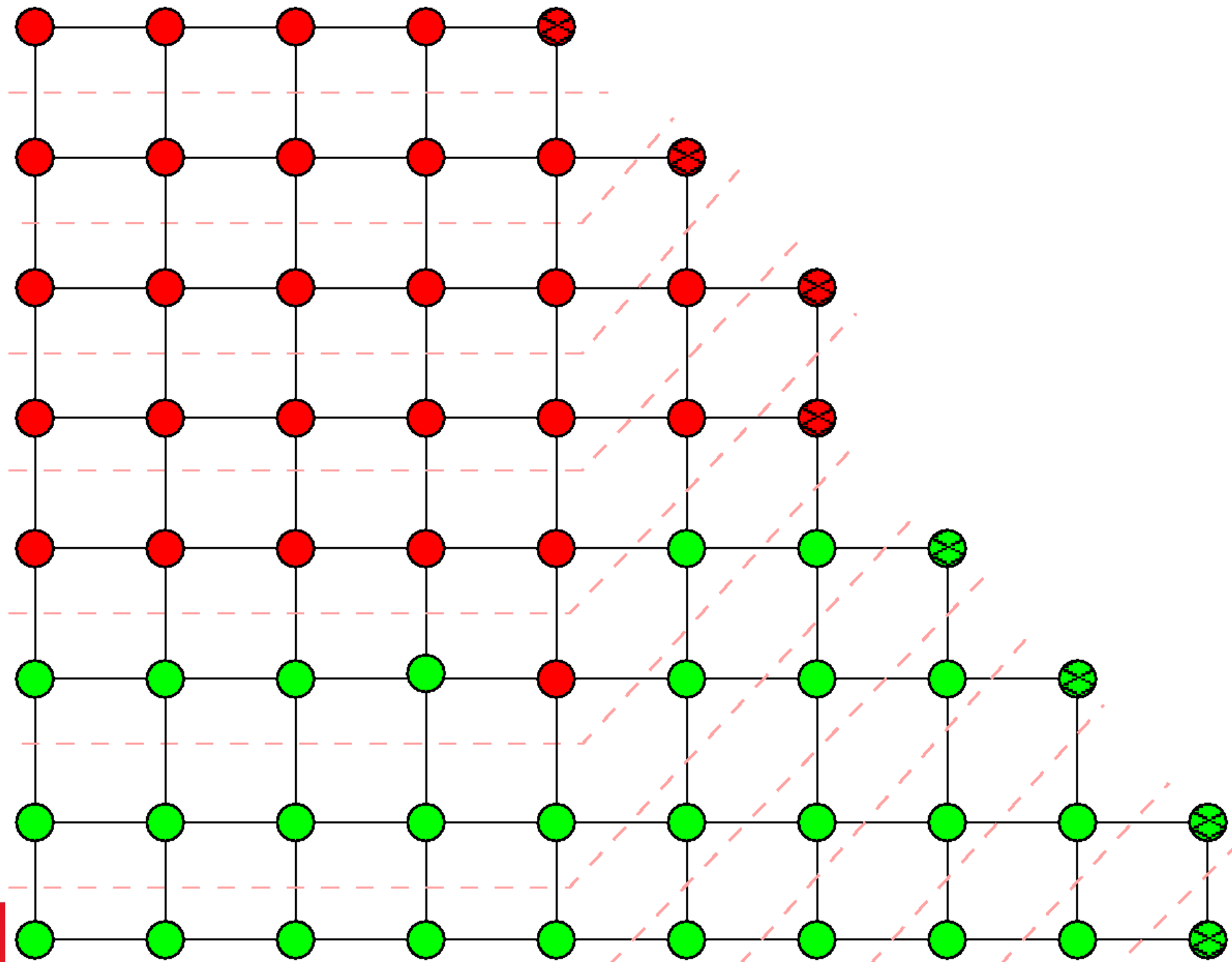


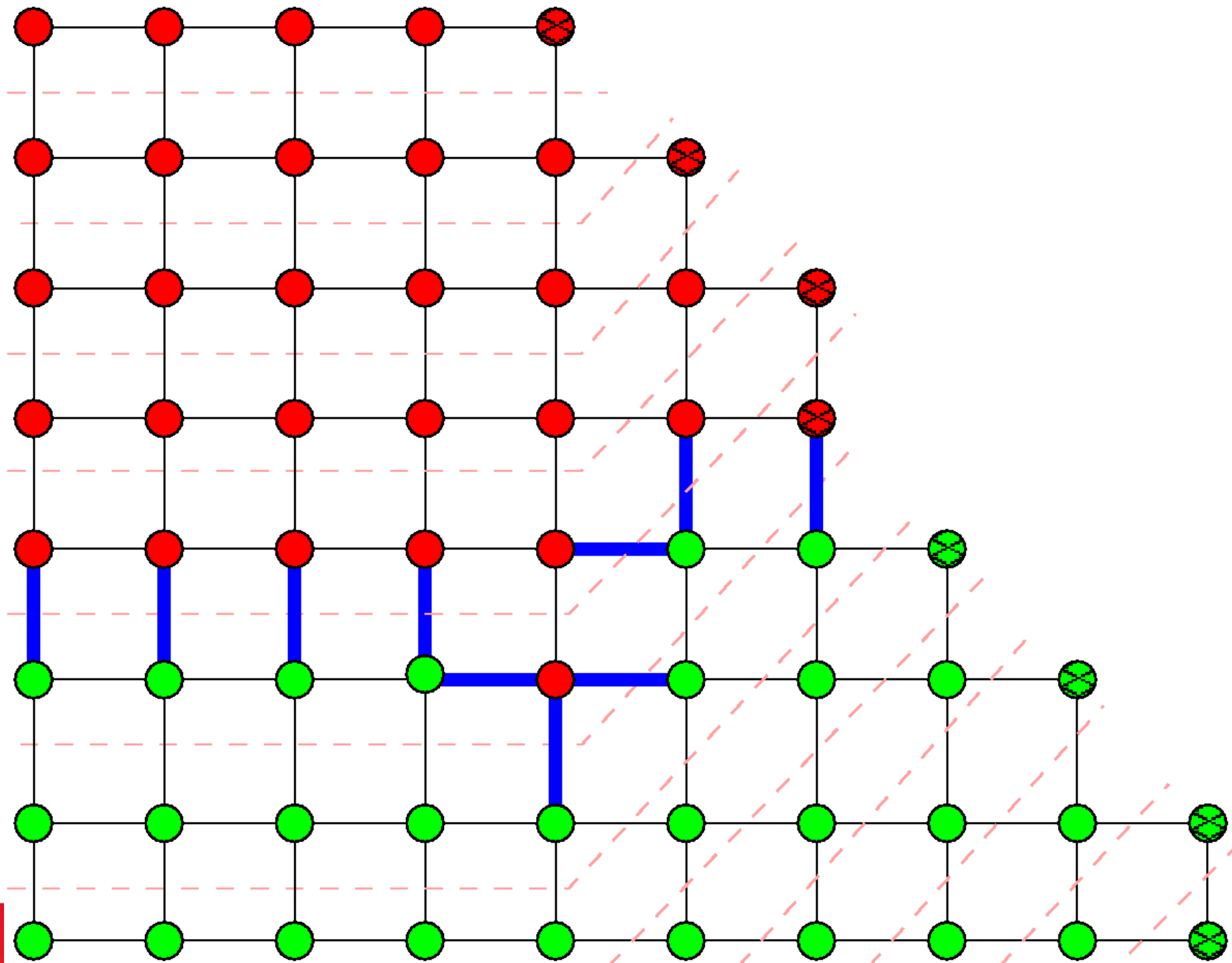


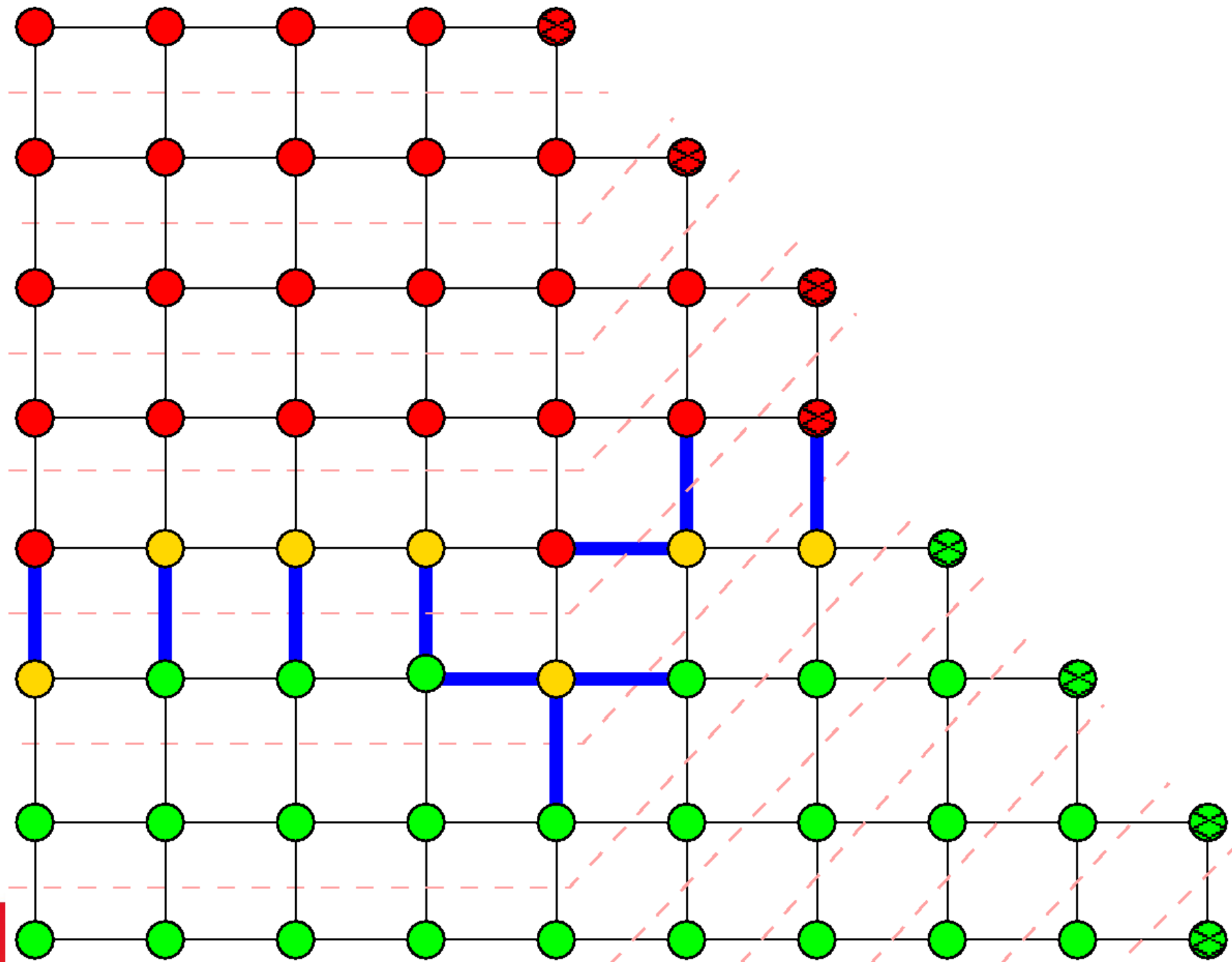


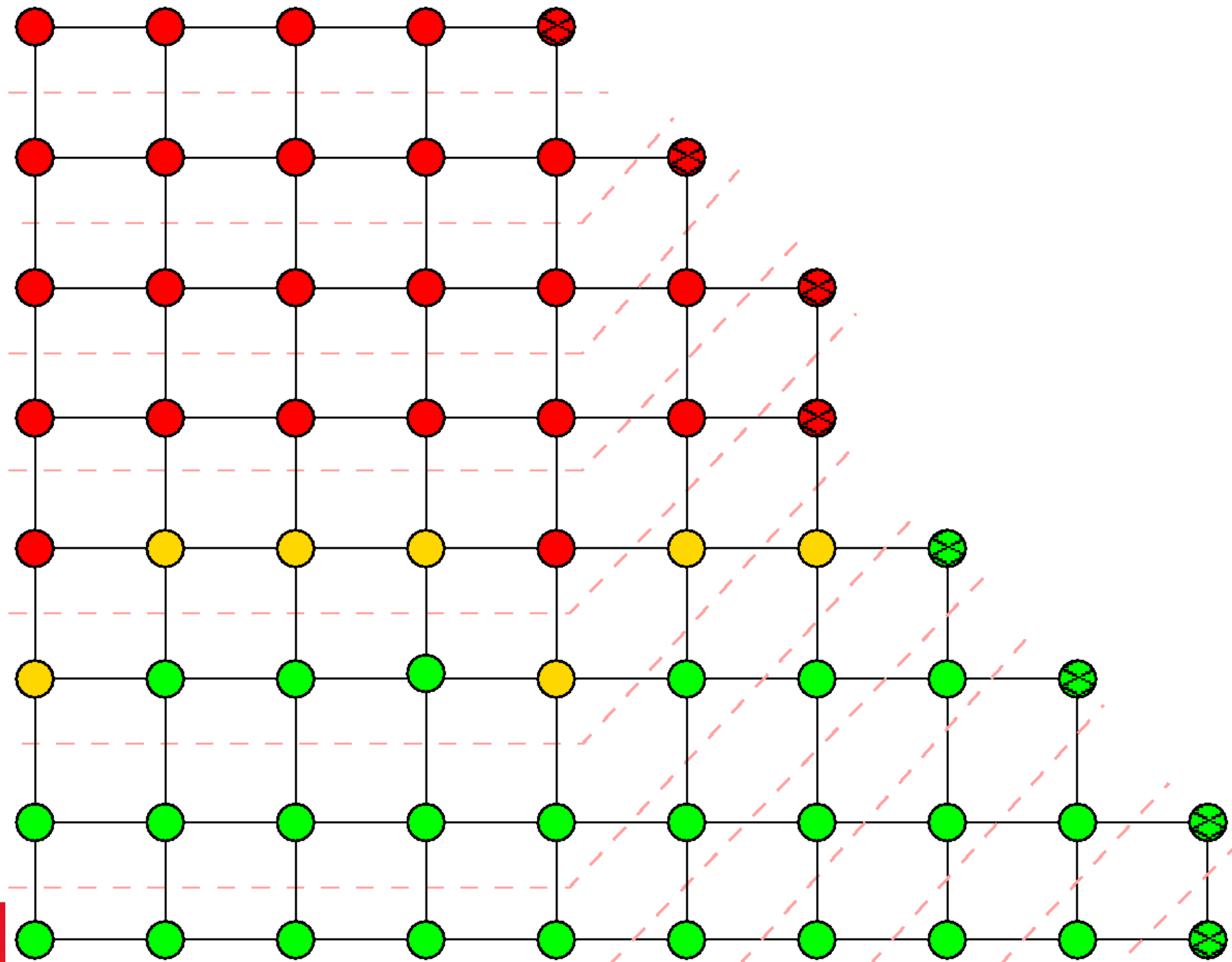




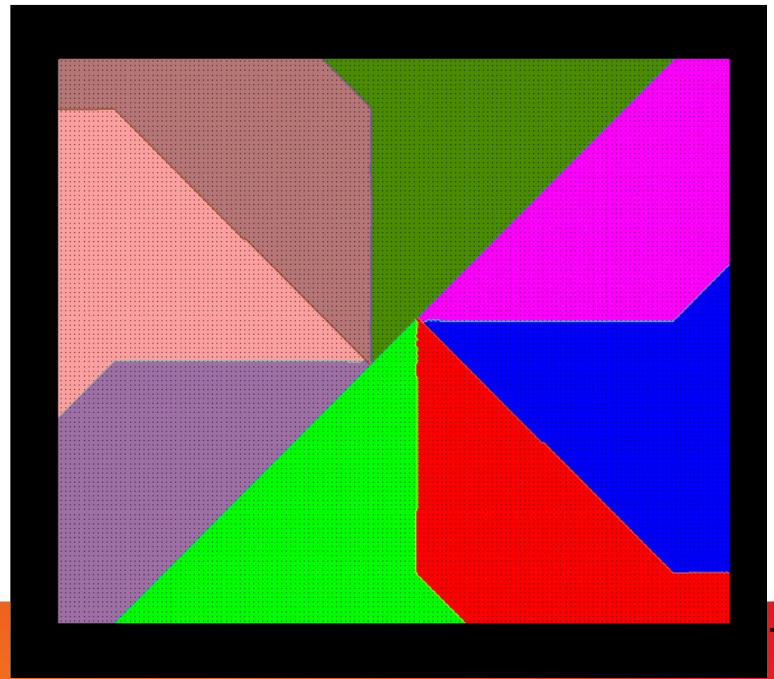
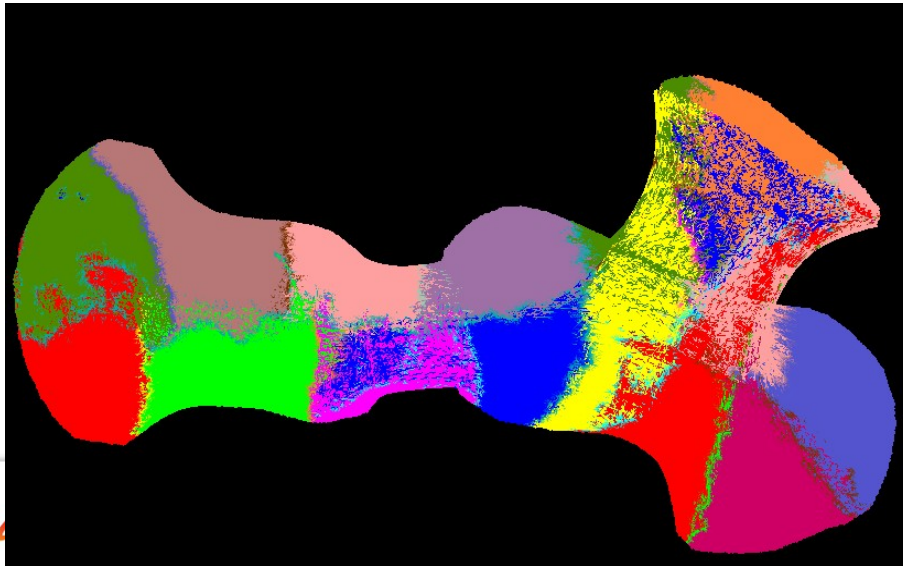
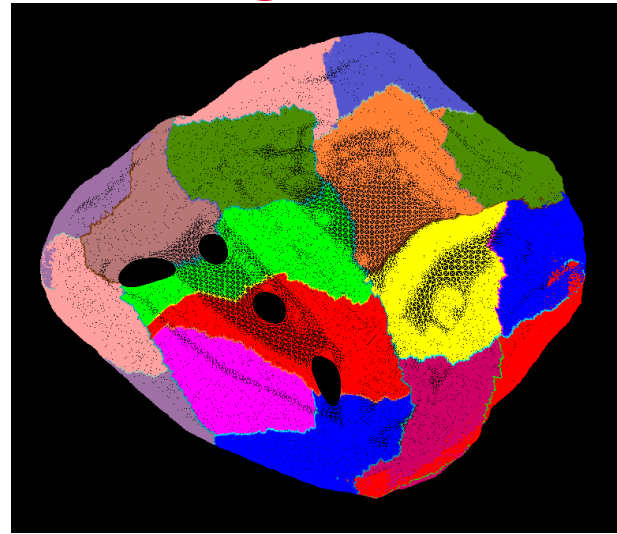
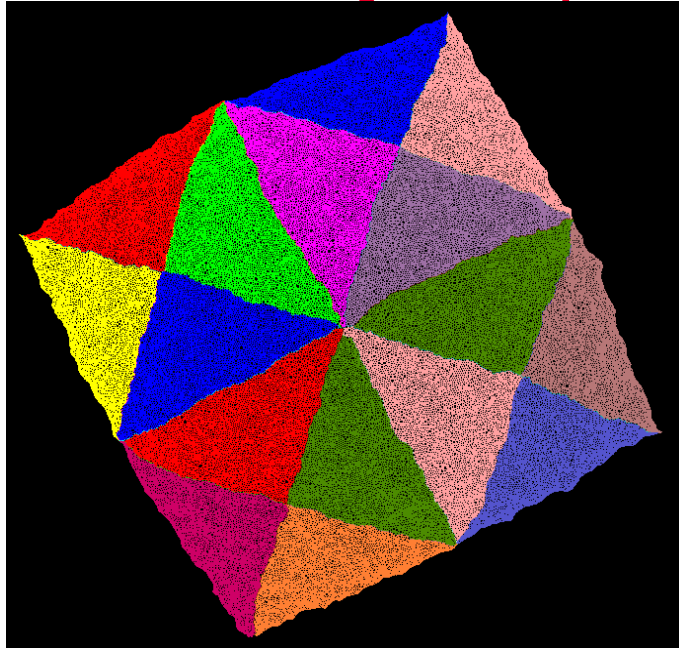




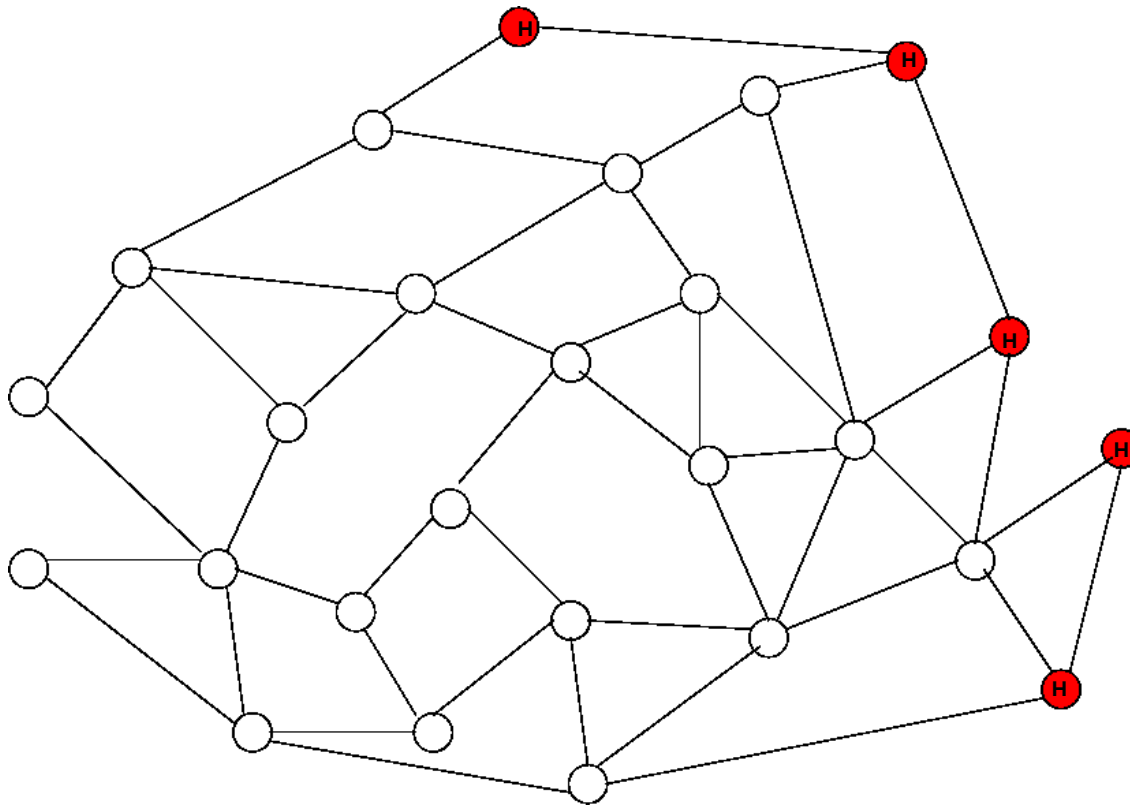




6 Double Greedy Graph Growing



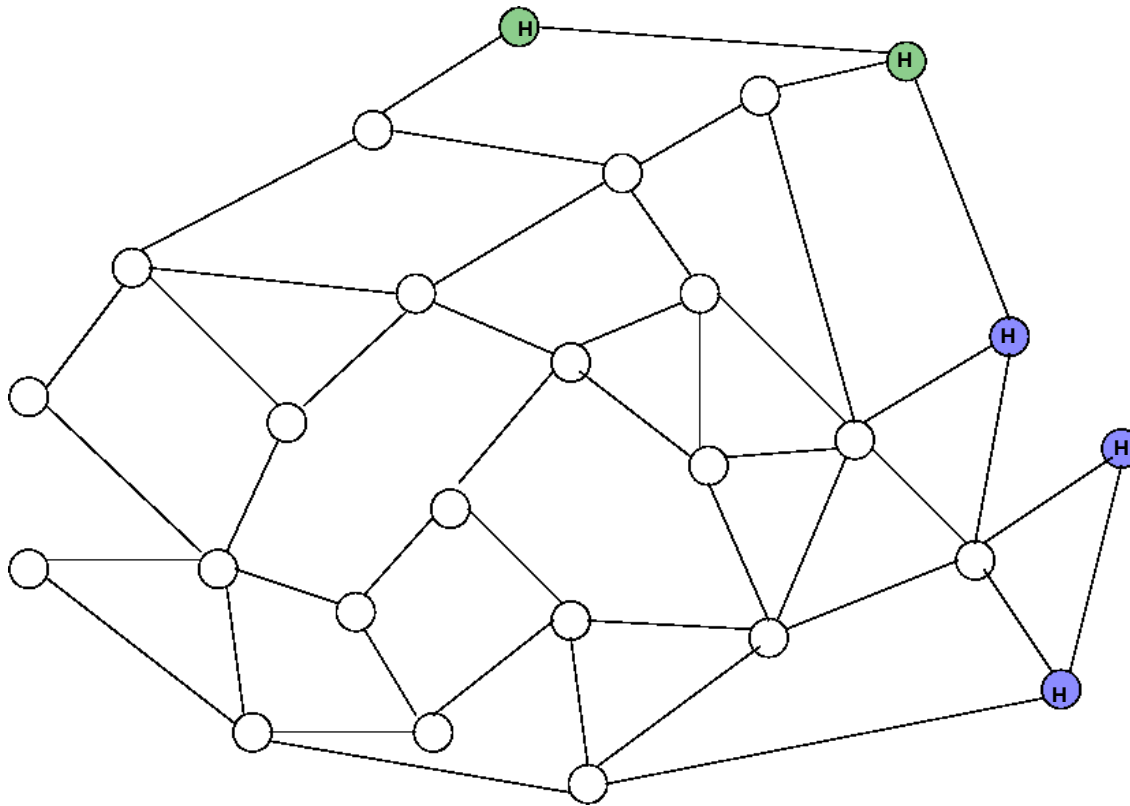
7 Halo-first Greedy Graph Growing



Idea:

- Split halo in H_0 and H_1 (using GG)
- Make grow P_0 and P_1 using H_0 and H_1 as set of seeds

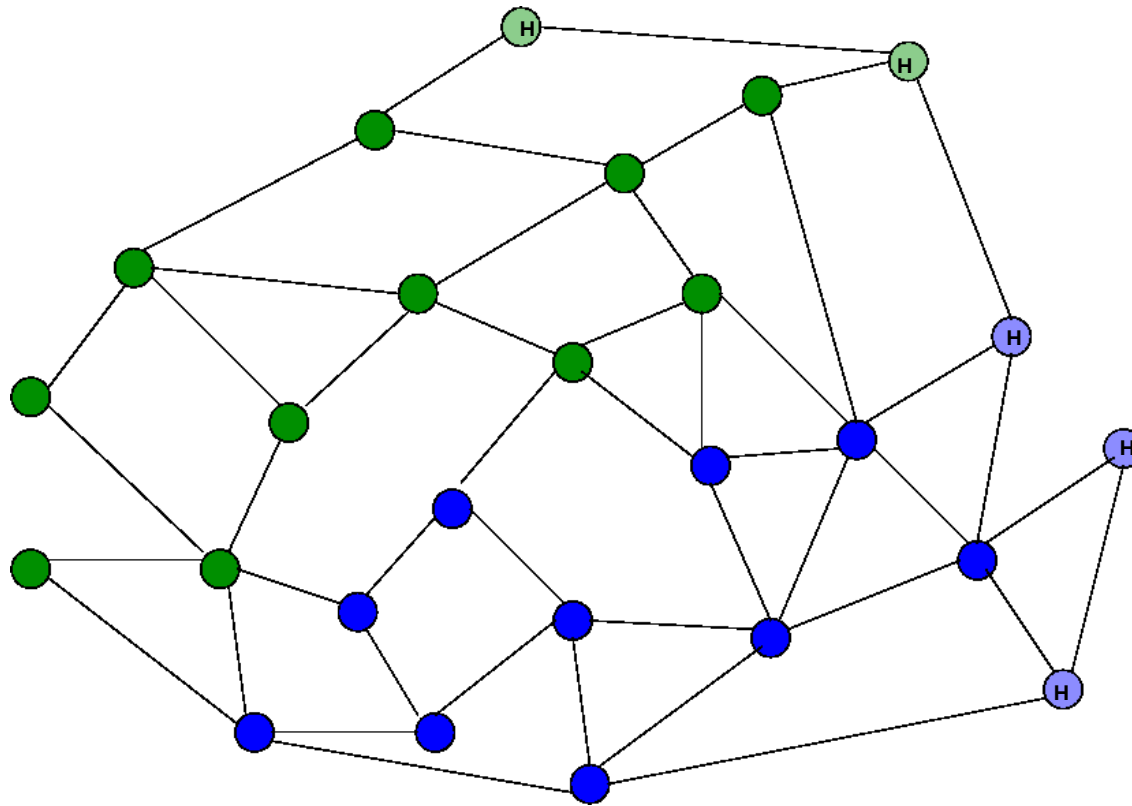
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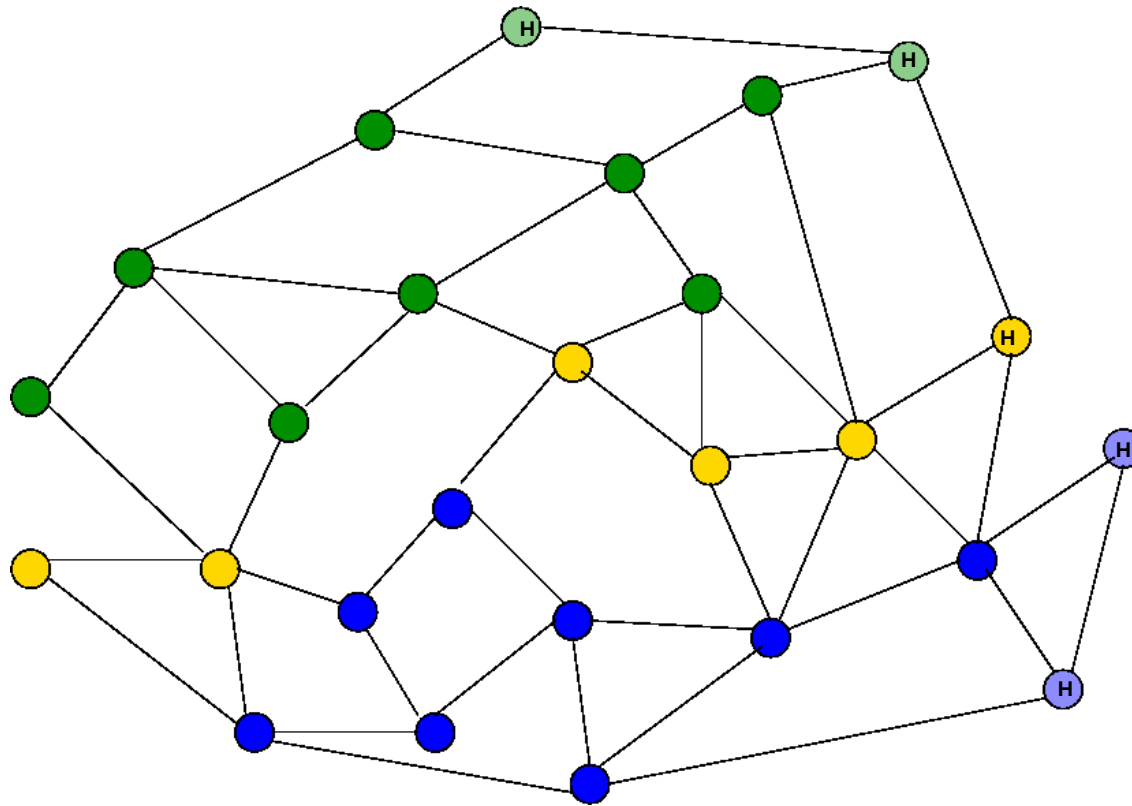
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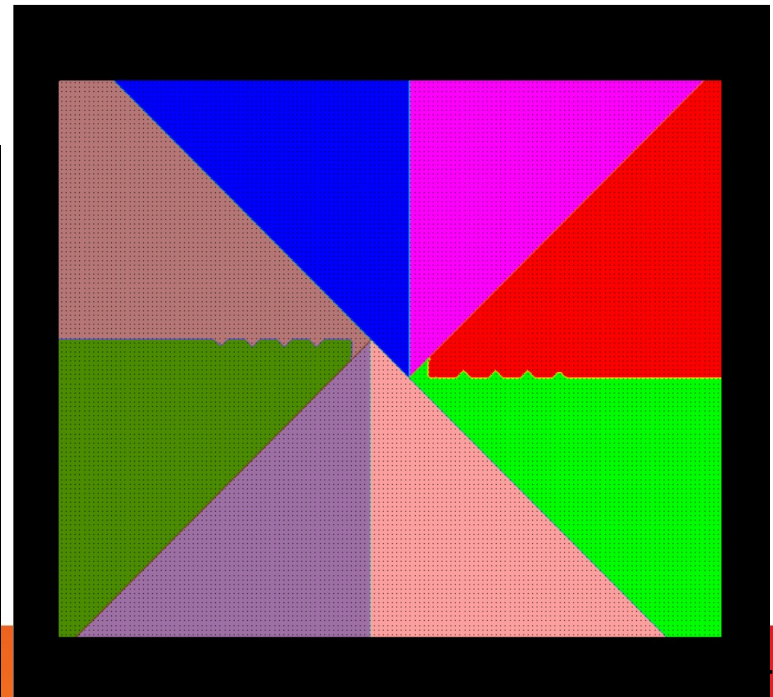
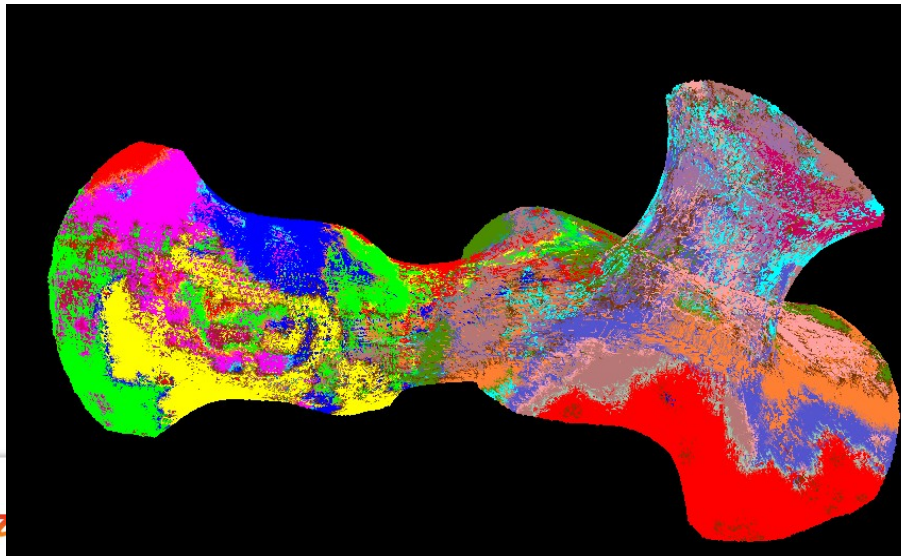
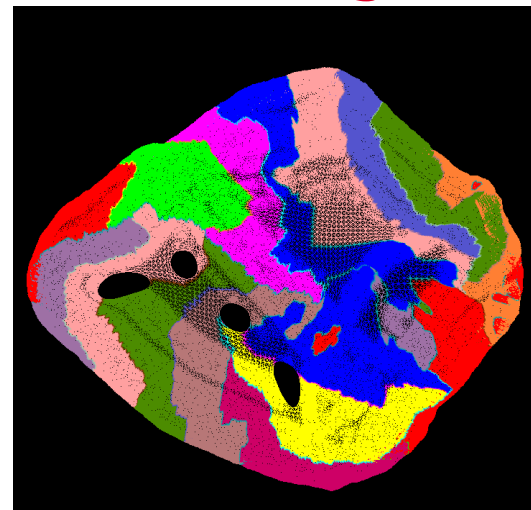
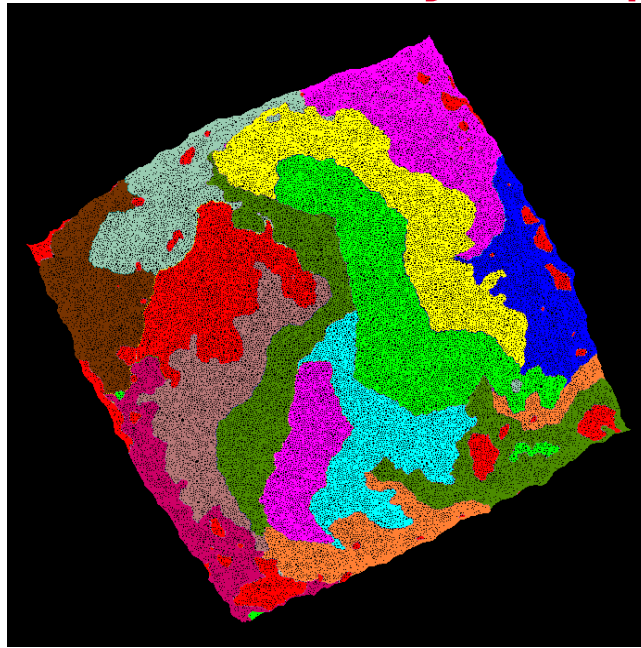
7 Halo-first Greedy Graph Growing



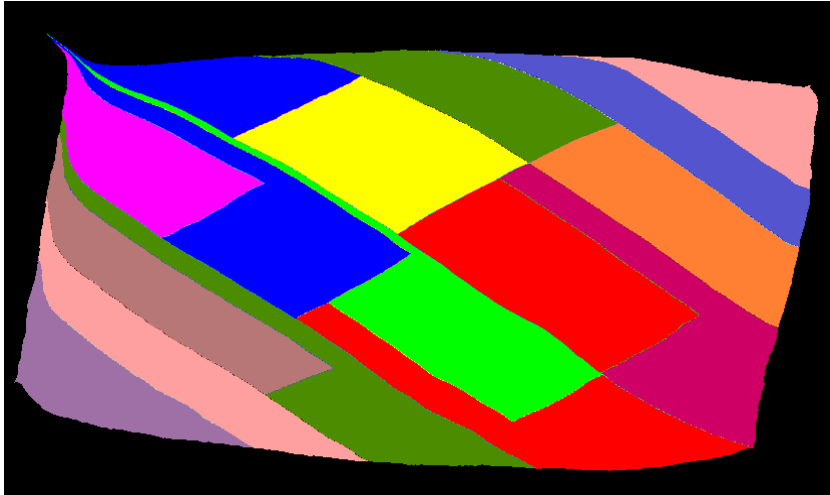
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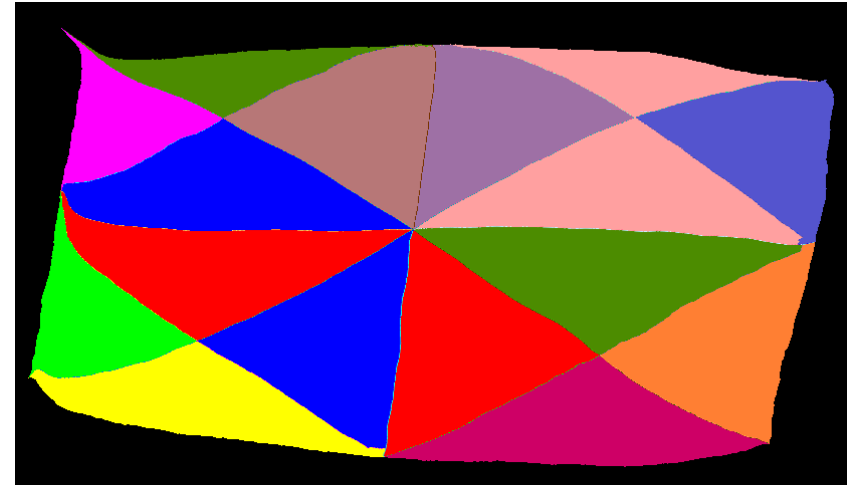
7 Halo-first Greedy Graph Growing



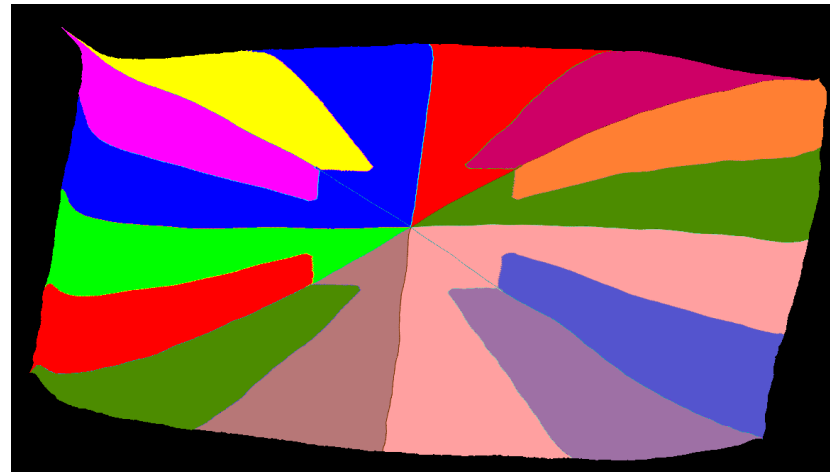
Matrix Ecology1, 1,000,000 unknowns
(without multilevel)



GG: Δ 1403, max 1758



DG: Δ 499, max 999



HF: Δ 254, max 1073

8 Remarks

Imbalance

Level 0

0

Level 1

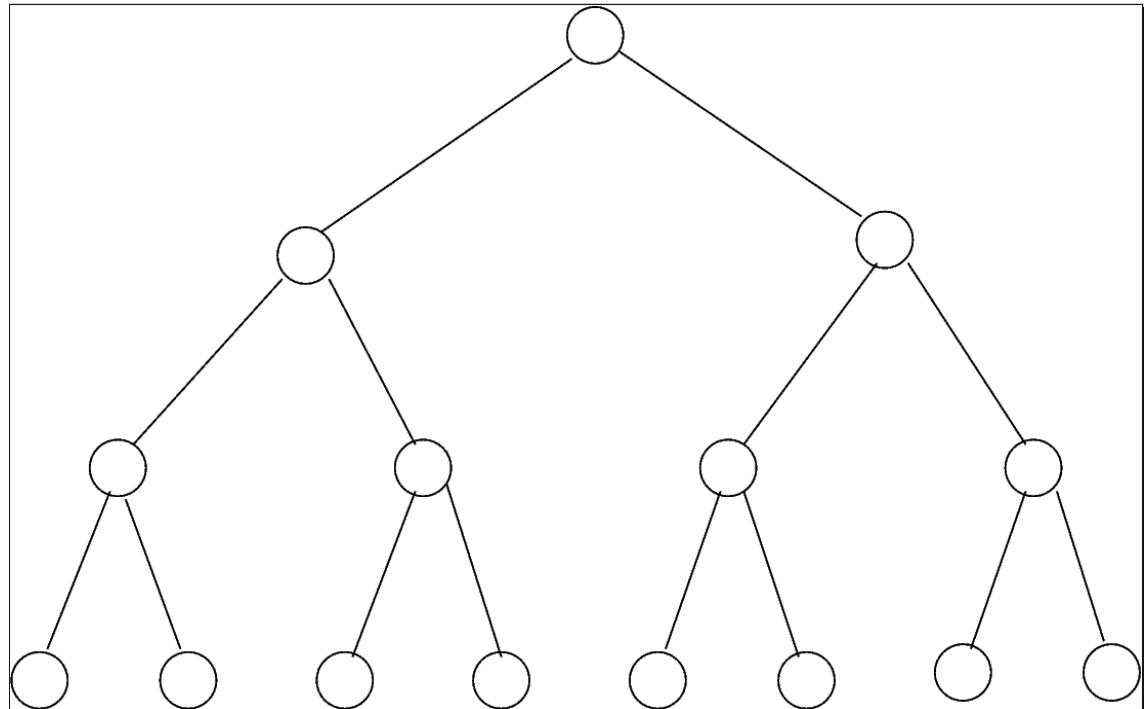
+ δ %

Level 2

+ δ %

Level 3

+ δ %



Total: $\delta \times \text{nb_levels}$ %

8 Remarks

Imbalance

Level 0

0

Level 1

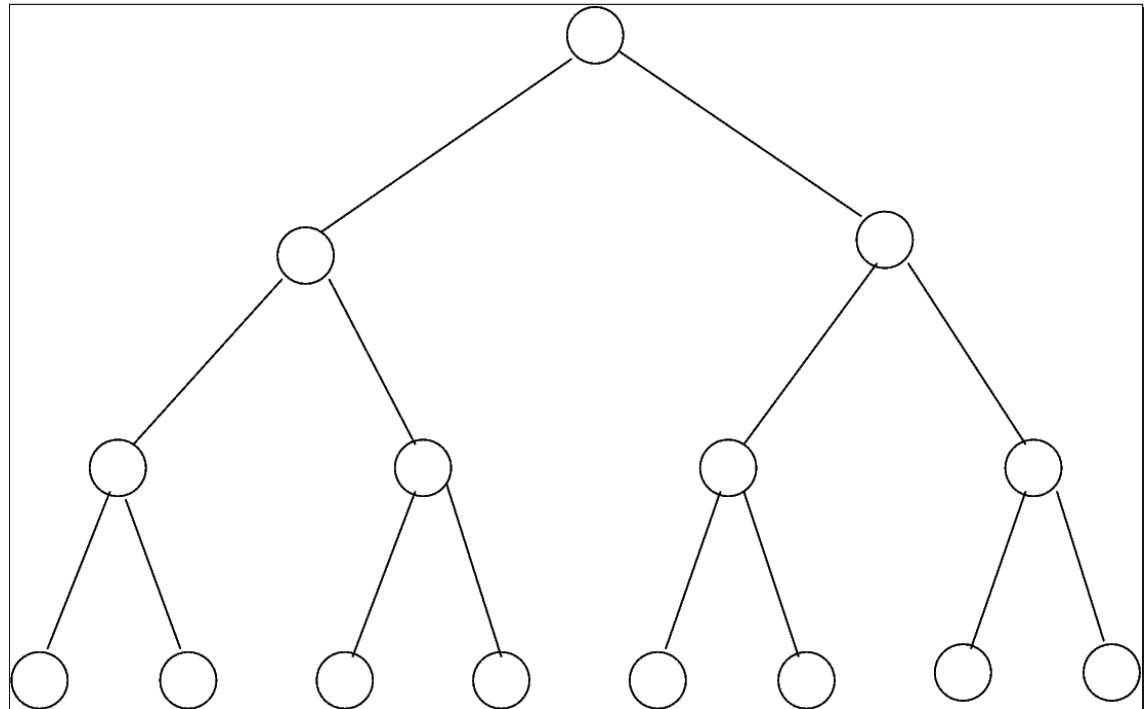
$+ \delta / 4\%$

Level 2

$+ \delta / 2\%$

Level 3

$+ \delta \%$



Total:

$< 2\delta \%$

In results,

« GG » denotes original Scotch

« GG* » denotes Scotch with this improvement

8 Results

- Interior imbalance: $\Delta = \max_{0 \leq i < ndom} |Dom_i| - \min_{0 \leq i < ndom} |Dom_i|$
- Interface imbalance: $\Delta_h = \max_{0 \leq i < ndom} |interface(Dom_i)| - \min_{0 \leq i < ndom} |interface(Dom_i)|$

Results on **16 domains** with multilevel + Fiduccia-Mattheyses + (DG or HF):

	Δ_h DG	Δ_h HF
• Almond ($n \approx 7 \times 10^6$):	2544	2263
• Nice-7 ($n \approx 8 \times 10^6$):	5618	4967
• 10millions ($n \approx 10 \times 10^6$):	4771	4381

8 Results

16 domains, DG

id	interface imbalance			interior imbalance		
	GG	% GG*	% DG	GG	% GG*	% DG
1	297	7,4	-19,2	1311	-69,1	-23,3
2	1112	1,6	-40,0	4678	-66,5	-78,9
3	522	-11,3	-39,7	1635	-13,9	-13,0
4	244	-9,0	-11,5	1568	-23,7	-31,1
5	475	-17,9	-3,8	4605	-85,6	-62,3
6	869	-21,3	-41,3	4107	-78,5	-49,6
7	905	49,4	26,4	4942	-69,1	-63,7
8	261	0,0	-46,7	420	0,0	79,8
9	365	-3,8	-44,9	8128	-82,8	-65,2
10	1002	14,0	-32,1	4852	-73,2	-44,6
11	509	-3,7	-44,4	2831	-84,1	27,5
12	569	-25,0	-59,1	22416	-79,5	-67,5
13	532	-11,8	-58,5	12049	-69,0	-49,5
14	756	-23,1	-46,3	17458	-61,9	-66,6
15	6678	6,6	-29,8	35466	-73,9	-68,4
16	564	-11,9	-62,9	15092	-65,5	-58,0
17	2130	18,6	-50,4	32202	-72,9	-67,7
18	335	17,0	-19,7	28057	-70,1	-64,9
19	2604	-16,4	-42,0	25853	-66,5	-59,5
20	9990	-14,2	-25,8	73635	-80,7	-16,5
21	927	0,6	-40,9	2377	-58,6	-59,5
22	3468	5,0	-78,5	3336	4,3	18,2
23	1869	7,1	-3,2	14424	-73,3	-64,4
24	2460	-9,1	-73,4	8940	-44,1	-60,6
25	6837	-11,6	-69,7	26877	-63,0	-68,9
26	780	-15,9	-53,8	24987	-58,3	-65,2
27	6168	-27,5	-68,4	67721	-68,7	-76,2
28	4344	-15,6	-41,4	240729	-76,9	-77,1
29	11539	8,6	-51,3	244959	-73,9	-77,2
30	9936	-6,9	-52,0	286992	-72,6	-8,5

8 Results

16 domains, HF

id	interface imbalance			interior imbalance		
	<i>GG</i>	% <i>GG</i> *	% <i>HF</i>	<i>GG</i>	% <i>GG</i> *	% <i>HF</i>
1	297	7,4	-29,3	1311	-69,1	-73,5
2	1112	1,6	-34,9	4678	-66,5	-74,2
3	522	-11,3	-63,4	1635	-13,9	-7,2
4	244	-9,0	103,3	1568	-23,7	-24,5
5	475	-17,9	-26,7	4605	-85,6	-74,3
6	869	-21,3	-48,2	4107	-78,5	-65,6
7	905	49,4	-24,2	4942	-69,1	-72,2
8	261	0,0	-69,0	420	0,0	-11,4
9	365	-3,8	-41,4	8128	-82,8	-69,2
10	1002	14,0	-66,9	4852	-73,2	-47,5
11	509	-3,7	-50,3	2831	-84,1	-19,1
12	569	-25,0	-70,1	22416	-79,5	-72,9
13	532	-11,8	-37,0	12049	-69,0	-52,3
14	756	-23,1	-20,4	17458	-61,9	-67,2
15	6678	6,6	-22,4	35466	-73,9	-68,2
16	564	-11,9	-54,4	15092	-65,5	-59,2
17	2130	18,6	-44,8	32202	-72,9	-73,0
18	335	17,0	14,6	28057	-70,1	-68,3
19	2604	-16,4	-15,8	25853	-66,5	-49,7
20	9990	-14,2	-55,4	73635	-80,7	-79,6
21	927	0,6	-49,4	2377	-58,6	-64,5
22	3468	5,0	-75,4	3336	4,3	16,1
23	1869	7,1	-24,2	14424	-73,3	-72,0
24	2460	-9,1	-55,9	8940	-44,1	-51,5
25	6837	-11,6	-65,5	26877	-63,0	-80,3
26	780	-15,9	-33,6	24987	-58,3	-66,0
27	6168	-27,5	-73,6	67721	-68,7	-74,5
28	4344	-15,6	-47,9	240729	-76,9	-73,2
29	11539	8,6	-57,0	244959	-73,9	-70,9
30	9936	-6,9	-55,9	286992	-72,6	-71,4

8 Results on 16 domains

Multilevel + FM + DG

Average gain over GG:

- Δ_h : - 40%
- Δ : - 45%

DG beats both GG and GG* on:

- Δ_h : 28 / 30 cases
- Δ : 9 / 30 cases

Multilevel + FM + HF

Average gain over GG:

- Δ_h : - 38%
- Δ : - 56%

HF beats both GG and GG* on:

- Δ_h : 26 / 30 cases
- Δ : 12 / 30 cases

HF beats DG on:

- 16 / 30 cases
 - 21 / 30 cases
- HF slightly better on most cases

8 Results multilevel + DG/HF, 16 to 512 domains

Almond

$n \approx 7 \times 10^6$

$nnz \approx 100 \times 10^6$

dom	interface imbalance Δ_h				interior imbalance Δ			
	GG	% GG*	% DG	% HF	GG	% GG*	% DG	% HF
16	4344	-15,6	-41,4	-47,9	240729	-76,9	-77,1	-73,2
32	3179	-34,8	-31,5	-0,5	133886	-73,8	-80,1	-76,9
64	2258	-5,8	-47,6	-17,8	83819	-80,5	-79,2	-79,1
128	1822	-29,5	-42,9	-32,6	48087	-78,4	-77,6	-80,9
256	1071	-2,2	-44,4	2,5	27695	-81,6	-77,9	-83,0
512	910	0,8	-17,1	-22,3	16243	-83,8	-80,0	-84,7

Nice-7

$n \approx 8 \times 10^6$

$nnz \approx 660 \times 10^6$

dom	interface imbalance Δ_h				interior imbalance Δ			
	GG	% GG*	% DG	% HF	GG	% GG*	% DG	% HF
16	11539	8,6	-51,3	-57,0	244959	-73,9	-77,2	-70,9
32	10991	-26,3	-45,7	-38,5	188834	-80,3	-81,0	-81,6
64	8997	-27,5	40,7	-30,8	101838	-75,9	-6,6	-80,2
128	5694	-14,4	11,7	-26,9	66792	-83,9	-1,9	-84,3
256	4554	-3,2	-33,1	-27,6	34314	-77,4	7,3	-82,4
512	3762	-16,7	-30,8	-33,1	19734	-79,1	-6,3	-84,2

10millions

$n \approx 10 \times 10^6$

$nnz \approx 160 \times 10^6$

dom	interface imbalance Δ_h				interior imbalance Δ			
	GG	% GG*	% DG	% HF	GG	% GG*	% DG	% HF
16	9936	-6,9	-52,0	-55,9	286992	-72,6	-8,5	-71,4
32	6666	-0,5	43,7	-56,6	188900	-69,5	13,0	-77,7
64	7036	-13,3	-47,4	-31,1	125444	-76,9	-18,8	-78,4
128	4564	-11,2	4,0	-48,7	79754	-82,9	-52,9	-78,8
256	3114	-6,2	163,5	-32,5	42931	-79,5	-30,2	-80,8
512	2336	-19,5	22,2	-54,2	25800	-83,5	49,3	-83,4

Impact on performances for MaPHYS

Matrix Almond, divided in 8 domains

	Natif	DG	HF
Max-min Schur size	6546	3221	1779
Avg Schur size (n)	10466	10532	11254
Avg Schur size (nnz)	114M	112M	127M
Total interface size	41604	41869	44768
Avg time facto (s)	632	596	593
Avg time precond (s)	163	117	129
Avg time solve (s)	147	85	118

Impact on performances for MaPHYS

Matrix Almond, divided in 16 domains

	Natif	DG	HF
Max-min Schur size	5805	3455	3307
Avg Schur size (n)	7523	7709	7900
Avg Schur size (nnz)	58M	60M	63M
Total interface size	59574	61057	62608
Avg time facto (s)	232	222	223
Avg time precond (s)	139	98	102
Avg time solve (s)	128	91	98

Impact on performances for MaPHYS

Matrix Almond, divided in 32 domains

	Natif	DG	HF
Max-min Schur size	3118	2765	2603
Avg Schur size (n)	5492	5672	5749
Avg Schur size (nnz)	31M	32M	33M
Total interface size	86551	89452	90664
Avg time facto (s)	87	84	84
Avg time precond (s)	58	62	54
Avg time solve (s)	91	59	50

9 Future work

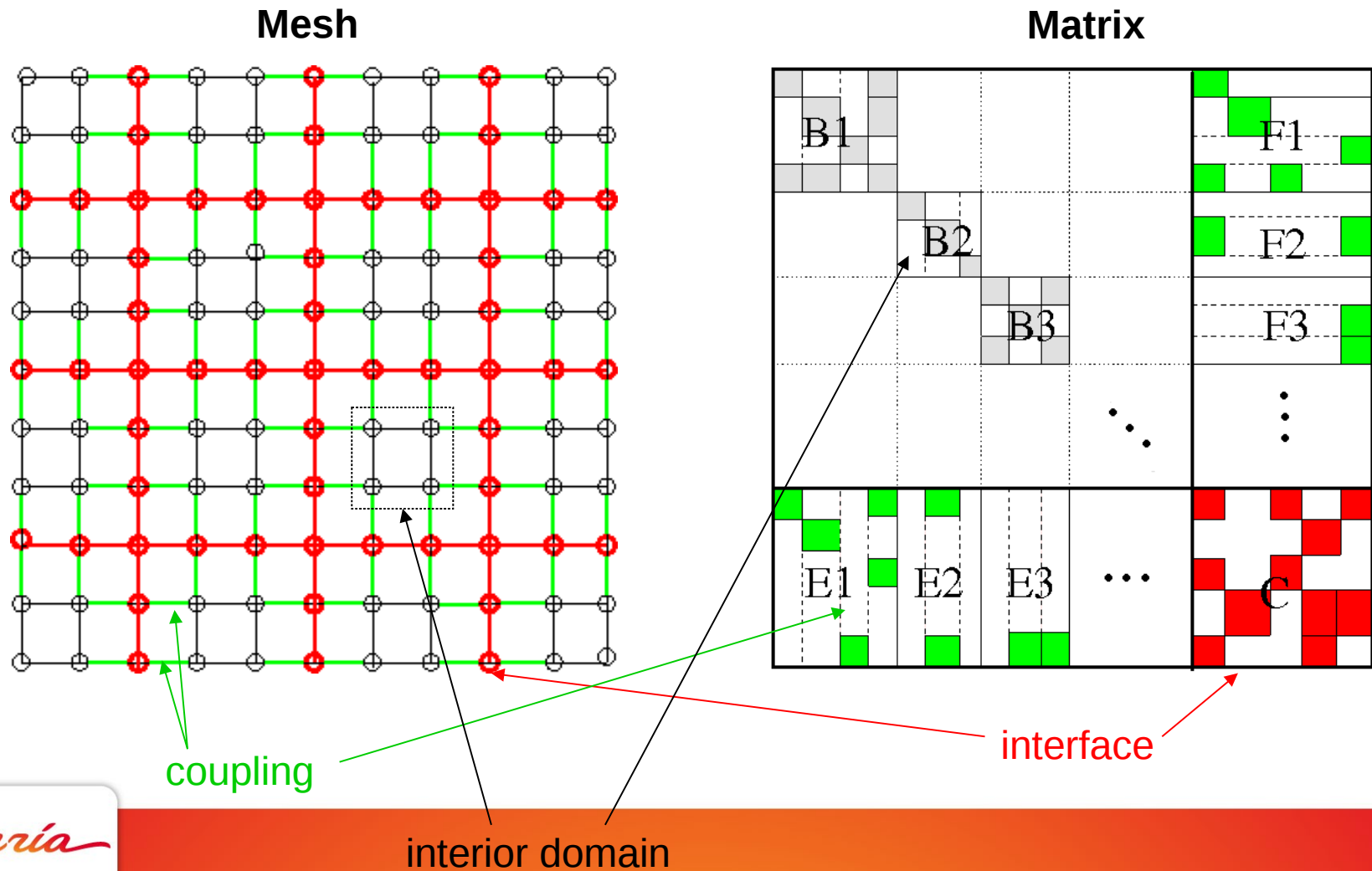
- In a parallel context, chose the best from the 3 variants (GG, DG, HF) (keep same complexity for the global reordering process, but time increases)
- An other important criteria to control : total size of the interface
- Comparison with k-way or other graph partitioning (Metis, ...)
- Release new algorithms in the master branch of Scotch package

Thanks for listening.
Questions ?



Memory optimization to build a Schur complement for hybrid solvers

Domain decomposition

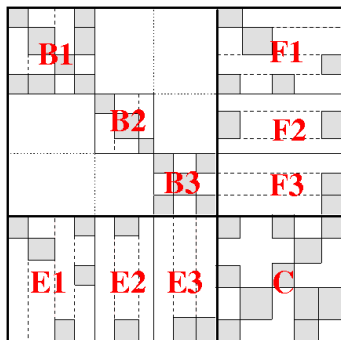


Domain decomposition

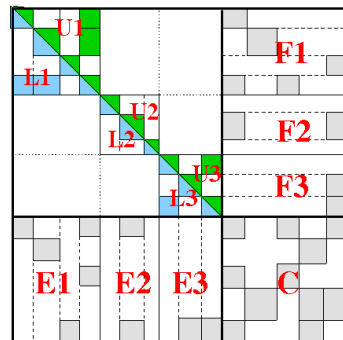
Step 1 :

Build an approximate factorization :

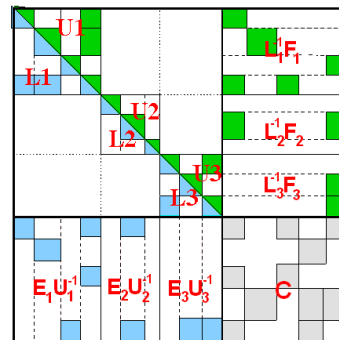
$$A \approx \tilde{L}\tilde{U} = \begin{pmatrix} L_B U_B & \\ & \tilde{L}_S \tilde{U}_S \end{pmatrix}$$



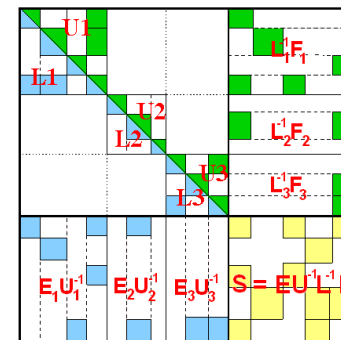
Initial Matrix



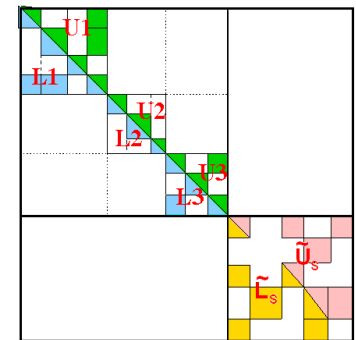
Factorize each domain



TRSM



Add contributions

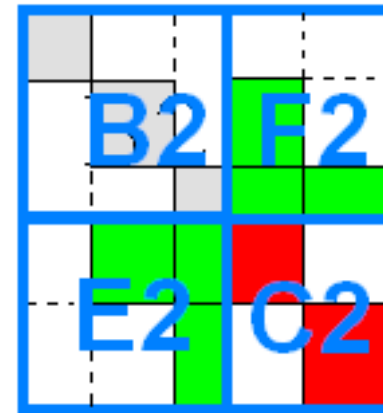
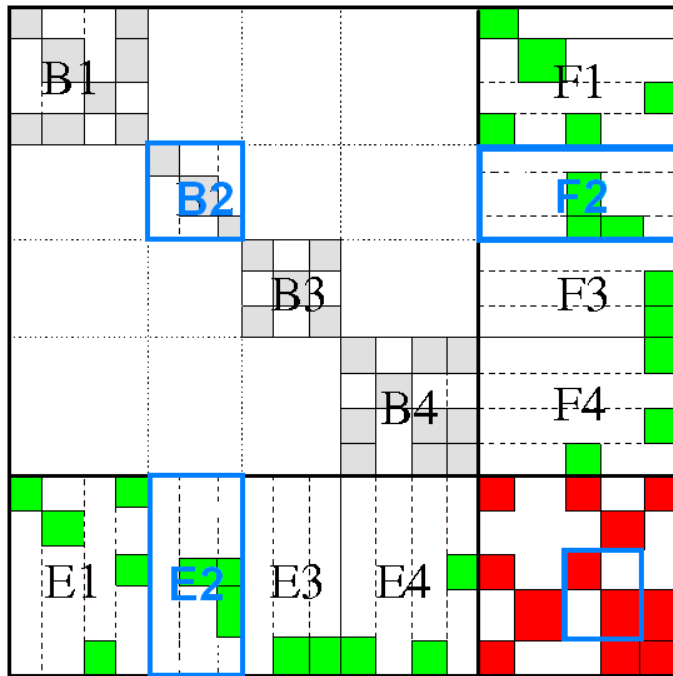


Incomplete factorization of S

Step 2 :

Iterative method to solve $Ax = b$ using \tilde{L} & \tilde{U} as preconditioner

Domain decomposition



Local matrix for subdomain 2

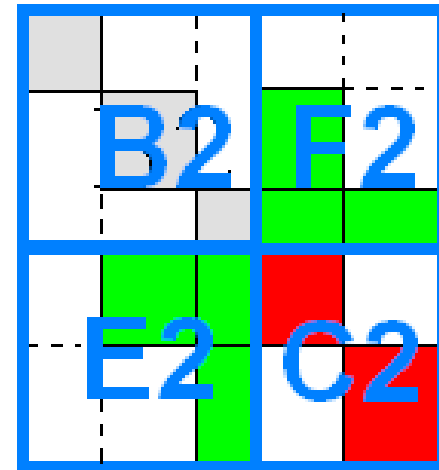
2 levels of parallelism :

- parallelism between subdomains
- parallel direct solver to factorize each subdomain

Memory optimization

Memory overcosts during the factorization of a subdomain :

- Aggregated blocs (Fan-In)
- Coupling blocs (E/F)



Idea 1 :

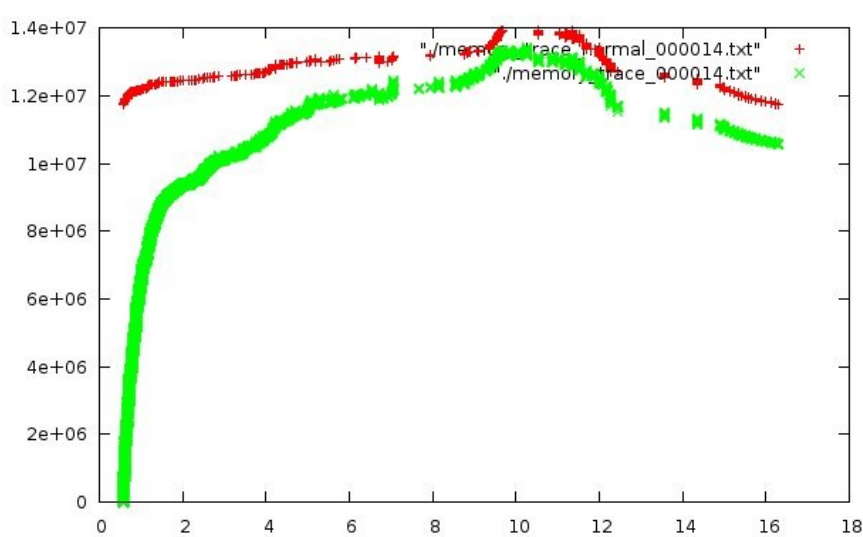
Dynamic allocations of column blocs (as late as possible)

Idea 2 :

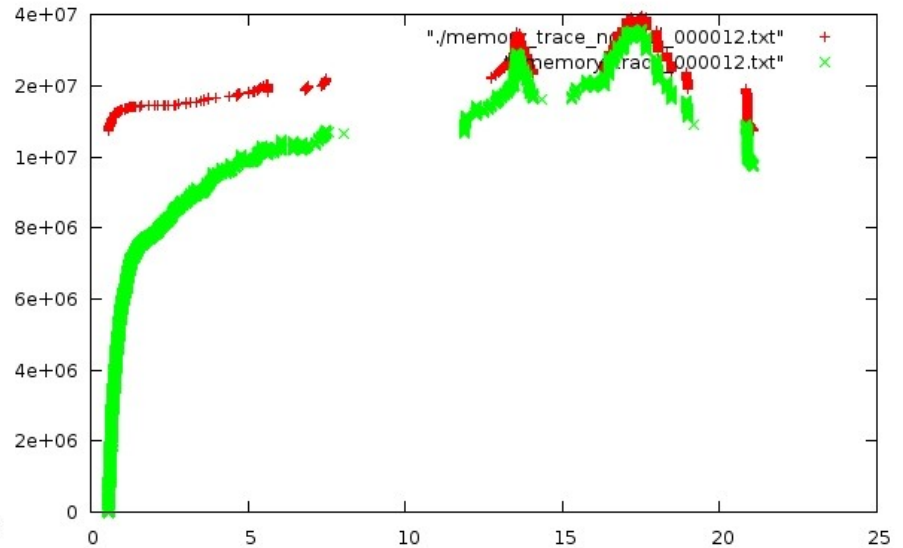
Free the coupling blocs as soon as possible

Memory Optimization

INLINE matrix, factorized using PaStiX with
16 processus and 4 threads per processus, size of
the interface about 1500



Processus 14



Processus 12

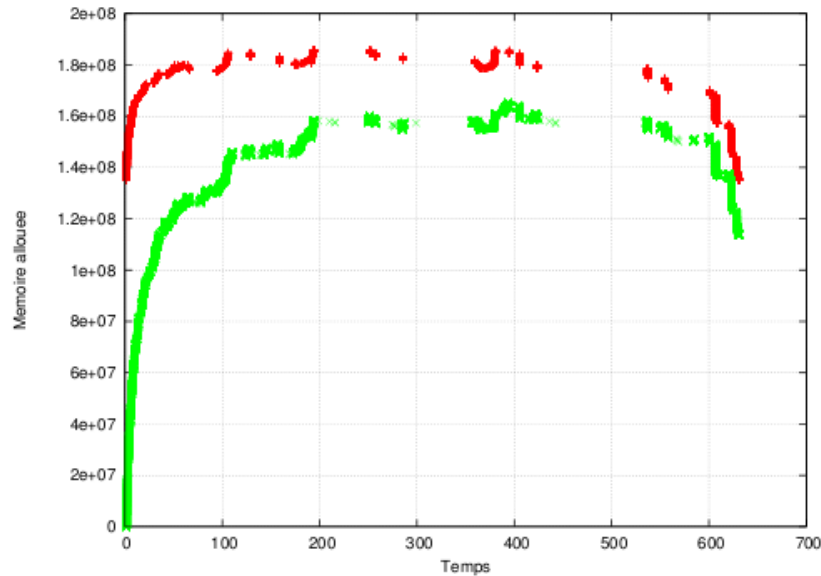
Memory Optimization

Idea 3 :

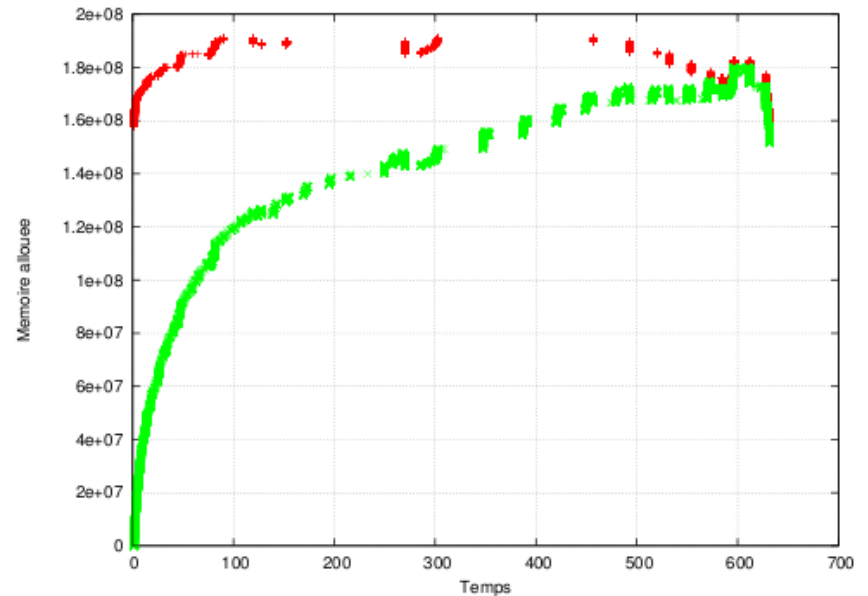
Use a « left looking version » to build the non-coupling part of columns blocs

Memory Optimization

domain 1 for AUDI matrix, split in 2 subdomains,
factorized with 4 processus and 4 threads per processus



Processus 1



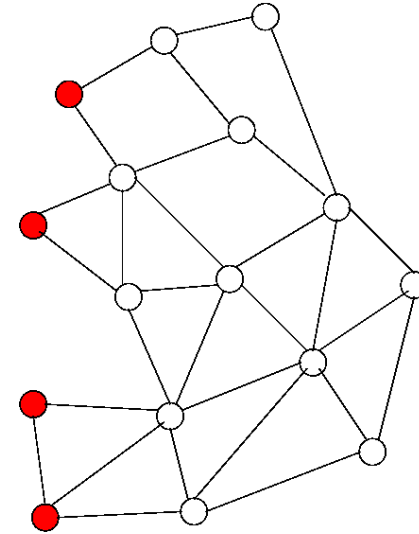
Processus 3

Some results

- left-right-looking version : from 1 to 4 MPI nodes, memory gain from 86 % to 10%
- in the case of hybrid solvers we expect small number of MPI node per subdomain
- Same gains when increasing the number of threads instead of MPI nodes

7 Halo-first Greedy Graph Growing

Problem : graph induced by halo may be disconnected ; we have to reconnect it before cutting halo



Algorithm :

Let begin with an empty induced graph

Let call $H = \{h_0, h_1, \dots, h_m\}$ the halo vertices.

Let P be a partition of the halo vertices, initially $P = \{\{h_0\}, \{h_1\}, \dots, \{h_m\}\}$

While $p \neq \{H\}$:

- find the shortest path between any two elements of P
- merge them
- add to the induced graph all vertices of the path

4 Fiduccia-Mattheyses algorithm

Original version

```
 $(P_0^*, S^*, P_1^*) \leftarrow (P_0, S, P_1);$ 
```

```
 $passnum \leftarrow 0;$ 
```

```
repeat
```

```
 $(P_0, S, P_1) \leftarrow (P_0^*, S^*, P_1^*);$ 
```

```
 $\Delta \leftarrow |P_0| - |P_1|;$ 
```

```
 $tabu \leftarrow \emptyset;$ 
```

```
 $movenum \leftarrow 0, enhanced \leftarrow false;$ 
```

```
 $pref \leftarrow mod(passnum, 2);$ 
```

```
while  $movenum < movenbr$  do
```

```
 $(f, v, i) \leftarrow getSep(S \setminus tabu, max(\Delta_{th}, |\Delta|), pref);$ 
```

```
if  $\neg f$  then /* No movable vertex */
```

```
  break;
```

Choose a vertex v in S
and a part i

```
/* Move  $v$  from separator to part  $i$  */;
```

```
 $R \leftarrow \{w | (v, w) \in E \text{ and } w \in P_{-i}\};$ 
```

```
 $S \leftarrow S \setminus \{v\} \cup R;$ 
```

```
 $P_i \leftarrow P_i \cup \{v\}, P_{-i} \leftarrow P_{-i} \setminus R;$ 
```

```
 $\Delta \leftarrow |P_0| - |P_1|;$ 
```

```
 $movenum++;$ 
```

```
 $tabu \leftarrow tabu \cup \{v\};$ 
```

Move v to i

```
if  $(P_0, S, P_1)$  is better than  $(P_0^*, S^*, P_1^*)$  then
```

```
   $(P_0^*, S^*, P_1^*) \leftarrow (P_0, S, P_1);$ 
```

```
   $movenum \leftarrow 0, enhanced \leftarrow true;$ 
```

If best partition ever, record it

```
 $passnum++;$ 
```

```
until  $\neg enhanced$  or  $(passnum = passnbr)$  ;
```

```
return  $(P_0^*, S^*, P_1^*);$ 
```

4 Fiduccia-Mattheyses algorithm

Original version

$(P_0^*, S^*, P_1^*) \leftarrow (P_0, S, P_1)$;

$passnum \leftarrow 0$;

repeat

$(P_0, S, P_1) \leftarrow (P_0^*, S^*, P_1^*)$;

$\Delta \leftarrow |P_0| - |P_1|$;

$tabu \leftarrow \emptyset$;

$movenum \leftarrow 0$ *enhanced* $\leftarrow false$;

$pref \leftarrow mod(passnum, 2)$;

while $movenum < movenbr$ **do**

$(f, v, i) \leftarrow getSep(S \setminus tabu, \max(\Delta_{th}, |\Delta|), pref)$;

if $\neg f$ **then** /* No movable vertex */

└ break;

/* Move v from separator to part i */;

$R \leftarrow \{w | (v, w) \in E \text{ and } w \in P_{-i}\}$;

$S \leftarrow S \setminus \{v\} \cup R$;

$P_i \leftarrow P_i \cup \{v\}, P_{-i} \leftarrow P_{-i} \setminus R$;

$\Delta \leftarrow |P_0| - |P_1|$;

$movenum++$;

$tabu \leftarrow tabu \cup \{v\}$;

if (P_0, S, P_1) is better than (P_0^*, S^*, P_1^*) **then**

└ $(P_0^*, S^*, P_1^*) \leftarrow (P_0, S, P_1)$;

└ $movenum \leftarrow 0$, *enhanced* $\leftarrow true$;

$passnum++$;

until $\neg enhanced$ or $(passnum = passnbr)$;

return (P_0^*, S^*, P_1^*) ;

- main loop: choose a vertex, move it, update best separator
- 1 pass = make moves until the last <movenbr> moves do not bring improvement

4 Fiduccia-Mattheyses algorithm

Original version

$(P_0^*, S^*, P_1^*) \leftarrow (P_0, S, P_1)$;

$passnum \leftarrow 0$;

repeat

$(P_0, S, P_1) \leftarrow (P_0^*, S^*, P_1^*)$;

$\Delta \leftarrow |P_0| - |P_1|$;

$tabu \leftarrow \emptyset$;

$movenum \leftarrow 0, enhanced \leftarrow false$;

$pref \leftarrow mod(passnum, 2)$;

while $movenum < movenbr$ **do**

$(f, v, i) \leftarrow getSep(S \setminus tabu, \max(\Delta_{th}, |\Delta|), pref)$;

if $\neg f$ **then** /* No movable vertex */

└ break;

/* Move v from separator to part i */;

$R \leftarrow \{w | (v, w) \in E \text{ and } w \in P_{-i}\}$;

$S \leftarrow S \setminus \{v\} \cup R$;

$P_i \leftarrow P_i \cup \{v\}, P_{-i} \leftarrow P_{-i} \setminus R$;

$\Delta \leftarrow |P_0| - |P_1|$;

$movenum++$;

$tabu \leftarrow tabu \cup \{v\}$;

if (P_0, S, P_1) is better than (P_0^*, S^*, P_1^*) **then**

└ $(P_0^*, S^*, P_1^*) \leftarrow (P_0, S, P_1)$;

└ $movenum \leftarrow 0, enhanced \leftarrow true$;

$passnum++$;

until $\neg enhanced$ or $(passnum = passnbr)$;

return (P_0^*, S^*, P_1^*) ;

- main loop: choose a vertex, move it, update best separator
- 1 pass = make moves until the last <movenbr> moves do not bring improvement
- tabu search

4 Fiduccia-Mattheyses algorithm

Original version

```
 $(P_0^*, S^*, P_1^*) \leftarrow (P_0, S, P_1);$   
 $passnum \leftarrow 0;$   
repeat  
|  $(P_0, S, P_1) \leftarrow (P_0^*, S^*, P_1^*);$   
|  $\Delta \leftarrow |P_0| - |P_1|;$   
|  $tabu \leftarrow \emptyset;$   
|  $movenum \leftarrow 0, enhanced \leftarrow false;$   
|  $pref \leftarrow mod(passnum, 2);$   
| while  $movenum < movenbr$  do  
| |  $(f, v, i) \leftarrow getSep(S \setminus tabu, \max(\Delta_{th}, |\Delta|), pref);$   
| | if  $\neg f$  then /* No movable vertex */  
| | |  $break;$   
| | /* Move  $v$  from separator to part  $i$  */;  
| |  $R \leftarrow \{w | (v, w) \in E \text{ and } w \in P_{-i}\};$   
| |  $S \leftarrow S \setminus \{v\} \cup R;$   
| |  $P_i \leftarrow P_i \cup \{v\}, P_{-i} \leftarrow P_{-i} \setminus R;$   
| |  $\Delta \leftarrow |P_0| - |P_1|;$   
| |  $movenum++;$   
| |  $tabu \leftarrow tabu \cup \{v\};$   
| | if  $(P_0, S, P_1)$  is better than  $(P_0^*, S^*, P_1^*)$  then  
| | |  $(P_0^*, S^*, P_1^*) \leftarrow (P_0, S, P_1);$   
| | |  $movenum \leftarrow 0, enhanced \leftarrow true;$   
|  $passnum++;$   
until  $\neg enhanced$  or  $(passnum = passnbr)$  ;  
return  $(P_0^*, S^*, P_1^*);$ 
```

- main loop: choose a vertex, move it, update best separator
- 1 pass = make moves until the last <movenbr> moves do not bring improvement
- tabu search
- passes keep going on while last pass bring improvement
- each pass begins with best separator ever found

4 Fiduccia-Mattheyses algorithm

Original version

$(P_0^*, S^*, P_1^*) \leftarrow (P_0, S, P_1);$

$passnum \leftarrow 0;$

repeat

$(P_0, S, P_1) \leftarrow (P_0^*, S^*, P_1^*);$

$\Delta \leftarrow |P_0| - |P_1|;$

$tabu \leftarrow \emptyset;$

$movenum \leftarrow 0, enhanced \leftarrow false;$

$pref \leftarrow mod(passnum, 2);$

while $movenum < movenbr$ **do**

$(f, v, i) \leftarrow getSep(S \setminus tabu, \max(\Delta_{th}, |\Delta|), pref);$

if $\neg f$ **then** /* No movable vertex */

└ break;

/* Move v from separator to part i */;

$R \leftarrow \{w | (v, w) \in E \text{ and } w \in P_{-i}\};$

$S \leftarrow S \setminus \{v\} \cup R;$

$P_i \leftarrow P_i \cup \{v\}, P_{-i} \leftarrow P_{-i} \setminus R;$

$\Delta \leftarrow |P_0| - |P_1|;$

$movenum++;$

$tabu \leftarrow tabu \cup \{v\};$

if (P_0, S, P_1) is better than (P_0^*, S^*, P_1^*) **then**

└ $(P_0^*, S^*, P_1^*) \leftarrow (P_0, S, P_1);$

└ $movenum \leftarrow 0, enhanced \leftarrow true;$

$passnum++;$

until $\neg enhanced$ or $(passnum = passnbr)$;

return $(P_0^*, S^*, P_1^*);$

• main loop: choose a vertex, move it, update best separator

• 1 pass =

make moves until the last <movenbr> moves do not bring improvement

• tabu search

• passes keep going on while last pass bring improvement

• each pass begins with best separator ever found

• preferred part switched at each pass

$(P_0^*, S^*, P_1^*) \leftarrow (P_0, S, P_1);$

$passnum \leftarrow 0;$

repeat

$(P_0, S, P_1) \leftarrow (P_0^*, S^*, P_1^*);$

$\Delta \leftarrow |P_0| - |P_1|, \bar{\Delta} \leftarrow |P_0|_h - |P_1|_h;$

$tabu \leftarrow \emptyset;$

$movenum \leftarrow 0, enhanced \leftarrow false;$

$pref \leftarrow mod(passnum, 2);$

while $movenum < movenbr$ **do**

$f \leftarrow false;$

if $|\bar{\Delta}| > \bar{\Delta}_{th}$ **then**

$(f, v, i) \leftarrow getHalo(S, tabu, -\bar{\Delta});$

if $\neg f$ **then**

$(f, v, i) \leftarrow getSep(S, tabu, max(\Delta_{th}, |\Delta|), pref);$

if $\neg f$ **then** /* No movable vertex */

\leftarrow break;

/* Move v from separator to part i */;

$R \leftarrow \{w | (v, w) \in E \text{ and } w \in P_{-i}\};$

$S \leftarrow S \setminus \{v\} \cup R;$

$P_i \leftarrow P_i \cup \{v\}, P_{-i} \leftarrow P_{-i} \setminus R;$

$\Delta \leftarrow |P_0| - |P_1|, \bar{\Delta} \leftarrow |P_0|_h - |P_1|_h;$

$movenum++;$

$tabu \leftarrow tabu \cup \{v\};$

if (P_0, S, P_1) is better than (P_0^*, S^*, P_1^*) **then**

$(P_0^*, S^*, P_1^*) \leftarrow (P_0, S, P_1);$

$movenum \leftarrow 0, enhanced \leftarrow true;$

$passnum++;$

until $\neg enhanced$ or $(passnum = passnbr)$;

return $(P_0^*, S^*, P_1^*);$

4 Fiduccia-Mattheyses algorithm

Modified version

GetSep choice based on (as before):

- part balance (if large imbalance)
- separator minimization
- preferred part

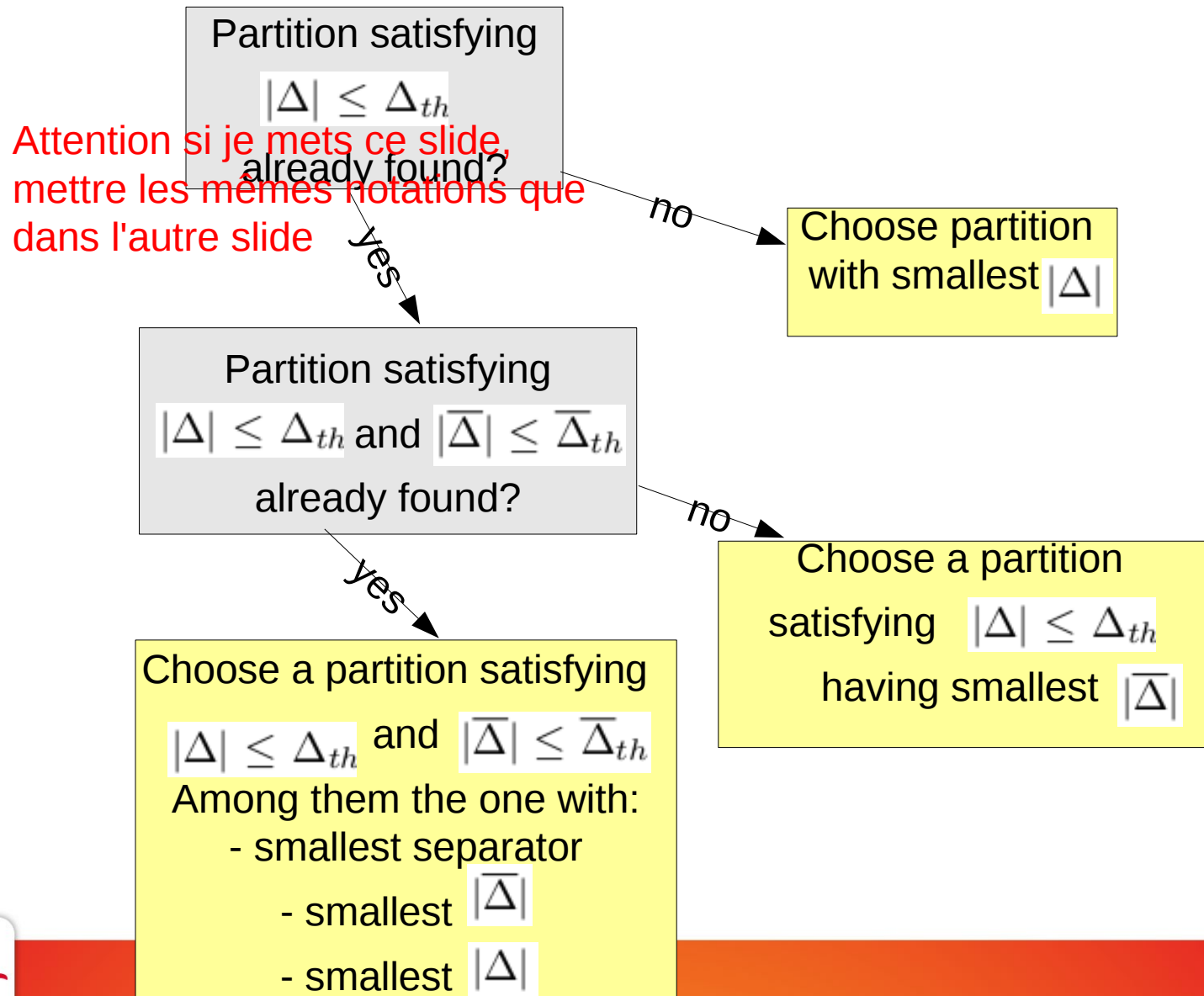
GetHalo choice based on:

- halo imbalance

Next slide :-)

4 Fiduccia-Mattheyses algorithm

Modified version, choice of « the best separator »



8 Results

16 domains, DG

id	interface imbalance			interior imbalance		
	GG	% GG*	% DG	GG	% GG*	% DG
1	297	7,4	-19,2	1311	-69,1	-23,3
2	1112	1,6	-40,0	4678	-66,5	-78,9
3	522	-11,3	-39,7	1635	-13,9	-13,0
4	244	-9,0	-11,5	1568	-23,7	-31,1
5	475	-17,9	-3,8	4605	-85,6	-62,3
6	869	-21,3	-41,3	4107	-78,5	-49,6
7	905	49,4	26,4	4942	-69,1	-63,7
8	261	0,0	-46,7	420	0,0	79,8
9	365	-3,8	-44,9	8128	-82,8	-65,2
10	1002	14,0	-32,1	4852	-73,2	-44,6
11	509	-3,7	-44,4	2831	-84,1	27,5
12	569	-25,0	-59,1	22416	-79,5	-67,5
13	532	-11,8	-58,5	12049	-69,0	-49,5
14	756	-23,1	-46,3	17458	-61,9	-66,6
15	6678	6,6	-29,8	35466	-73,9	-68,4
16	564	-11,9	-62,9	15092	-65,5	-58,0
17	2130	18,6	-50,4	32202	-72,9	-67,7
18	335	17,0	-19,7	28057	-70,1	-64,9
19	2604	-16,4	-42,0	25853	-66,5	-59,5
20	9990	-14,2	-25,8	73635	-80,7	-16,5
21	927	0,6	-40,9	2377	-58,6	-59,5
22	3468	5,0	-78,5	3336	4,3	18,2
23	1869	7,1	-3,2	14424	-73,3	-64,4
24	2460	-9,1	-73,4	8940	-44,1	-60,6
25	6837	-11,6	-69,7	26877	-63,0	-68,9
26	780	-15,9	-53,8	24987	-58,3	-65,2
27	6168	-27,5	-68,4	67721	-68,7	-76,2
28	4344	-15,6	-41,4	240729	-76,9	-77,1
29	11539	8,6	-51,3	244959	-73,9	-77,2
30	9936	-6,9	-52,0	286992	-72,6	-8,5

8 Results

16 domains, HF

id	interface imbalance			interior imbalance		
	<i>GG</i>	% <i>GG</i> *	% <i>HF</i>	<i>GG</i>	% <i>GG</i> *	% <i>HF</i>
1	297	7,4	-29,3	1311	-69,1	-73,5
2	1112	1,6	-34,9	4678	-66,5	-74,2
3	522	-11,3	-63,4	1635	-13,9	-7,2
4	244	-9,0	103,3	1568	-23,7	-24,5
5	475	-17,9	-26,7	4605	-85,6	-74,3
6	869	-21,3	-48,2	4107	-78,5	-65,6
7	905	49,4	-24,2	4942	-69,1	-72,2
8	261	0,0	-69,0	420	0,0	-11,4
9	365	-3,8	-41,4	8128	-82,8	-69,2
10	1002	14,0	-66,9	4852	-73,2	-47,5
11	509	-3,7	-50,3	2831	-84,1	-19,1
12	569	-25,0	-70,1	22416	-79,5	-72,9
13	532	-11,8	-37,0	12049	-69,0	-52,3
14	756	-23,1	-20,4	17458	-61,9	-67,2
15	6678	6,6	-22,4	35466	-73,9	-68,2
16	564	-11,9	-54,4	15092	-65,5	-59,2
17	2130	18,6	-44,8	32202	-72,9	-73,0
18	335	17,0	14,6	28057	-70,1	-68,3
19	2604	-16,4	-15,8	25853	-66,5	-49,7
20	9990	-14,2	-55,4	73635	-80,7	-79,6
21	927	0,6	-49,4	2377	-58,6	-64,5
22	3468	5,0	-75,4	3336	4,3	16,1
23	1869	7,1	-24,2	14424	-73,3	-72,0
24	2460	-9,1	-55,9	8940	-44,1	-51,5
25	6837	-11,6	-65,5	26877	-63,0	-80,3
26	780	-15,9	-33,6	24987	-58,3	-66,0
27	6168	-27,5	-73,6	67721	-68,7	-74,5
28	4344	-15,6	-47,9	240729	-76,9	-73,2
29	11539	8,6	-57,0	244959	-73,9	-70,9
30	9936	-6,9	-55,9	286992	-72,6	-71,4

8 Results multilevel + DG/HF, 16 to 512 domains

Almond

$n \approx 7 \times 10^6$

$nnz \approx 100 \times 10^6$

dom	interface imbalance			interior imbalance		
	<i>GG</i>	% <i>DG</i>	% <i>HF</i>	<i>GG</i>	% <i>DG</i>	% <i>HF</i>
16	4344	-41,4	-47,9	240729	-77,1	-73,2
32	3179	-31,5	-0,5	133886	-80,1	-76,9
64	2258	-47,6	-17,8	83819	-79,2	-79,1
128	1822	-42,9	-32,6	48087	-77,6	-80,9
256	1071	-44,4	2,5	27695	-77,9	-83,0
512	910	-17,1	-22,3	16243	-80,0	-84,7

Nice-7

$n \approx 8 \times 10^6$

$nnz \approx 660 \times 10^6$

dom	interface imbalance			interior imbalance		
	<i>GG</i>	% <i>DG</i>	% <i>HF</i>	<i>GG</i>	% <i>DG</i>	% <i>HF</i>
16	11539	-51,3	-57,0	244959	-77,2	-70,9
32	10991	-45,7	-38,5	188834	-81,0	-81,6
64	8997	40,7	-30,8	101838	-6,6	-80,2
128	5694	11,7	-26,9	66792	-1,9	-84,3
256	4554	-33,1	-27,6	34314	7,3	-82,4
512	3762	-30,8	-33,1	19734	-6,3	-84,2

10millions

$n \approx 10 \times 10^6$

$nnz \approx 160 \times 10^6$

dom	interface imbalance			interior imbalance		
	<i>GG</i>	% <i>DG</i>	% <i>HF</i>	<i>GG</i>	% <i>DG</i>	% <i>HF</i>
16	9936	-52,0	-55,9	286992	-8,5	-71,4
32	6666	43,7	-56,6	188900	13,0	-77,7
64	7036	-47,4	-31,1	125444	-18,8	-78,4
128	4564	4,0	-48,7	79754	-52,9	-78,8
256	3114	163,5	-32,5	42931	-30,2	-80,8
512	2336	22,2	-54,2	25800	49,3	-83,4