Computation with MIP and beyond

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Outline, Assumptions and Notation

- We consider a general Mixed Integer Program in the form:

$$\min\{c^T x : Ax \geq b, x \geq 0,\ x_j \text{ integer},\ j \in \mathcal{I}\} \tag{1}$$

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- It looks like a major (crucial) step to get to nowadays MIP solvers has been the ultimate proof that cutting plane generation – in conjunction with branching – could work in general, i.e., after the success in the TSP context:
  - 1994 Balas, Ceria & Cornuéjols: lift-and-project
  - 1996 Balas, Ceria, Cornuéjols & Natraj: gomory cuts revisited

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- 1,734 MIP instances, time limit of 30,000 CPU seconds, computing times as geometric means normalized wrt Cplex 11.0 (equivalent if within 10%).

Cplex versions	year	better	worse	time
11.0	2007	0	0	1.00
10.0	2005	201	650	1.91
9.0	2003	142	793	2.73
8.0	2002	117	856	3.56
7.1	2001	63	930	4.59
6.5	1999	71	997	7.47
6.0	1998	55	1060	21.30
5.0	1997	45	1069	22.57
4.0	1995	37	1089	26.29
3.0	1994	34	1107	34.63
2.1	1993	13	1137	56.16
1.2	1991	17	1132	67.90

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9.0	2003	1,035	55.9%	2.6%
8.0	2002	987	53.3%	2.5%
7.1	2001	941	50.8%	4.3%
6.5	1999	861	46.5%	13.4%
6.0	1998	613	33.1%	1.0%
5.0	1997	595	32.1%	1.8%
4.0	1995	561	30.3%	4.4%
3.0	1994	479	25.9%	6.2%
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- The key feature of Cplex v. 6.5 was indeed extensive cutting plane generation.

MIP Evolution, Cutting Planes

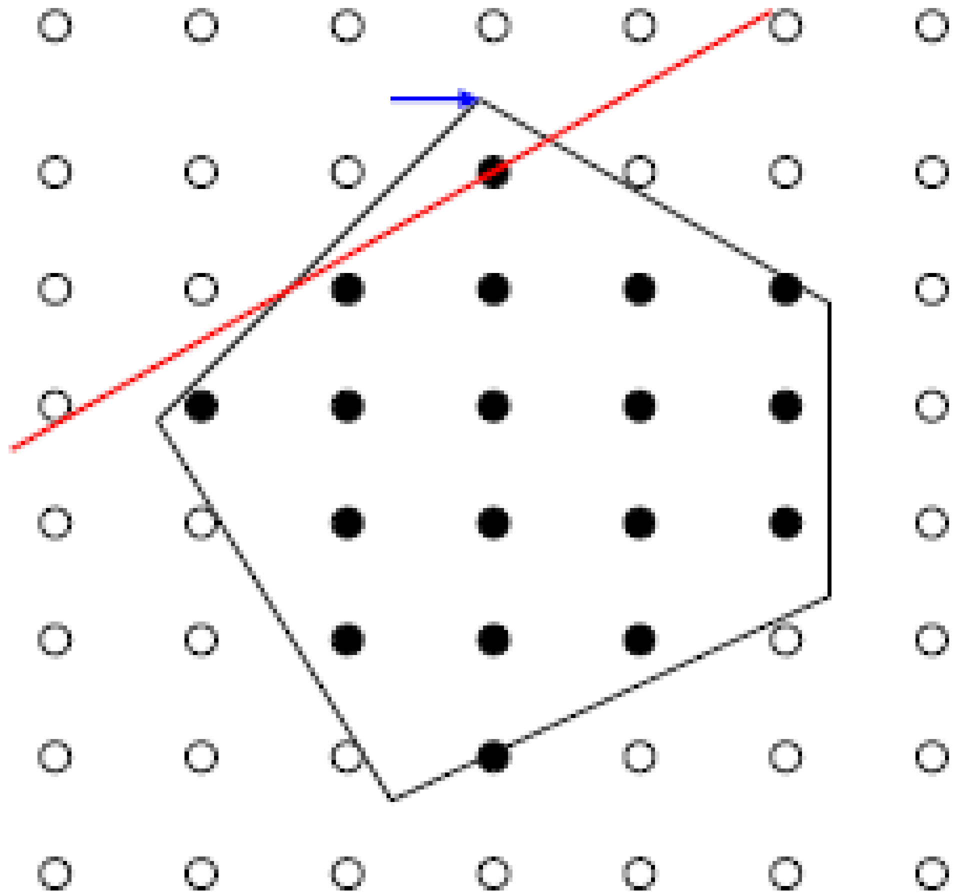

Figure 1: Strengthening the LP relaxation by cutting planes.

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- Moreover, the MIP computation has reached such an effective and stable quality to allow the solution of sub-MIPs in the algorithmic process, the MIPping approach. [Fischetti & Lodi]
  These sub-MIPs are solved both for cutting plane generation and in the primal heuristic context.

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  - callbacks:
    allow flexibility to accommodate the user code so as to take advantage of specific knowledge

MIP Challenges

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- Some difficult MIPs:

  - bad modeling:
    * the model has numerical difficulties
    * the MIP modeling capability is not sufficient wrt the real problem

  - large problems

  - knapsack constraints with huge coefficients and general integer variables with large bounds

  - scheduling models with disjunctive constraints and fundamental continuous variables

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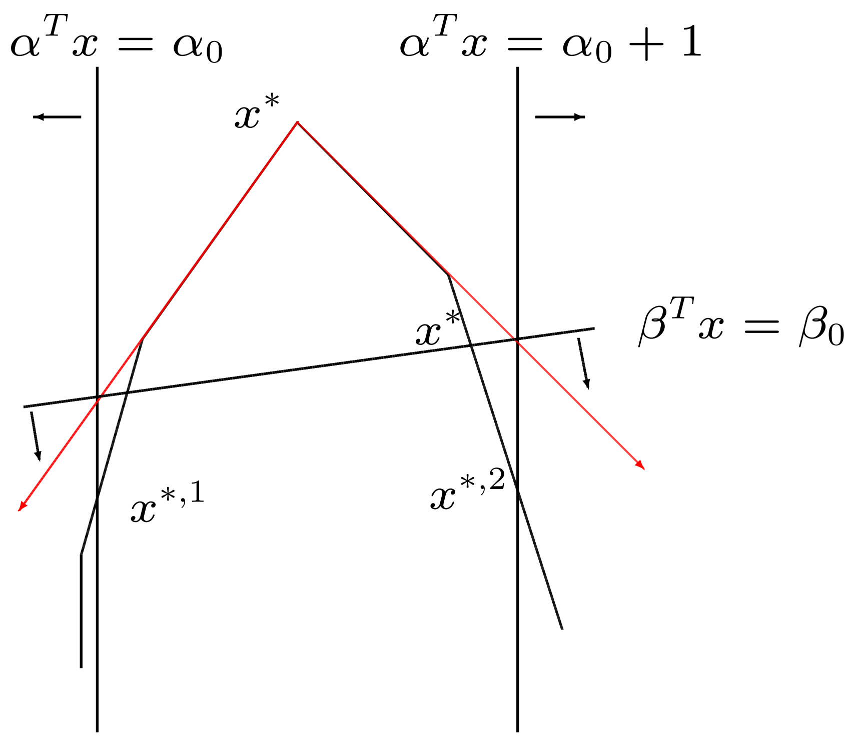
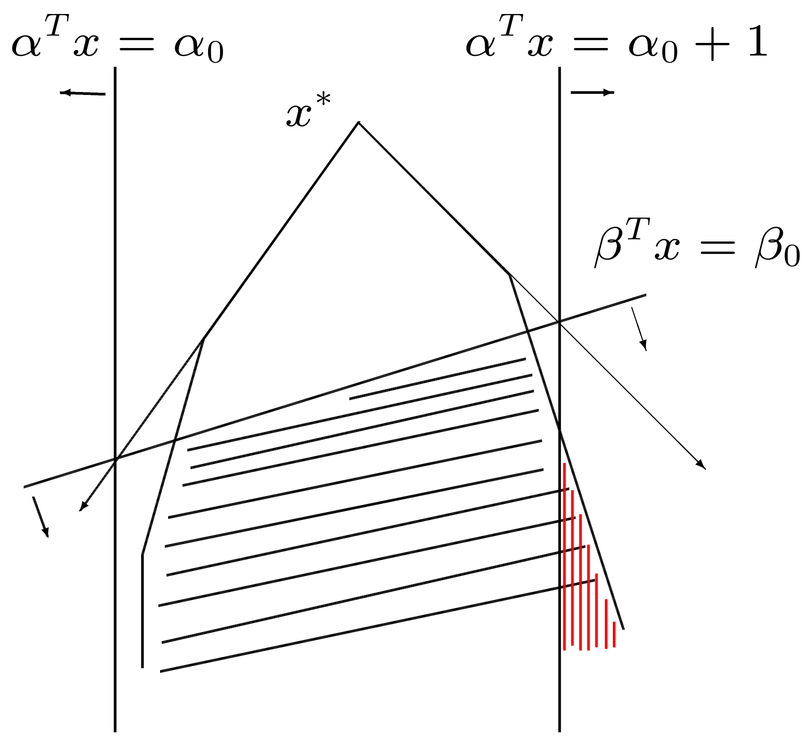
- The performance of MIP solvers can/must be improved in many different directions. Among them, my favorite ones are:
  - branching vs cutting
  - sophisticated techniques for general integer and continuous variables
  - performance variability
  - revisiting good "old" methods
  - cutting planes exploitation
  - symmetric MIPs

MIP Challenges: branching vs cutting



first wisdom



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- Finally, branching on appropriate disjunctions has been recently proposed in the context of highly symmetric MIPs. [Ostrowsky, Linderoth, Rossi & Smriglio]

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- Cutting plane generation has been a key step for the success of MIP solvers but: are we using cuts in the best way?By far not!
- Fundamental questions about the use of cutting planes remain open:
  - stabilization issues
  - cut selection
  - cut interaction
  - correlation within rounds of cuts

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- Good "old" methods have been rediscovered and revisited during the years and it is hard to believe that we understand them fully, at least computationally. Recently:
  – strong Benders cutting planes [Fischetti, Salvagnin & Zanette],
  – lexicographic [Zanette, Fischetti & Balas]
  – cutting planes from group relaxation [Gomory; Richard; Dey; Wolsey; Dash & Günlük;. . .]

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2. Bonmin (Basic Open-source Nonlinear Mixed INteger programming, [Bonami et al.]) has been developed for Convex MINLP within the framework of the MIP solver Cbc [Forrest].

MIP Modeling, CP and SCIP

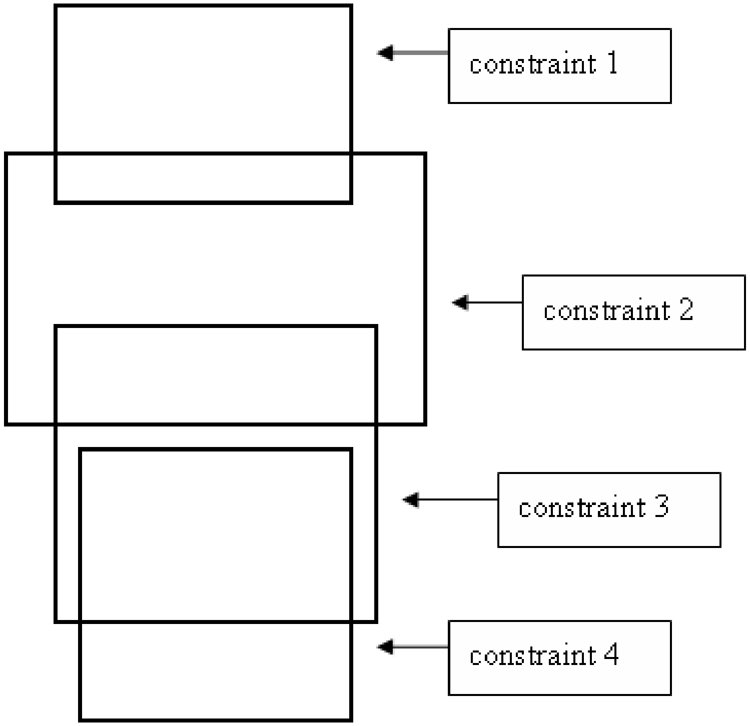
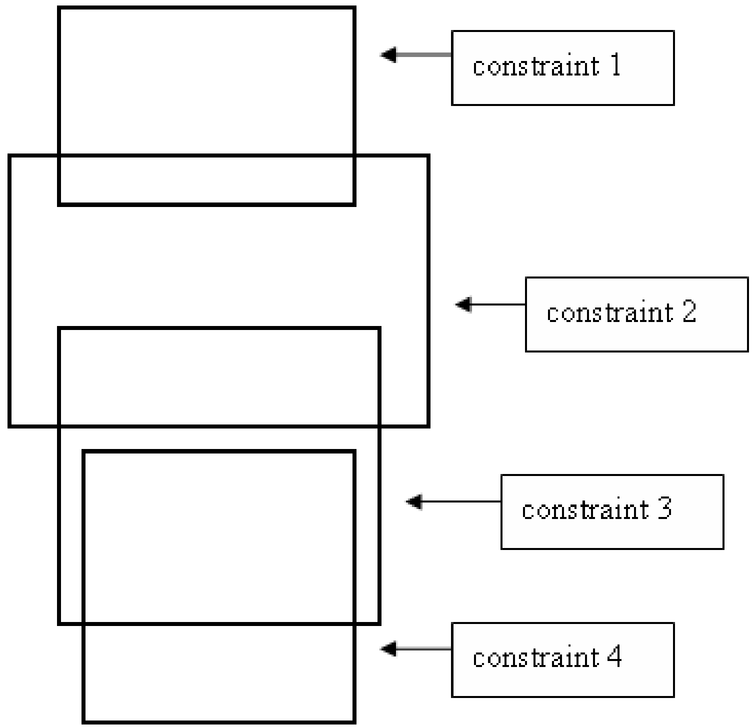


Figure 2: Modeling in the CP paradigm.

MIP Modeling, CP and SCIP



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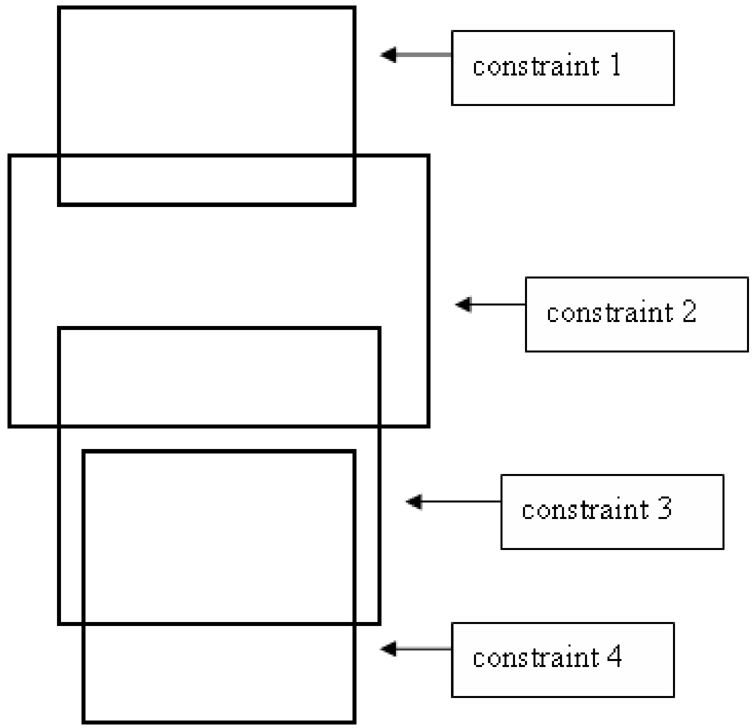

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- A global constraint defines combinatorially a portion of the feasible region, i.e., it is able to check feasibility of an assignment of values to variables.
- Moreover, a global constraint contains an algorithm which prunes (filters) values from the variable domains so as to reduce as much as possible the search space.

MIP Modeling, (Non-)Convex MINLP and Bonmin

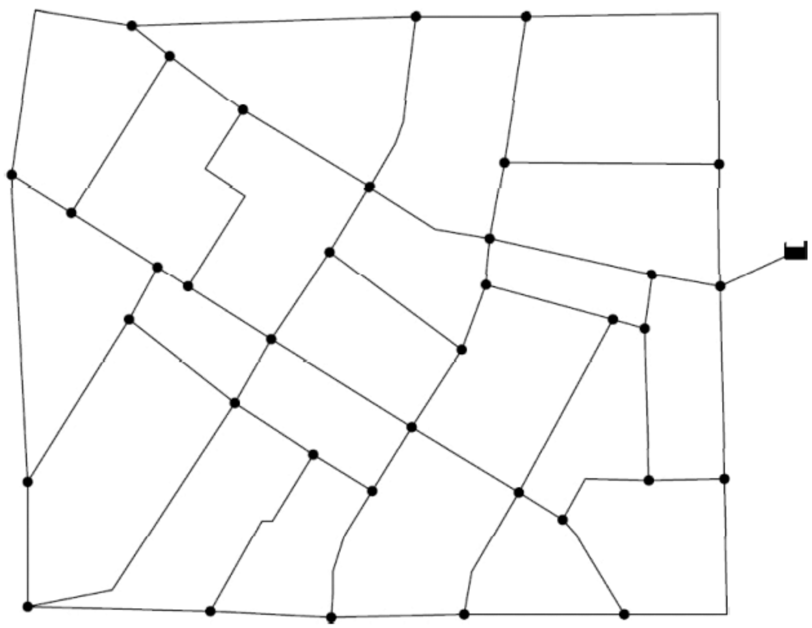

Figure 3: A network design example in the water distribution, instance `fossolo`.

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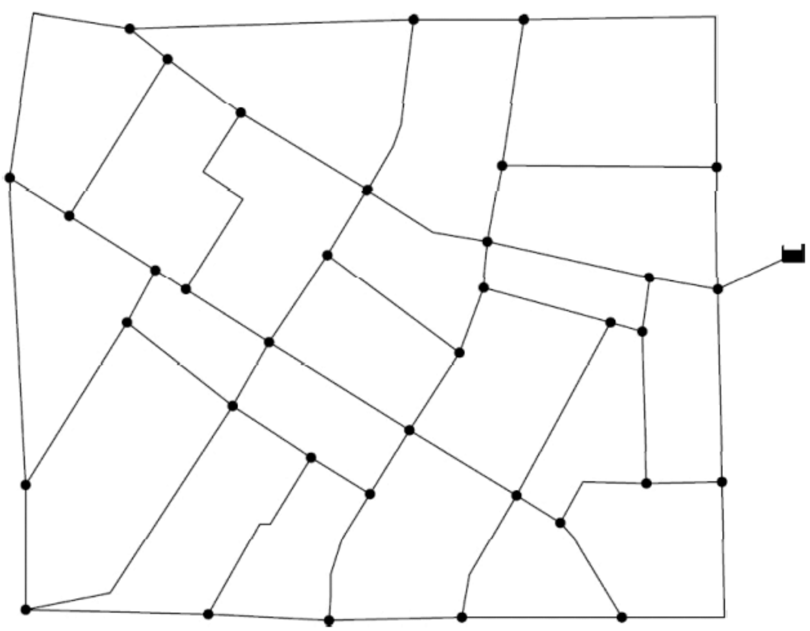

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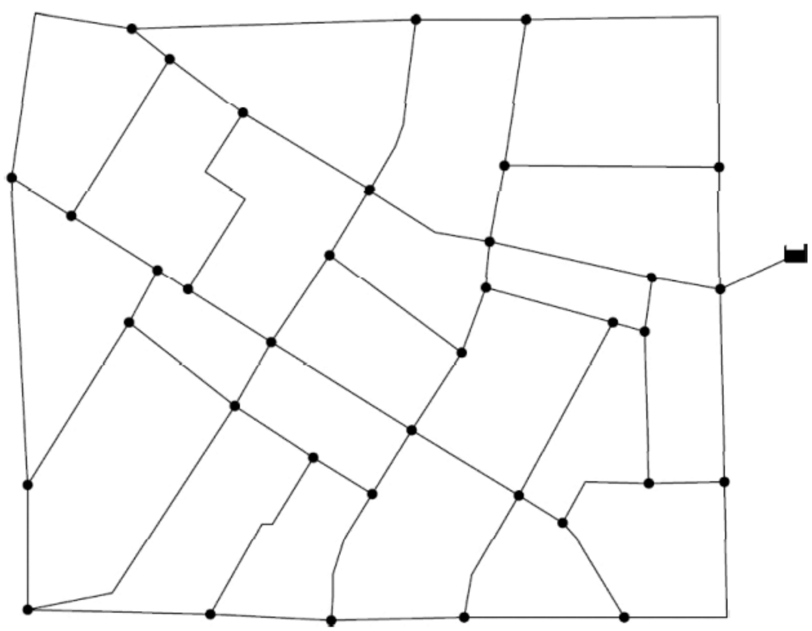

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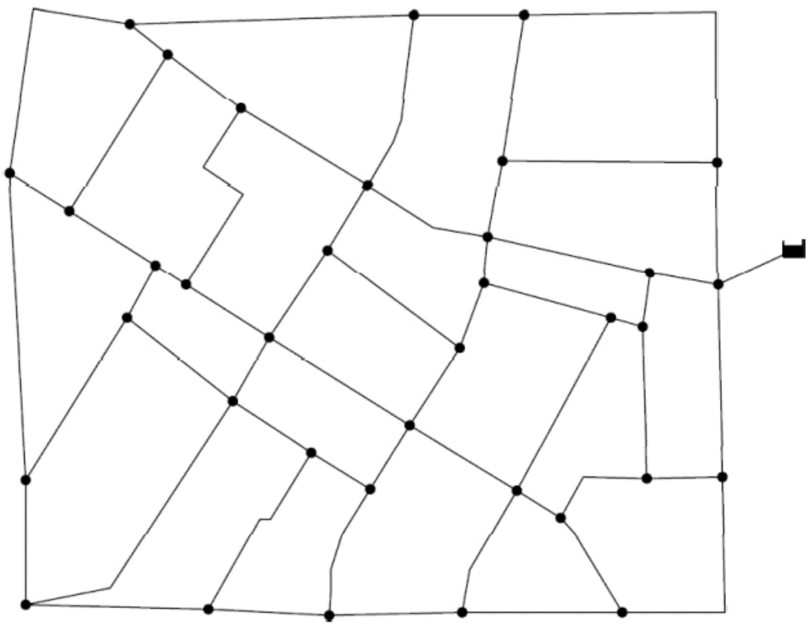

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Computation in MIP: Conclusion

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- In summary: still a long way to go!