

Filtering Decomposable Global Cost Functions



Strong local consistencies for filtering weighted constraint networks
ANR -10-BLA-0214 French Research Project (FiCoLoFo)

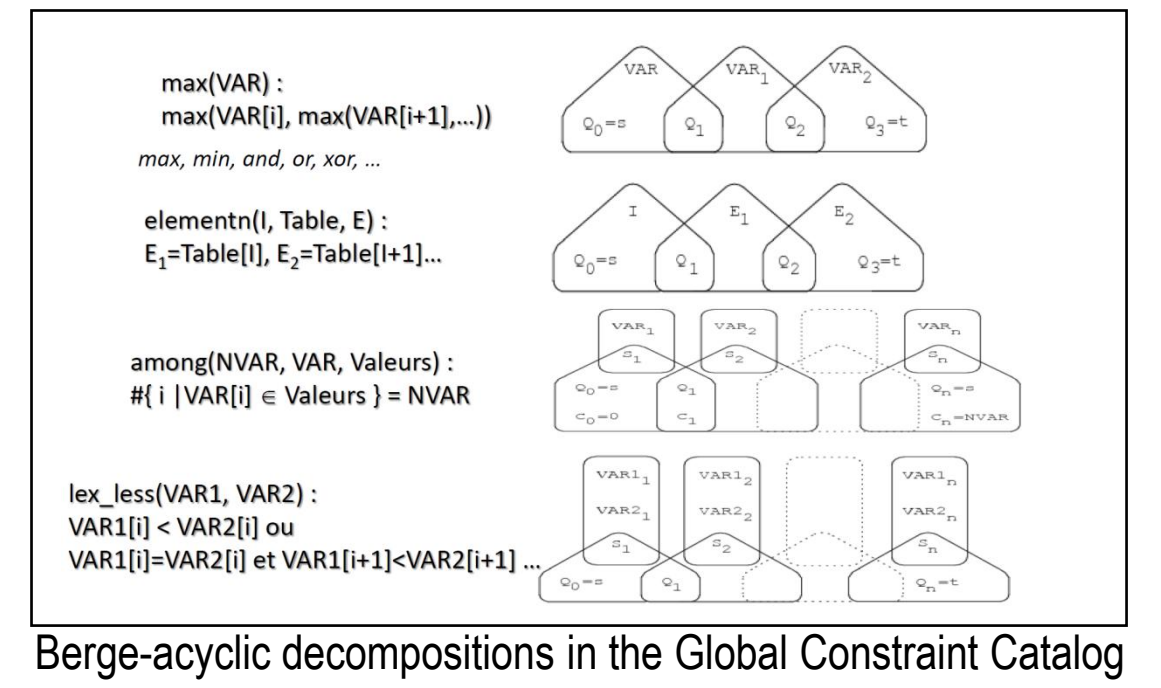
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Summary

Combinatorial optimization problems are naturally expressed as cost function networks. Recently, global cost functions have been introduced with dedicated flow-based filtering algorithms (Lee and Leung, JAIR 2012), leading to a new Cost Function Programming paradigm. In this paper, we explore the possibility of decomposing global cost functions by adding intermediate variables in such a way that enforcing soft local consistency on the decomposition achieves the same level of consistency on the original global cost function. We give conditions under which directional and virtual arc consistency offer such guarantees. We conclude by experiments on decomposable cost functions showing that decompositions may be very useful to easily integrate efficient – *incremental* – global cost functions in solvers.

Preliminaries: Cost Function Networks and Filtering Global Cost Functions using Soft Local Consistency

Combinatorial optimization for cost function networks

(Shapiro, Haralick, IEEE PAMI 81)

- n variables
 - finite domains
- e local/global functions
 - scope, function with costs
 - arity r
- Costs $\in \{0, \dots, +\infty\}$ finite or infinite integer (maximum cost k)

$$X = \{X_1, \dots, X_n\}$$

$$X_i \in D_i, |D_i| \leq d$$

$$F = \{f_1, \dots, f_e\}$$

$$\text{Minimize } \sum_F f_i(X)$$

NP-hard

$$f(A, B, D) = 3A^2 \times B \times D$$

AllDifferent(A,B,D)

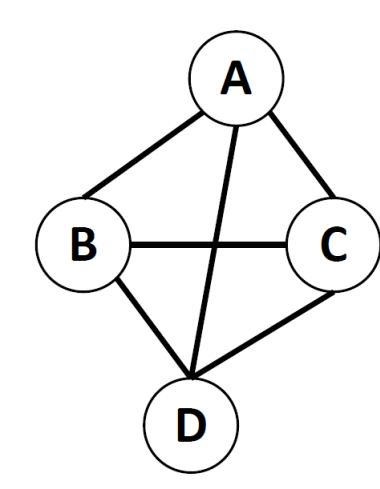
A	B	D	f(A,B,D)
1	2	3	12
1	3	2	7
2	1	3	9
...	...	...	f(...)

A	B	D	f(A,B,D)
1	2	3	0
1	3	2	+\infty
2	1	3	0
...	...	...	f(...)

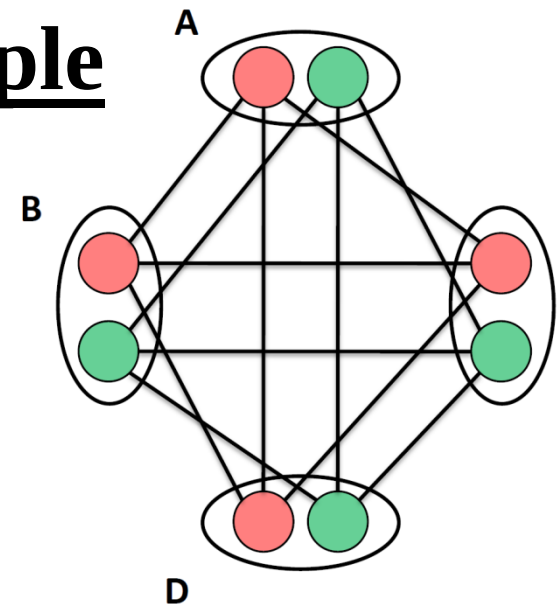
Existing global cost functions

- Soft (*relaxed*) constraints (Petit et al, CP 2001), (Hoeve et al, J. Heuristics 2006)
 - softAllDifferent, softGCC, softAmong, softRegular, ...
 - Semantic of violation (number of variables to be changed, number of violated elementary constraints, ...)
- Constraints integrating unary costs (R  gin, Constraints 2002), (Trick, AOR 2003), (Demasse   et al, Constraint 2006)
 - GCC_with_costs, knapsack, costRegular, ...
- Functions integrating complex costs (Katsirelos et al, AOR 2011)
 - weightedRegular (costs associated to automaton transitions)

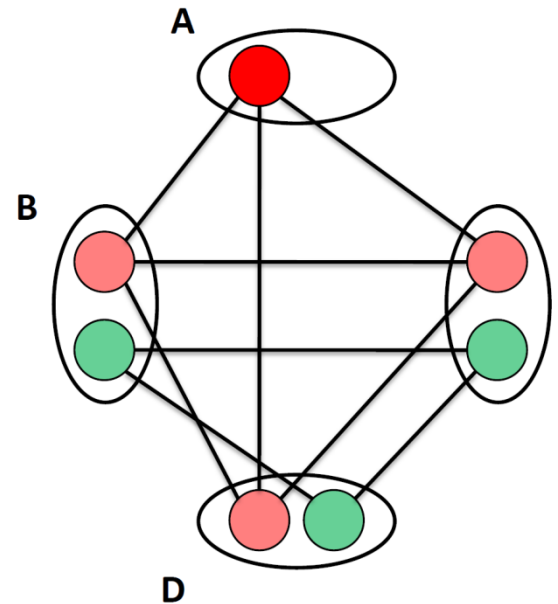
Min-2coloring example



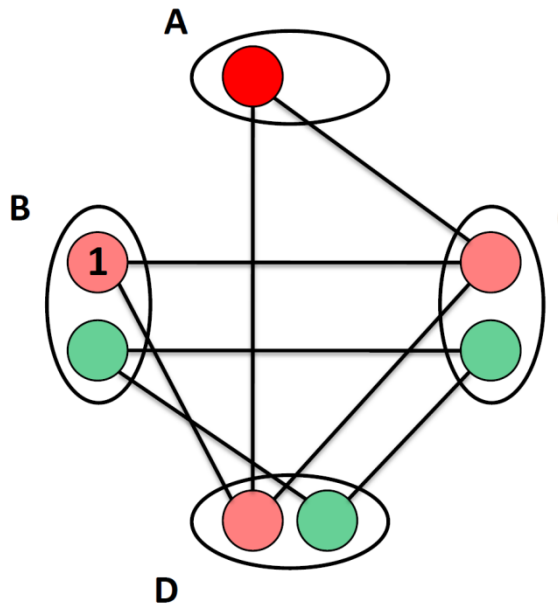
$X=\{A,B,C,D\}$
 $F=\{f(A,B), f(A,C), f(A,D), f(B,C), f(B,D), f(C,D)\}$



micro-structure
(each edge has a unit cost)



assign red to A



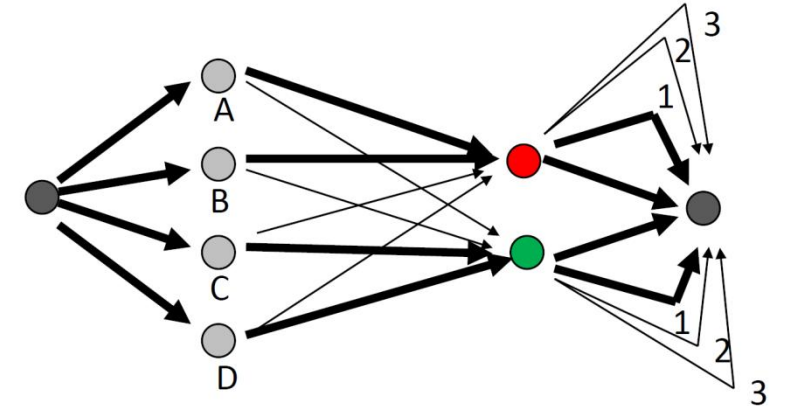
Arc consistent equivalent problem (AC)
(Schiex, CP 2000)

Filtering of cost functions

- Using a cost variable associated to each global constraint (Petit et al, ICTAI 2000)
- Using equivalence preserving problem transformations exploiting special cost functions: $f_\emptyset$ and $f(X_i)$, $\forall X_i \in X$
 - Chaotic transformations (AC, DAC, FDAC, EDAC) See next and below
 - Planned transformations (OSAC, VAC)

Filtering softAllDiff

(Lee and Leung, JAIR 2012)



(each edge has a unit capacity)

Monolithic approach based on min-cost max-flow algorithm

Contribution: Softening Decomposable Global Constraints and Enforcing Soft Local Consistency on Berge-acyclic Decompositions

1 Definition : cost function decomposition

Polynomial transformation parameterized by p

$f(T) \xrightarrow{\text{green arrow}} (T \cup E, F)$ cost function network such that

- $\forall f'(S) \in F, |S| \leq p$ bounded arity by p
- $\forall t \in D^T, f(t) = \min_{t' \in D^{T \cup E}, t'[T]=t} \sum_{f'(S) \in F} f'(t'[S])$ preserves cost distribution

2 Theorem: softening global constraints

- Let $c(T) \xrightarrow{\text{green arrow}} (T \cup E, C)$ constraint network
- Let $\forall c'(S) \in C, g \bullet c'$ new cost function such that

$\forall t' \in S, g \bullet c'(t') \leq c'(t')$ softening of constraint c' by g
Then
($T \cup E, g \bullet C$) is a relaxation of $c(T)$

3 Theorem: DAC solves Berge-acyclic decompositions

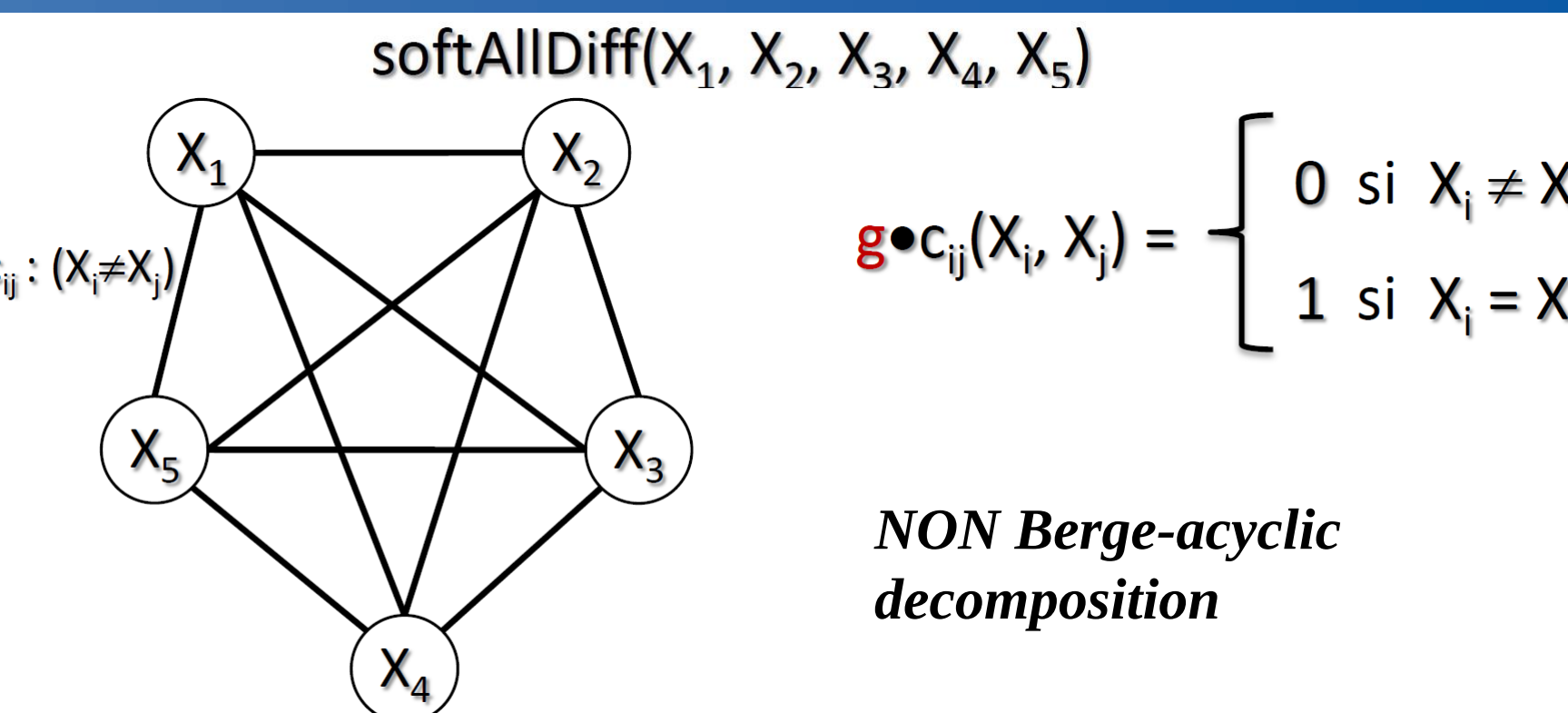
$f(T) \xrightarrow{\text{green arrow}} (T \cup E, F)$ Berge-acyclic cost function network

$\exists$ order $(X_1, \dots, X_m)$ on $T \cup E$ such that
 $X_1 \in T$,
 $f(X_1)$ obtained by filtering $DAC(T, f(T) \cup \{f(X_i) \mid X_i \in T\})$
 $=$
 $f(X_1)$ obtained by filtering $DAC(T \cup E, F \cup \{f(X_i) \mid X_i \in T\})$

4 Theorem: VAC solves Berge-acyclic pb

$f(T) \xrightarrow{\text{green arrow}} (T \cup E, F)$ Berge-acyclic network

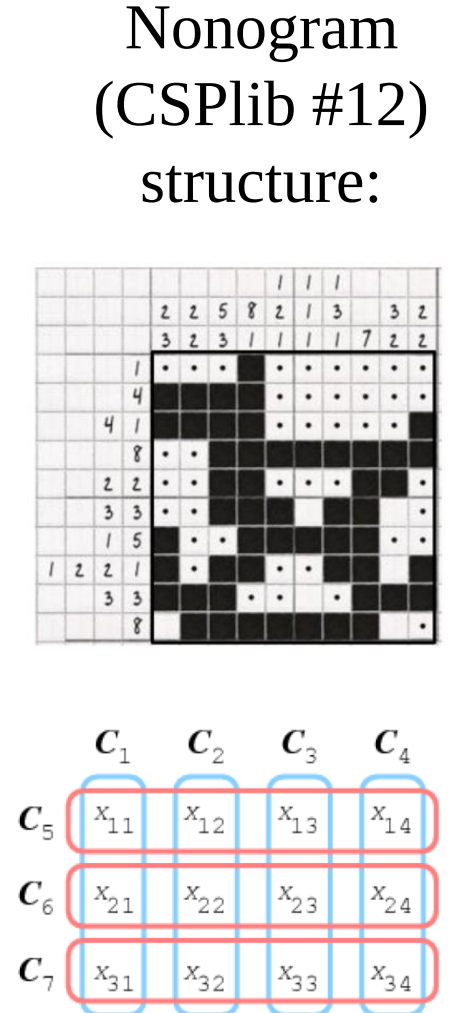
$f_\emptyset$ by $VAC(T, f(T) \cup \{f(X_i) \mid X_i \in T\})$
 $=$
 $f_\emptyset$ by $VAC(T \cup E, F \cup \{f(X_i) \mid X_i \in T\})$



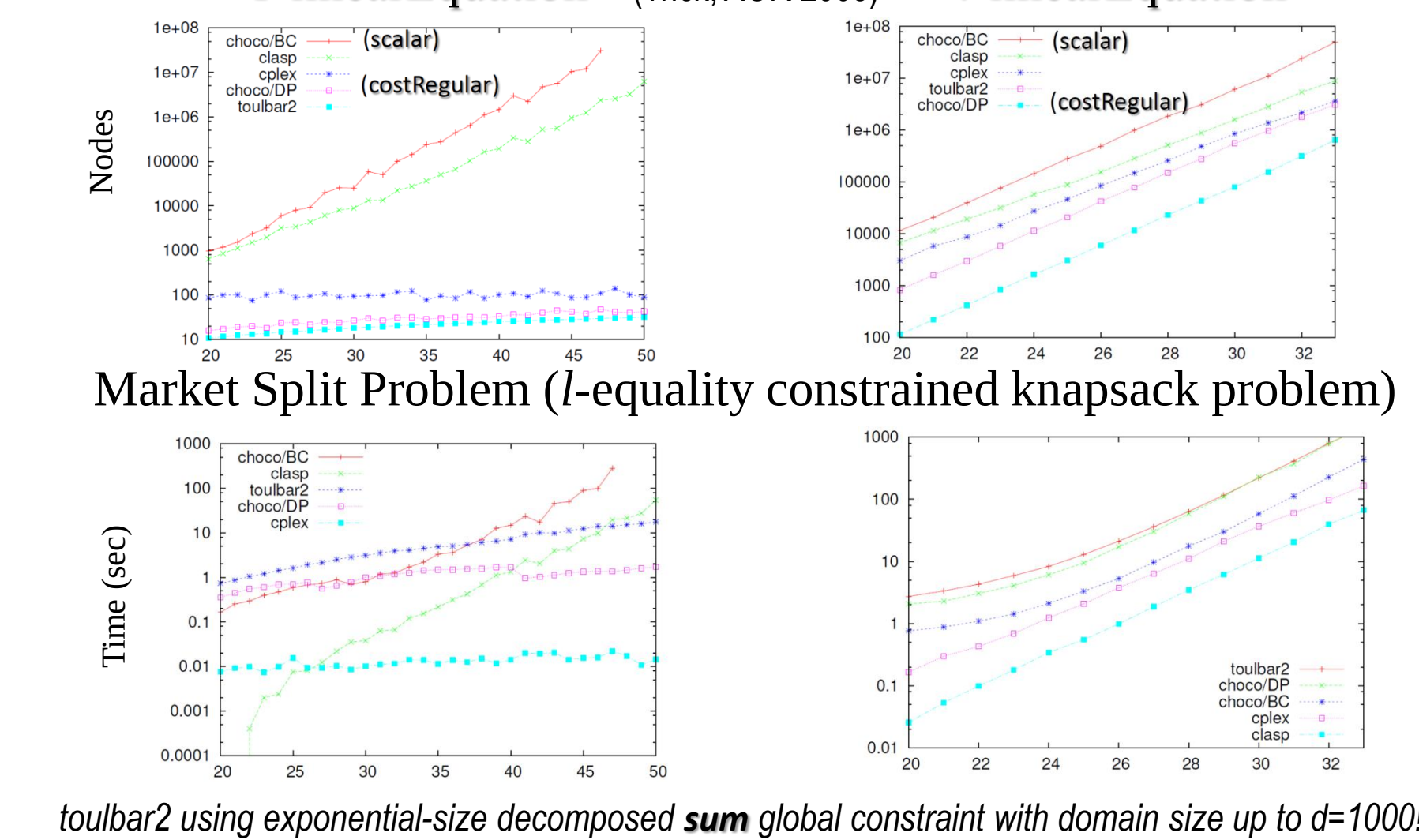
NON Berge-acyclic decomposition

Experimental Results: Random Problem, Soft Nonogram, Market Split Problem, Crop Allocation Problem, Capacitated Warehouse Location Problem

Simple problem with 1 random softRegular and random unary costs							
n	S	Q	Monolithic filter	Monolithic solve	Decomposed filter	Decomposed solve	
25	5	10	0.12	0.51	0.00	0.00	
		80	2.03	9.10	0.08	0.08	
		10	0.64	2.56	0.01	0.01	
25	10	80	10.64	43.52	0.54	0.56	
25	20	10	3.60	13.06	0.03	0.03	
		80	45.94	177.5	1.51	1.55	
50	5	10	0.45	3.54	0.00	0.00	
		80	11.85	101.2	0.17	0.17	
50	10	10	3.22	20.97	0.02	0.02	
		80	51.07	380.5	1.27	1.31	
50	20	10	15.91	100.7	0.06	0.07	
		80	186.2	1,339	3.38	3.47	



Randomized softened nonograms 2n softRegular					
Size	Solved	Time	Solved	Time	
6 x 6	100%	1.98	100%	0.00	
8 x 8	96%	358	100%	0.52	
10 x 10	44%	2,941	100%	30.2	
12 x 12	2%	3,556	82%	1,228	
14 x 14	0%	3,600	14%	3,316	
White-noise nonograms 2n regular with unary costs					
Size	Solved	Time	Solved	Time	
20 x 20	100%	1.88	100%	0.93	
25 x 25	100%	14.78	100%	3.84	
30 x 30	96%	143.6	96%	99.01	
35 x 35	80%	459.9	94%	218.2	
40 x 40	46%	1,148	66%	760.8	
45 x 45	14%	1,627	32%	1,321	



Crop Allocation Farming Problem using regular, same & softGcc									
n	e	Optimum	Monolithic Time(s)	Nodes	Decomposed Time(s)	Nodes	0/1 ILP (SCIP) Time(s)	Nodes	
B1234-LU15*	135	360	704	10,33	118	0.13	30	0.09	1
B1234-LU30*	270	712	1560	147.82	384	0.69	212	0.33	1
B1234-LU60*	540	1384	3852	2952.05	2700	7.59	2508	63.48	575
B1234-LU120*	1080	2728	7520	-	-	651.18	58192	153.64	932

Capacitated Warehouse Location Problem using exponential-size decomposed sum			
Problem Size	Mistral	Toulbar2* 0/1 vars	0/1 ILP (SCIP)
5 x 10	0.04 second	0.06 second	0.01 second
	13,273 nodes	310 nodes	1 node
19 x 20	-	86.23 seconds	0.03 second
	-	752,075	1 node

Experiments using **NumberJack** (common model in python accessing multiple solvers)