

# The Feasibility Jump: an LP-free Lagrangian MIP heuristic

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"Participants are invited to create novel general-purpose primal heuristics for mixed-integer linear optimization problems. Participants are encouraged to develop LP-free heuristics, however, everyone is allowed to solve auxiliary convex optimization problems."

- Most primal heuristics start after solving the LP relaxation:
  - Feasibility pump, RINS, RENS, Local branching, Pivot and shift, rounding heuristics, etc.



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- ...and solving the LP relaxation can take some time!

	Gurobi 9.5 root	Gurobi 9.5 first sol default	Gurobi 9.5 first sol feas emph
<ul> <li>highschool1-aigio</li> </ul>	9.17 s	501 s	552 s
– neos-5052403-cygnet	31.6 s	86.8 s	44.4 s
– s250r10	55.0 s	61.4 s	8.62 s



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– neos-5052403-cygnet	31.6 s	86.8 s	44.4 s	2.87 s
– s250r10	55.0 s	61.4 s	8.62 s	7.92 s



- Feasible solutions can greatly help a MIP solver:
  - Providing primal bounds, which in turn help the pruning of the branching tree
  - As input to more sophisticated heuristics (e.g., RINS)
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- Can be extremely relevant in real-life applications<sup>1</sup>:

Heuristic	CPLEX	Heuristic + CPLEX		
Standalone heuristic	Standalone MIP	Solutions from the heuristic are used as "warm starts"		
1.0x < 1 sec	~ 2.0x ~ 1 hour	~ 0.8x ~ 1 min		

1. Fischetti, M., Sartor, G. and Zanette, A., 2015. MIP-and-refine matheuristic for smart grid energy management. *International Transactions in Operational Research*, 22(1), pp.49-59.



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• Sometimes all the customers want is a "good" feasible solution as fast as possible

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- Penalty-based metaheuristics<sup>1</sup>
- Propagation-based heuristics<sup>2</sup>
- ...and that's it!

- 1. Lei, Z., Cai, S., Luo, C. and Hoos, H., 2021, July. Efficient Local Search for Pseudo Boolean Optimization. In International Conference on Theory and Applications of Satisfiability Testing (pp. 332-348). Springer, Cham.
- 2. Berthold, T. and Hendel, G., 2015. Shift-and-propagate. Journal of Heuristics, 21(1), pp.73-106.



• It's a Lagrangian method

$$- \min_{s.t.} \frac{1}{Ax} \sum_{x \le b} \to \min_{x \ge 0} \lambda^T (b - Ax) := \min_{x \ge 0} L(x, \lambda)$$

- 1. Solve  $\min L(x; \lambda^*)$
- 2. Update  $\lambda^*$
- 3. Repeat



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#### Three levels of approximation:

- 1. Change the value of **one** variable at a time
- 2. Each variable can "jump" only to a single new value
- 3. The neighborhood defined by 1. and 2. is updated lazily



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#### Up to 1 million iterations per second!



- At the time it is computed, this is the value, different from the incumbent, that maximizes its score



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#### • The score

- The decrease in the total weighted constraint violation:  $\max\{\lambda^T(b - Ax), 0\} - \max\{\lambda^T(b - Ax^*), 0\}$ 

Total violation before Total violation after



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#### • Example

- $x_1 + x_2 = 5, x_1, x_2 \in \{1, 2, 3\}, x_1^*, x_2^* = 0.$ 
  - 1. Jump values and scores:  $(v_1: 3, s_1: 3), (v_2: 3, s_2: 3)$ . We choose  $x_1$ . New incumbent:  $x_1^* = 3, x_2^* = 0$ .



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Consider the problem:

 $x_1 + x_2 = 2,$   $x_2 + x_3 \ge 3,$  $x_1, x_2, x_3 \in \{0, 1, 2, 3, 4\}$ 

And the (infeasible) incumbent solution:

 $x_1^* = 0, x_2^* = 0, x_3^* = 0$ 



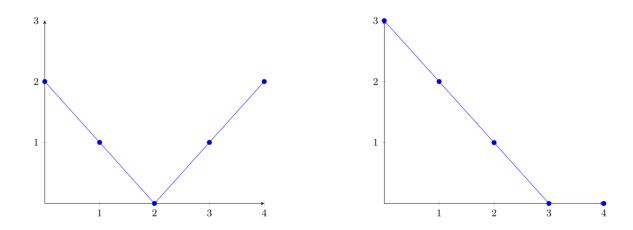
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Constraint violation functions for variable  $x_2$ 





 $\mathbf{2}$ 

1

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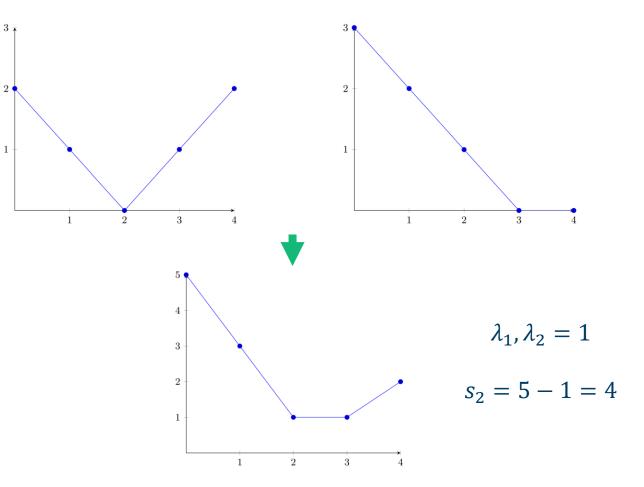
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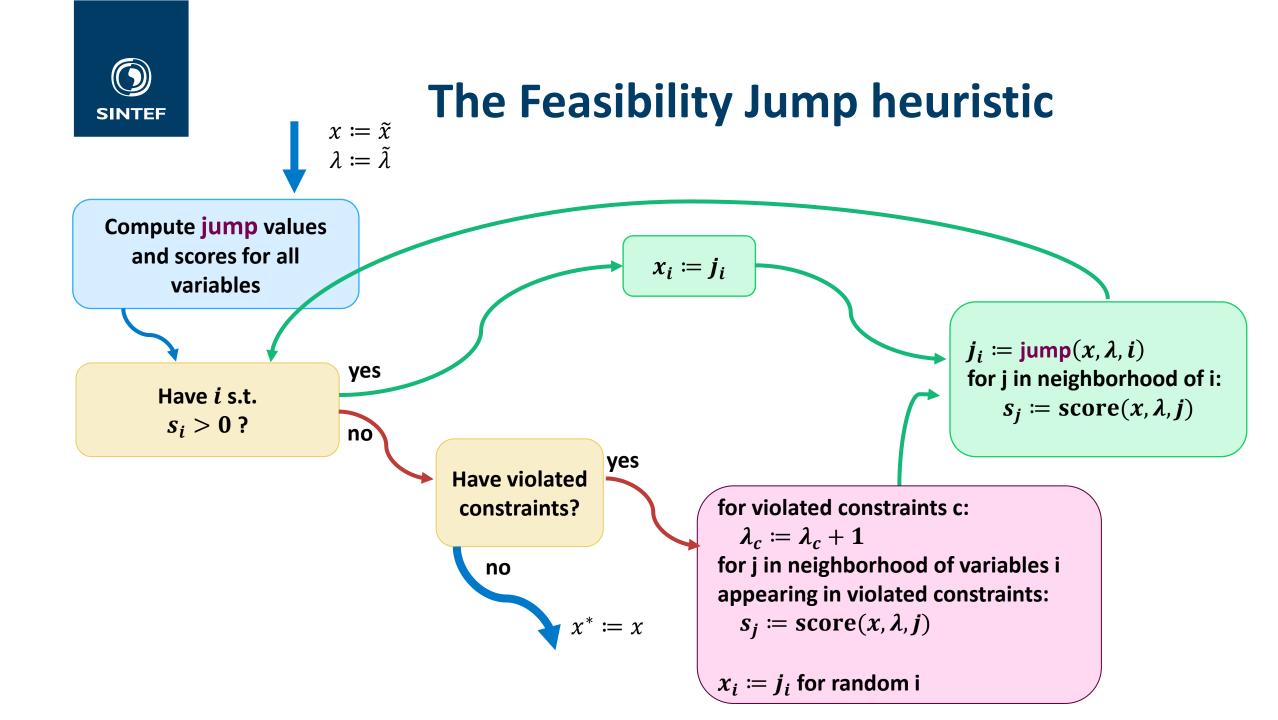
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Technology for a better society

Constraint violation functions for variable  $x_2$ 



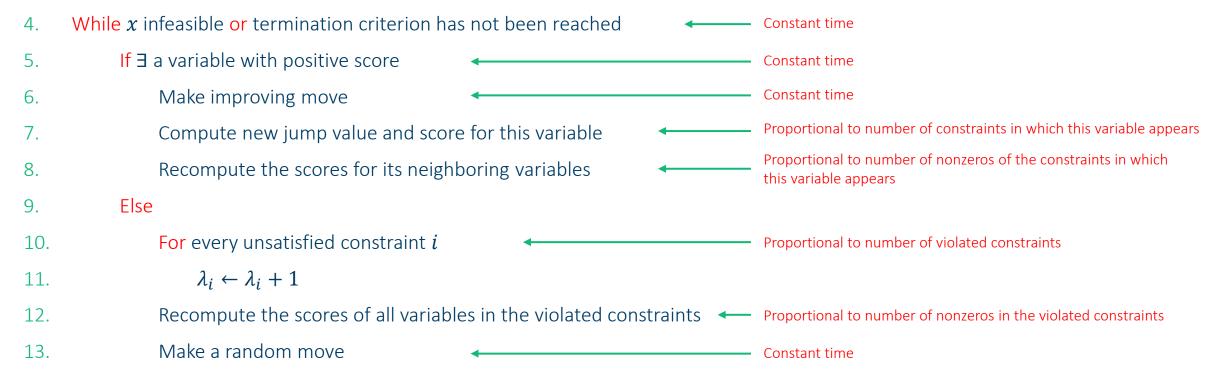




- 1. Initialize Lagrangian multipliers  $\lambda$  to 1
- 2. Initialize solution x
- 3. Assign to each variable a jump value and compute its corresponding score
- 4. While *x* infeasible or termination criterion has not been reached
- 5. If **B** a variable with positive score
- 6. Make improving move
- 7. Compute new jump value and score for this variable
- 8. Recompute the scores for its neighboring variables
- 9. Else
- 10. For every unsatisfied constraint *i*
- 11.  $\lambda_i \leftarrow \lambda_i + 1$
- 12. Recompute the scores of all variables in the violated constraints
- 13. Make a random move



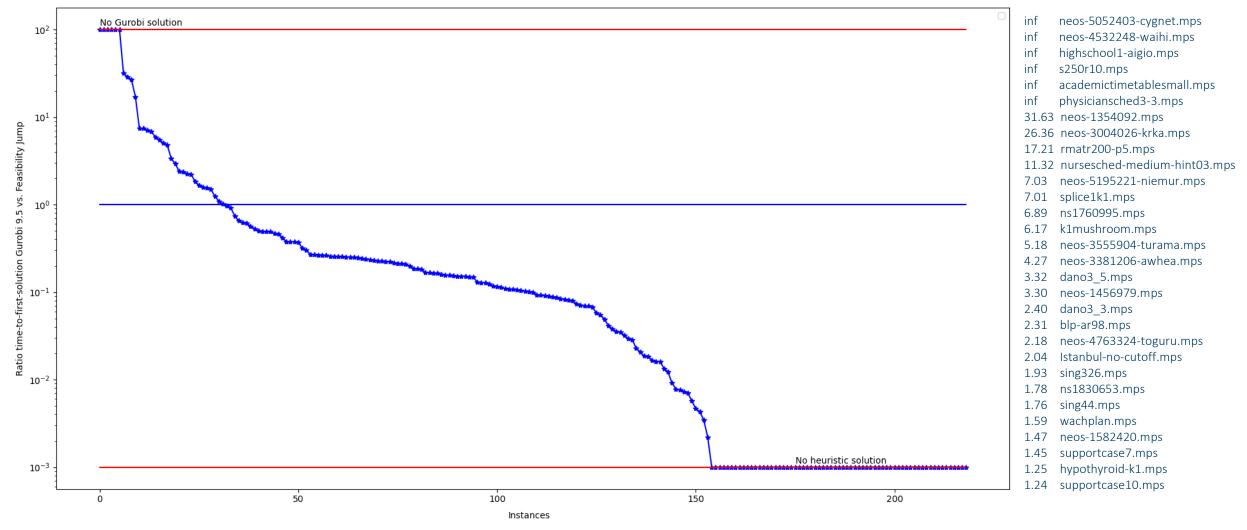
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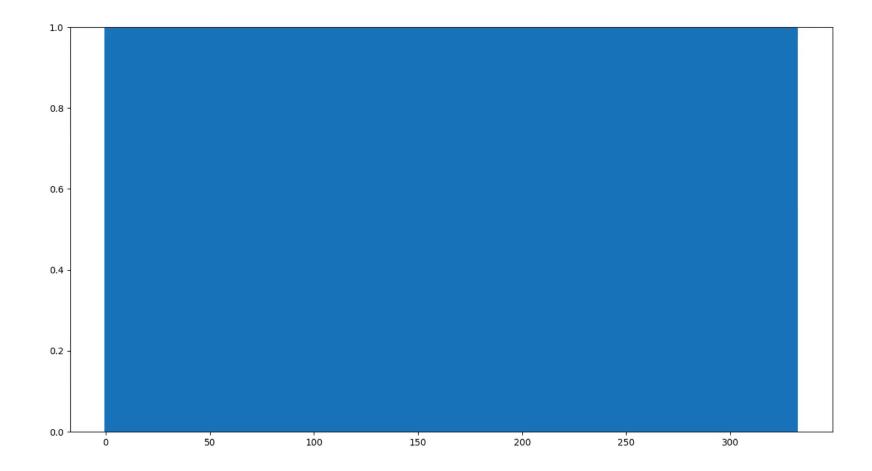


- 240 real-world MIP instances commonly used to compare solvers
- With 1 minute timeout, can we find any feasible solutions?
  - Gurobi 9.5: 213/240
  - Feasibility Jump (competition version): 154/240

# **SINTEF** Time to first solution: best instances









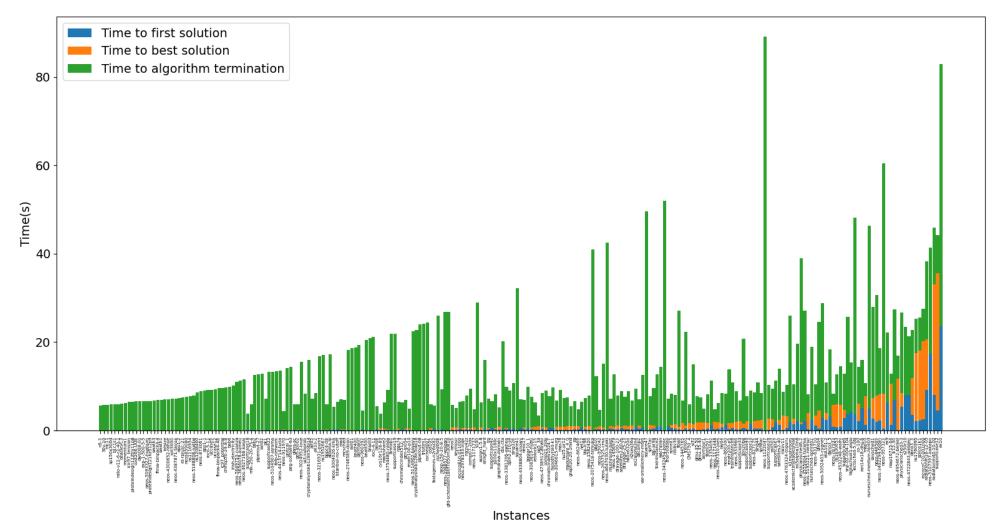
- Reference implementation available at <u>https://github.com/sintef/feasibilityjump</u>
- We heard from several implementers of comprehensive optimization solvers
- They reported performance gains from adding Feasibility Jump to their toolbox of heuristics
  - FICO Xpress
    - Example: time to first feasible solution of **academictimetablesmall.mps**
    - In version 8.14: 248.0 s
    - In version 9.2: 4.2 s
  - Google OR-tools
  - COPT Cardinal Optimizer
  - HiGHS



- When does it work and why?
- Machine learning:
  - Better scoring function?
  - Better weighting function?
  - Parameter tuning?
- Local search improvements
  - Additional values other than the jump value?
  - Other memory-based mechanism?
  - Multiple-variable neighborhood?
- When do we terminate?
- Structure-based presolve
- Feasibility Pump + Jump









## **Results on the MIP competition test instances**

Instance		Last sol. time (s)	Termination time (s)	First sol. objective	
academictimetablesmall.mps	1.07	1.2	15.39	10120	3586
comp07-2idx.mps	0.04	0.04	10.03	1569	1569
cryptanalysiskb128n5obj16.mps		-	22.11	-	-
eil33-2.mps	0.02	0.02	9.33	1642.57	1642.57
highschool1-aigio.mps	2.75	2.88	12.45	14924	12956
mcsched.mps	0.14	0.28	6.88	476402	474281
neos-1354092.mps	0.9	0.9	10.94	400591	400591
neos-3024952-loue.mps	-	-	17.30	-	-
neos-3555904-turama.mps	2.83	2.83	27.78	-34.7	-34.7
neos-4532248-waihi.mps	0.95	9.31	13.94	643.2	581.76
neos-4722843-widden.mps	-	-	19.35	-	-
ns1760995.mps	1.86	21.97	28.82	-140.45	-150.81
ns1952667.mps	-	-	14.59	-	-
peg-solitaire-a3.mps	-	-	14.24	-	-
qap10.mps	0.22	0.25	12.69	534	440
rail01.mps	-	-	19.20	-	-
rococoC10-001000.mps	21.27	21.27	27.77	42727	42727
seymour.mps	0.01	0.29	5.27	491	475
<pre>supportcase10.mps</pre>	1.05	1.05	8.78	17	17



