GO Competition Challenge 2: Analysis and Lessons Learned

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Partners

More information:

https://GOCompetition.Energy.gov

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Grid Optimization (GO) Competition Goals

- Accelerate the development of transformational and disruptive methods for solving optimization problems related to the electric power grid
- Provide a transparent, fair, and comprehensive evaluation of new solution methods.
- Challenge 2 – September 2020 – October 2021 (4 divisions completed)
  - $2.4 million in prizes awarded to 9 teams
  - 15 teams participated in the Final Event, C1 winning teams funded by prize money
  - 11 million CPU-hours
  - Data from Georgia Tech, Texas A&M, UW-Madison

Challenge 2 Problem Formulation

- Built on Challenge 1 SCOPF problems (a minimization problem)
  - Single period ACOPF with security constraints
  - Short term operational actions – 5 to 15 minutes prior to real time
  - Use in planning – pre-determine actions that can be deployed in real time

- Outline for today:
  - Problem hardness
  - Penalties
  - Flexible demand
  - Solve time
  - Solution ensembles
  - Transmission switching
  - Use of HPC

Problem Hardness Measures

A priori method

How much potential for improvement?

$$H_{prior} = \frac{\text{relaxed upper bound cost delta}}{\text{cost of feasible ACOPF solution}}$$

A posteriori methods

How much benefit from selecting the best algorithms?

$$H_{post,0} = \frac{\text{best score} - \text{2nd score}}{\text{2nd score}}$$

$$H_{post,1} = \frac{stdev(\text{5 best scores})}{avg(\text{5 best scores})}$$

$$H_{post,2} = \frac{stdev(\text{5 best scores})}{max(\text{5 best scores})}$$

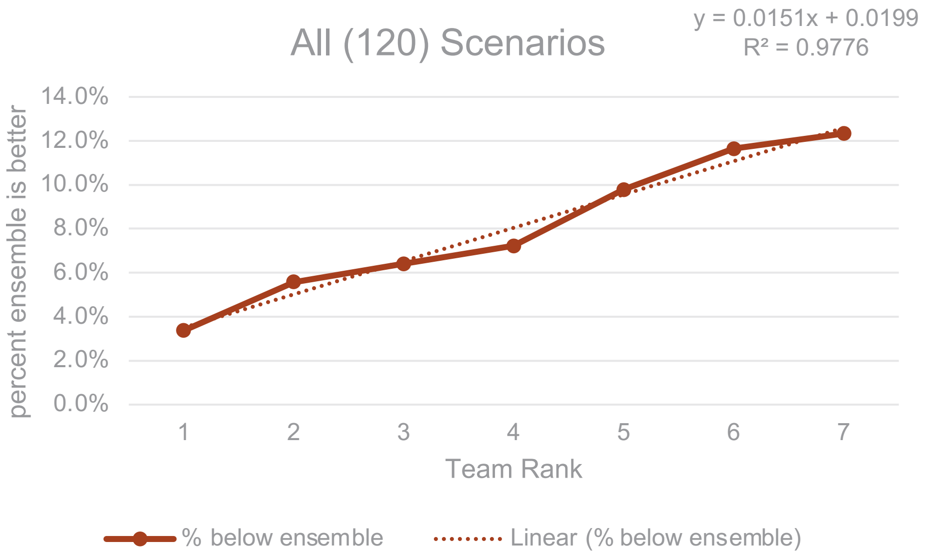
Pearson Coefficient with H_{prior}:

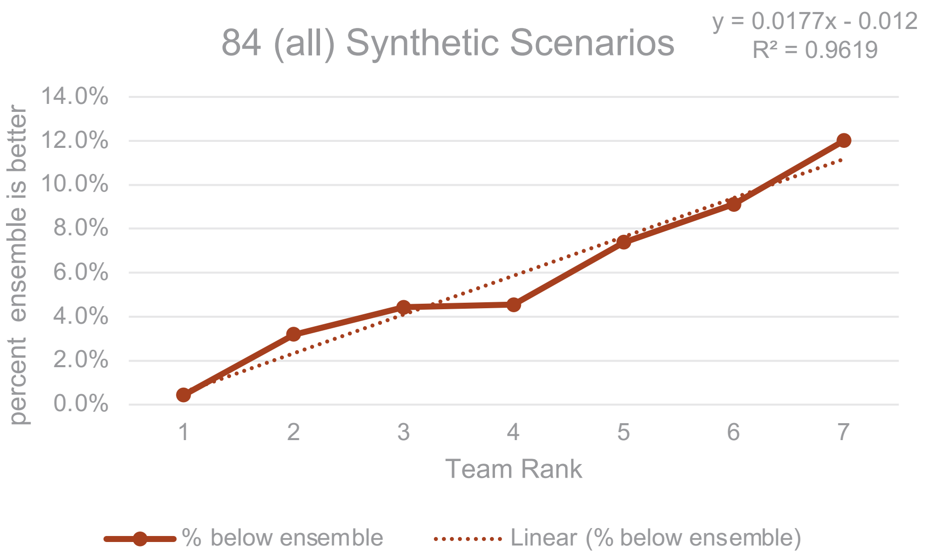
Scenarios (#)	$H_{post,0}$	$H_{post,1}$	$H_{post,2}$
All (120)	-0.1327	-0.0692	-0.0692
Synthetic (84)	-0.2055	-0.1593	-0.1608
Industry (36)	0.811	0.917	0.915

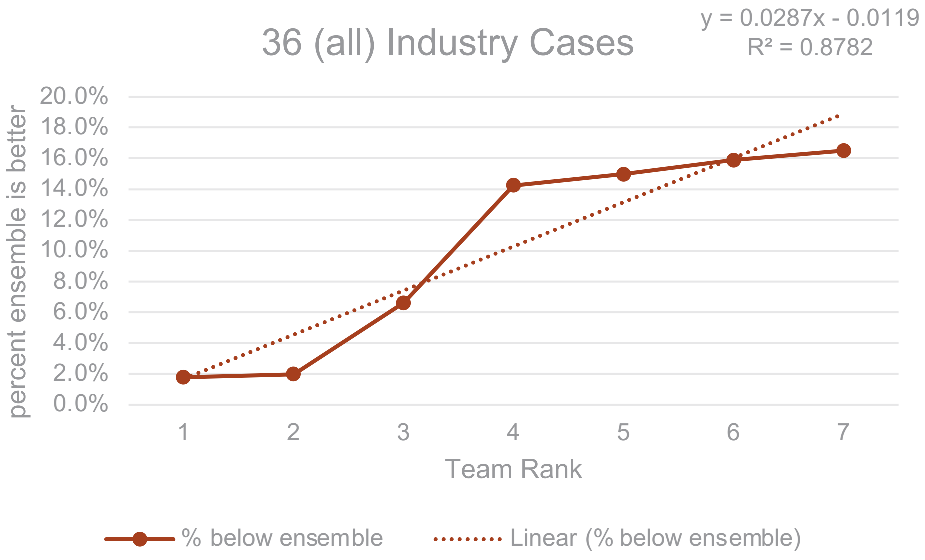
- Synthetic datasets: Correlation is 0.35-0.5 when H_{prior} is small.
- Offshoot: a priori difficulty is harder to measure when there is a large opportunity to improve the solution.

Synthetic and Industry Dataset Differences

Comparison of individual team performance to ensemble (best score from each scenario)



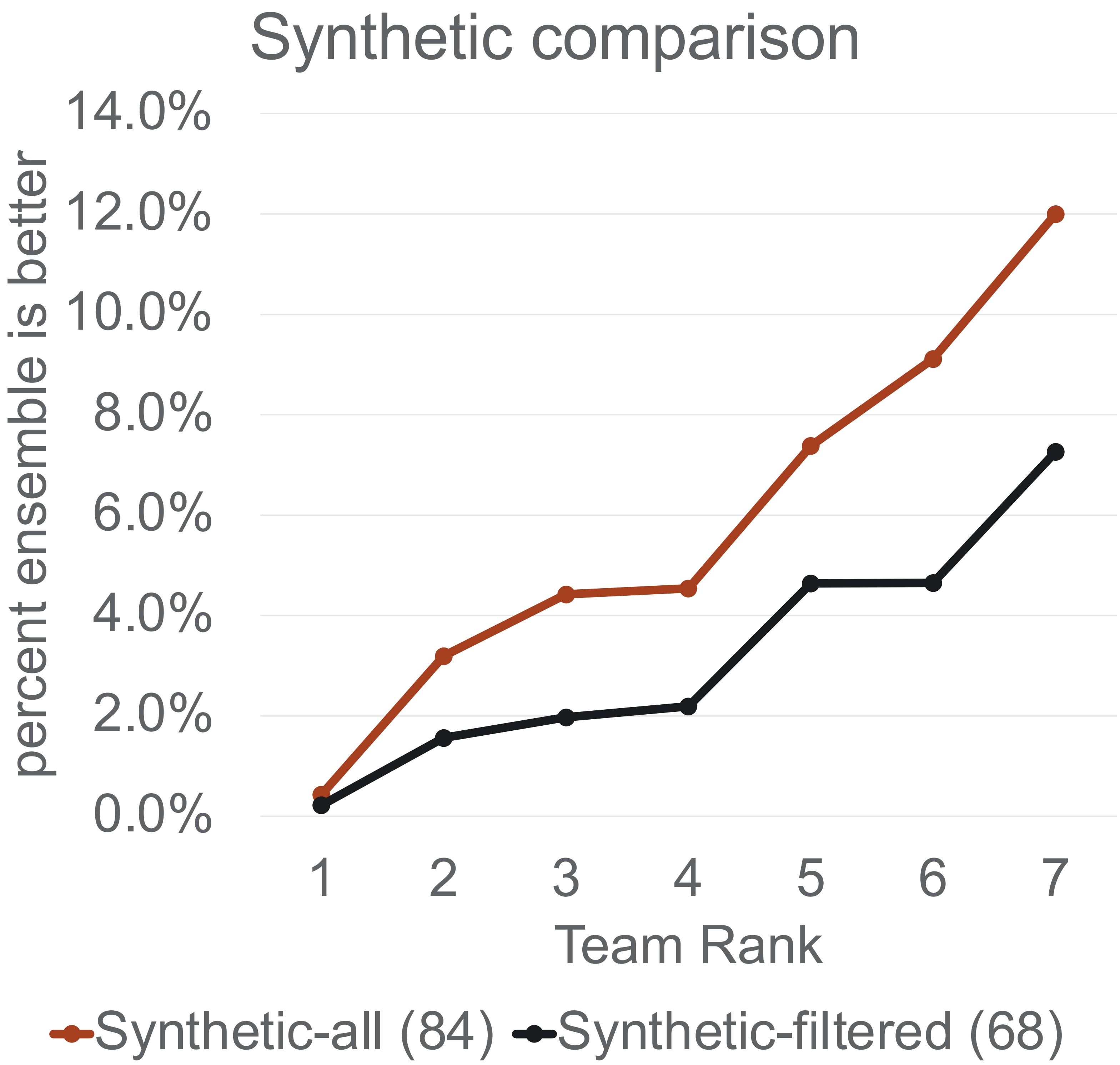




- All & synthetic networks: smooth linear score increase compared to the ensemble.
- Industry: only 3 teams within 12% of the ensemble score.
- This raises a question of whether industry case difficulties were caused by coding errors (e.g., parsing) or because the optimization problems were inherently more difficult.

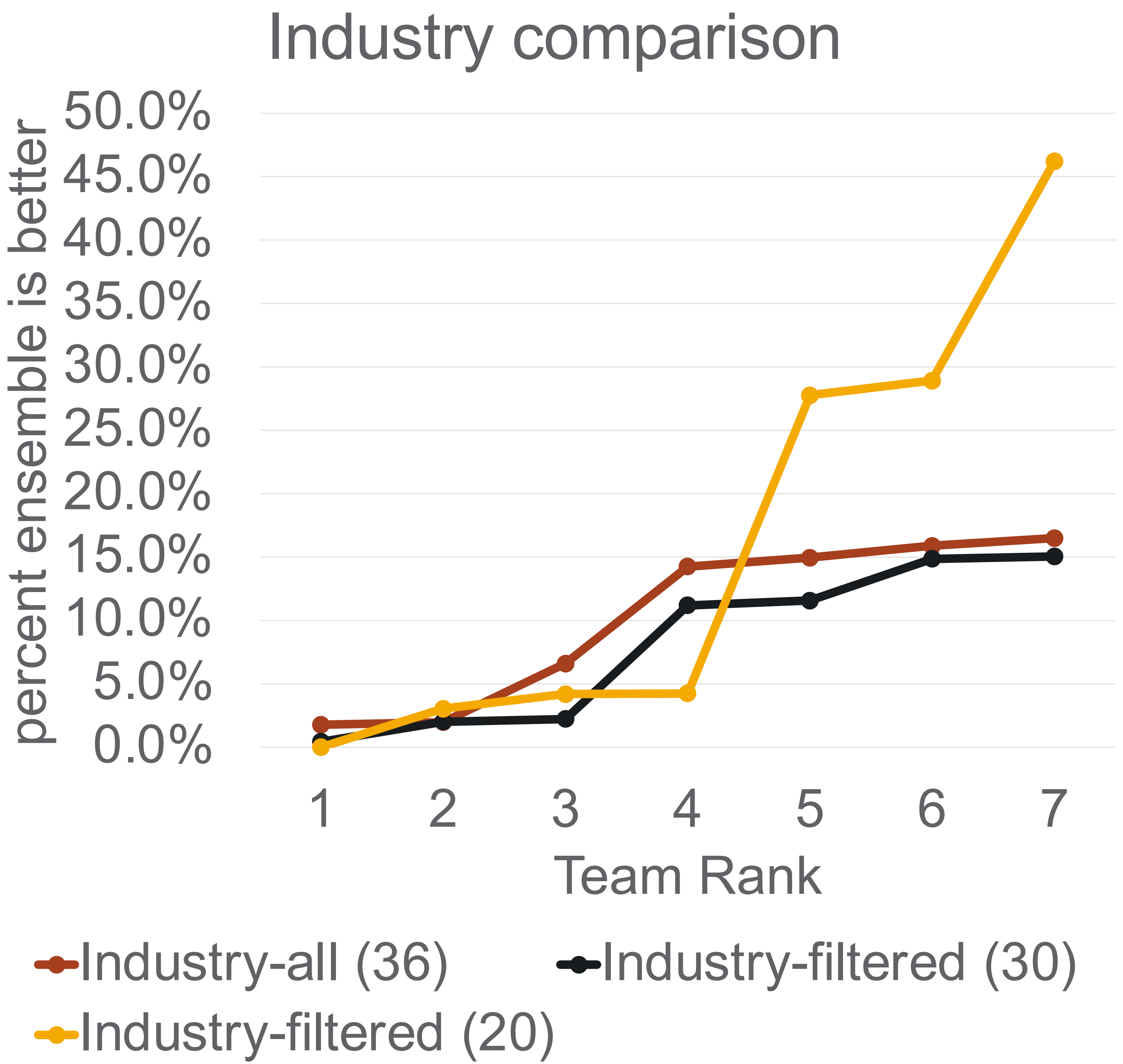
Synthetic case comparison

- Excluded 16 cases that caused failures in top-performing solvers.
- Result: more consistency between scores.
- This means that the excluded cases were difficult for all teams.



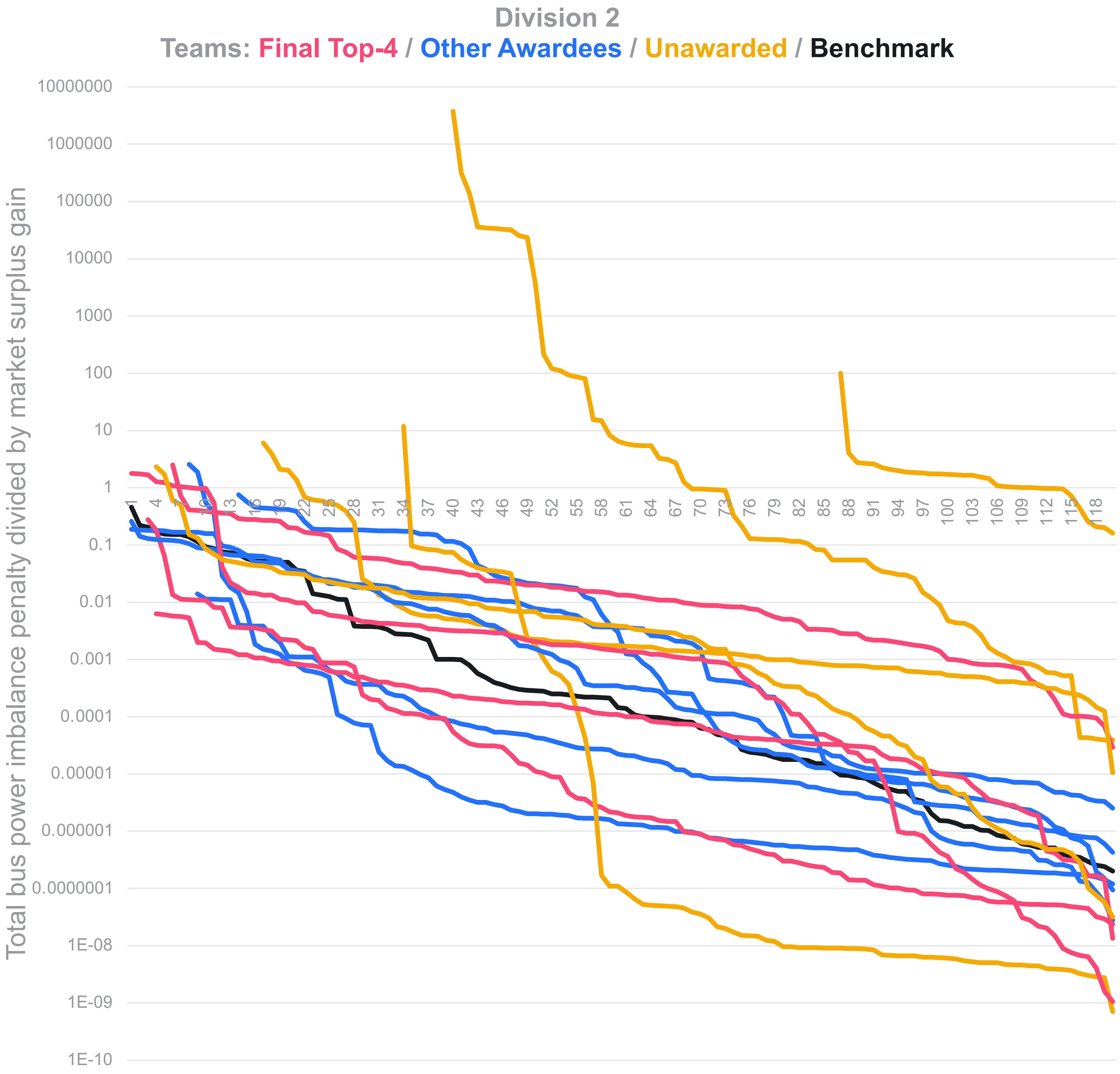
Industry case comparison

- **Filter 1**: remove 6 cases w/ failures from 4 teams
  - Curve moves lower, so all teams had difficulty.
- **Filter 2**: remove all 10 French network cases
  - Many teams perform much worse.
  - French network failures were specific to one team



Effect of penalties

- Plotted on right: bus imbalance penalties relative to MS gain score.
  - Sorted in decreasing order
  - “Missing” data (rightward shift) for solutions replaced by MSpp
- Imbalance penalties had very little influence among top teams.
- Improving prior point solution was very important to win prize money.



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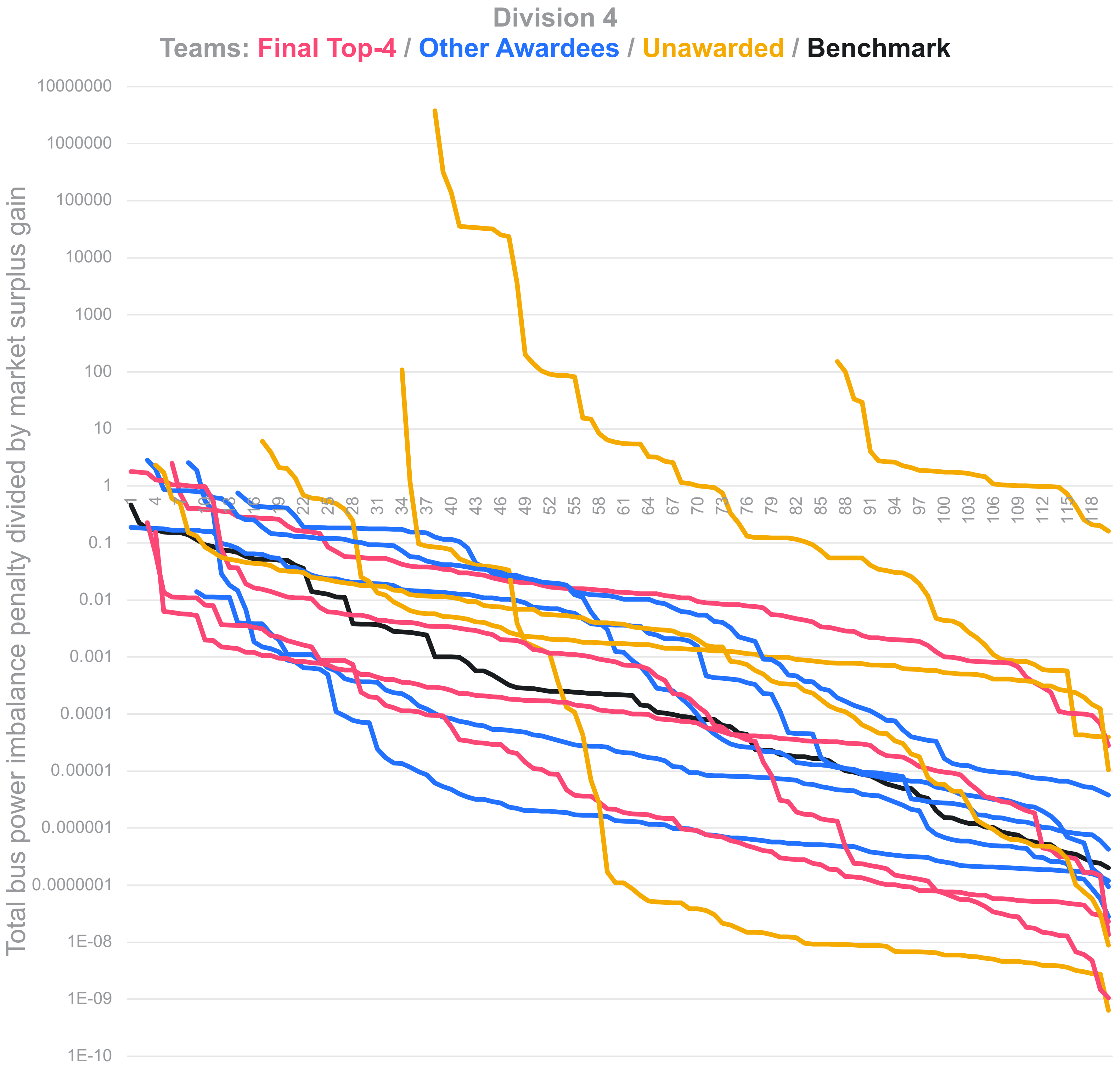
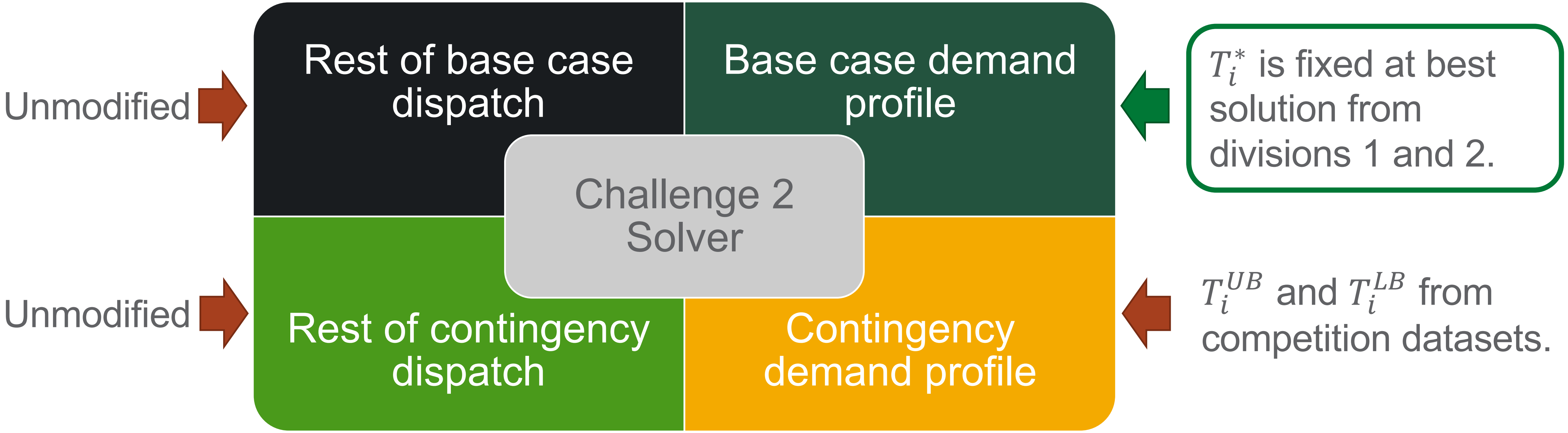
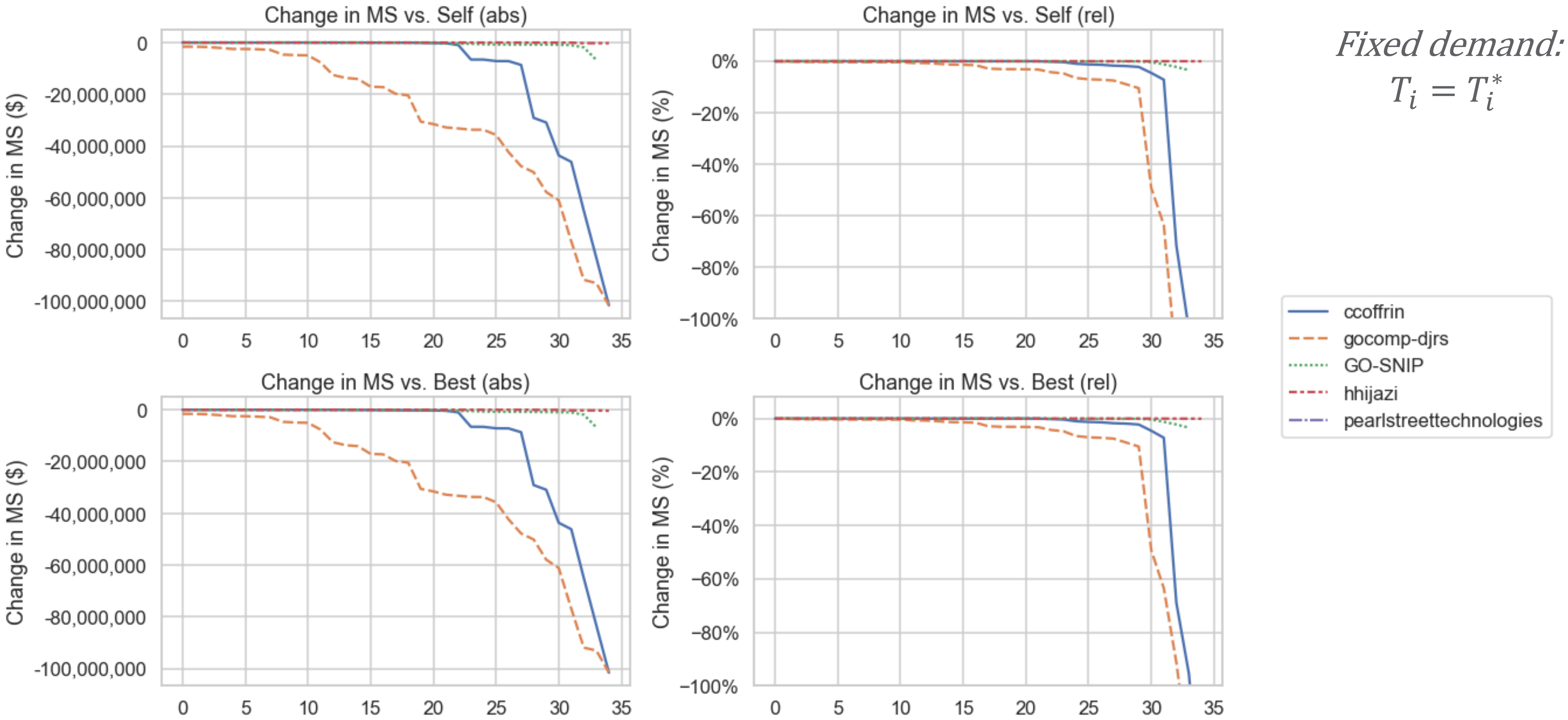


Effect of flexible demand on solution quality

- Solvers provided optimal load profiles given the value of bid-in demand.
  - Could this “optimal” load profile be fixed and then improved by other solvers?
  - Or, is load flexibility a necessary part of the optimization routines?
- Experimental set up was complicated due to Challenge 2 formulation, because the same upper and lower bounds are applied to pre- and post-contingency demand constraints.
- Load flexibility played an important role in managing contingencies, since almost all contingency constraints could be solved with post-contingency load curtailments.



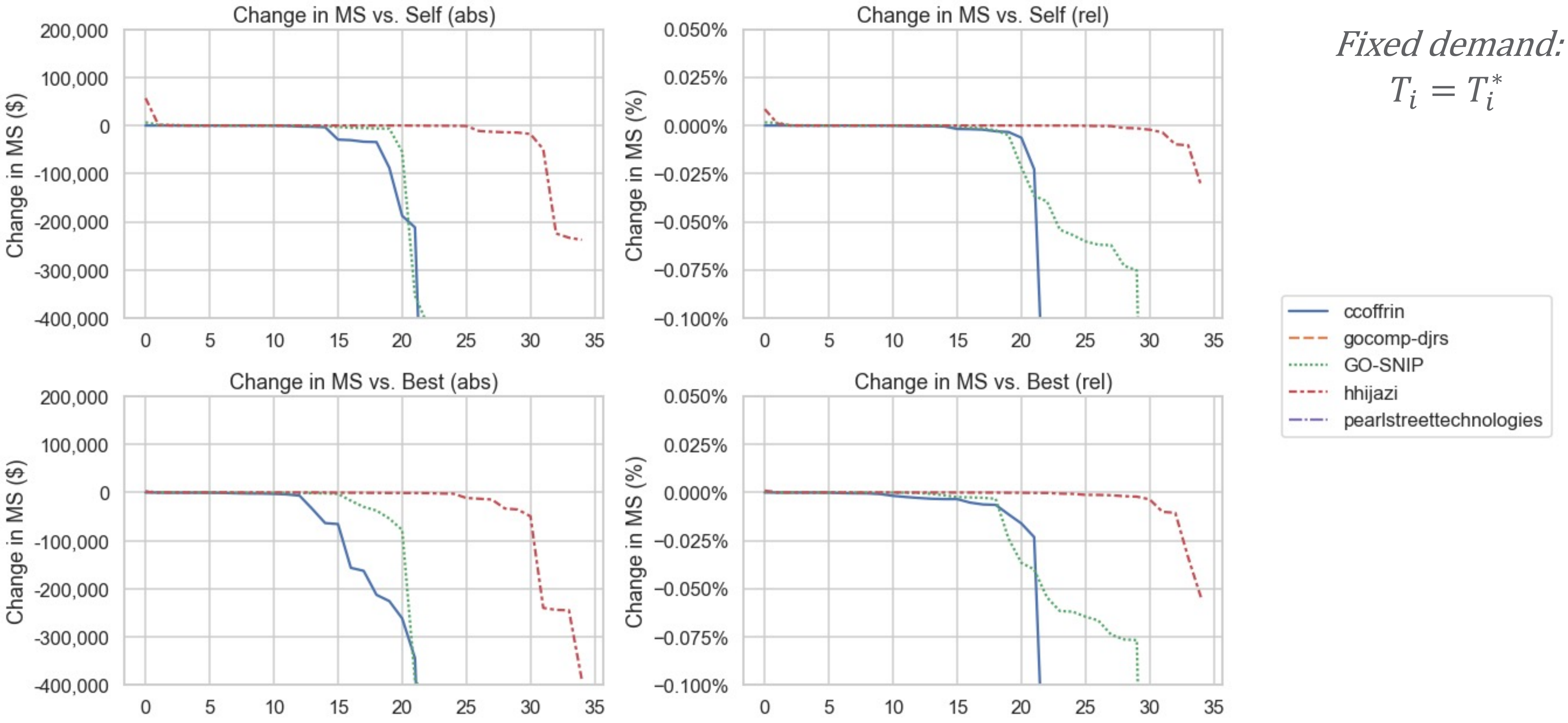
Many solvers had difficulty incorporating fixed loads during ex post analysis.



Fixed demand:

$$T_i = T_i^*$$

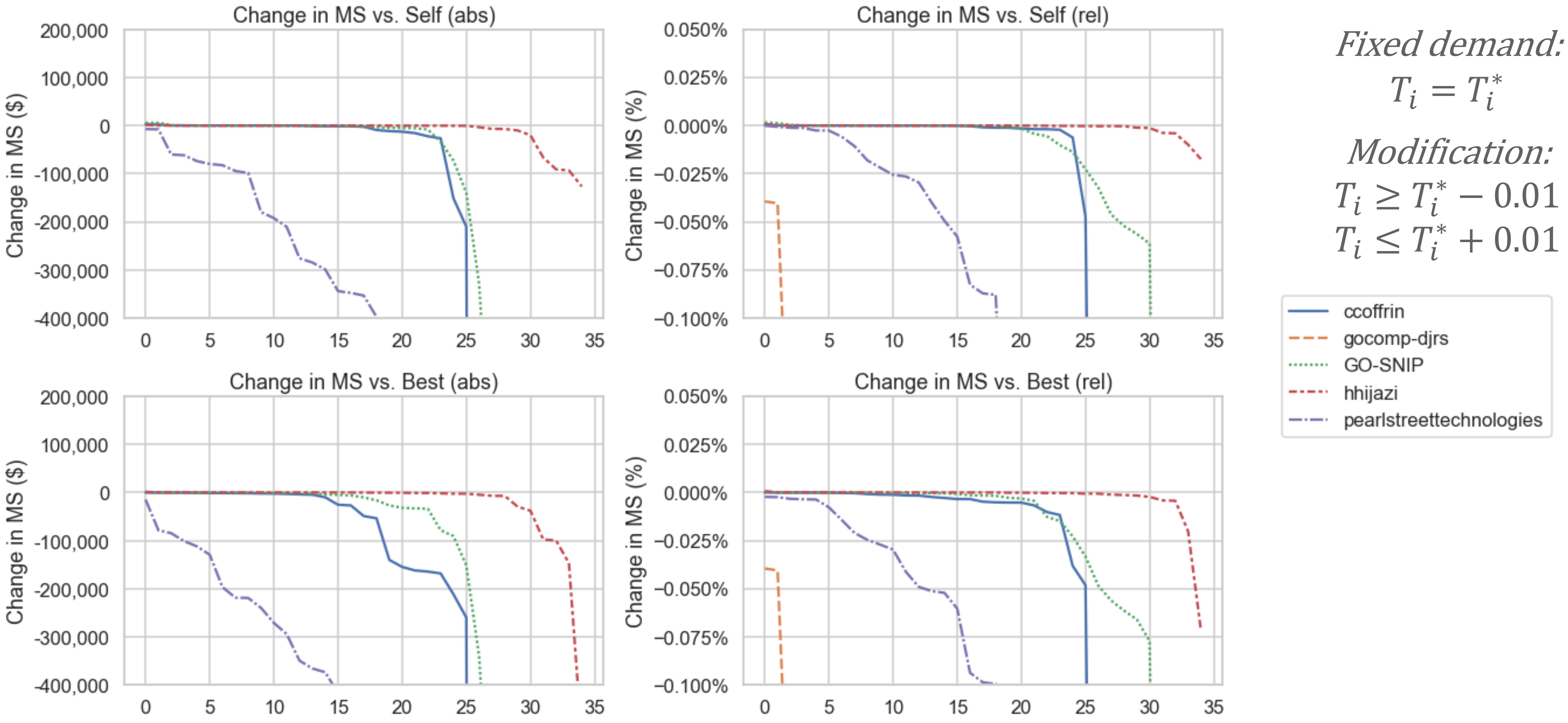
Rarely, fixed demand could improve an individual score but not the best score.



Fixed demand:

$$T_i = T_i^*$$

Modification with ± 0.01 feasibility neighborhood: Still no improvements.



Fixed demand:

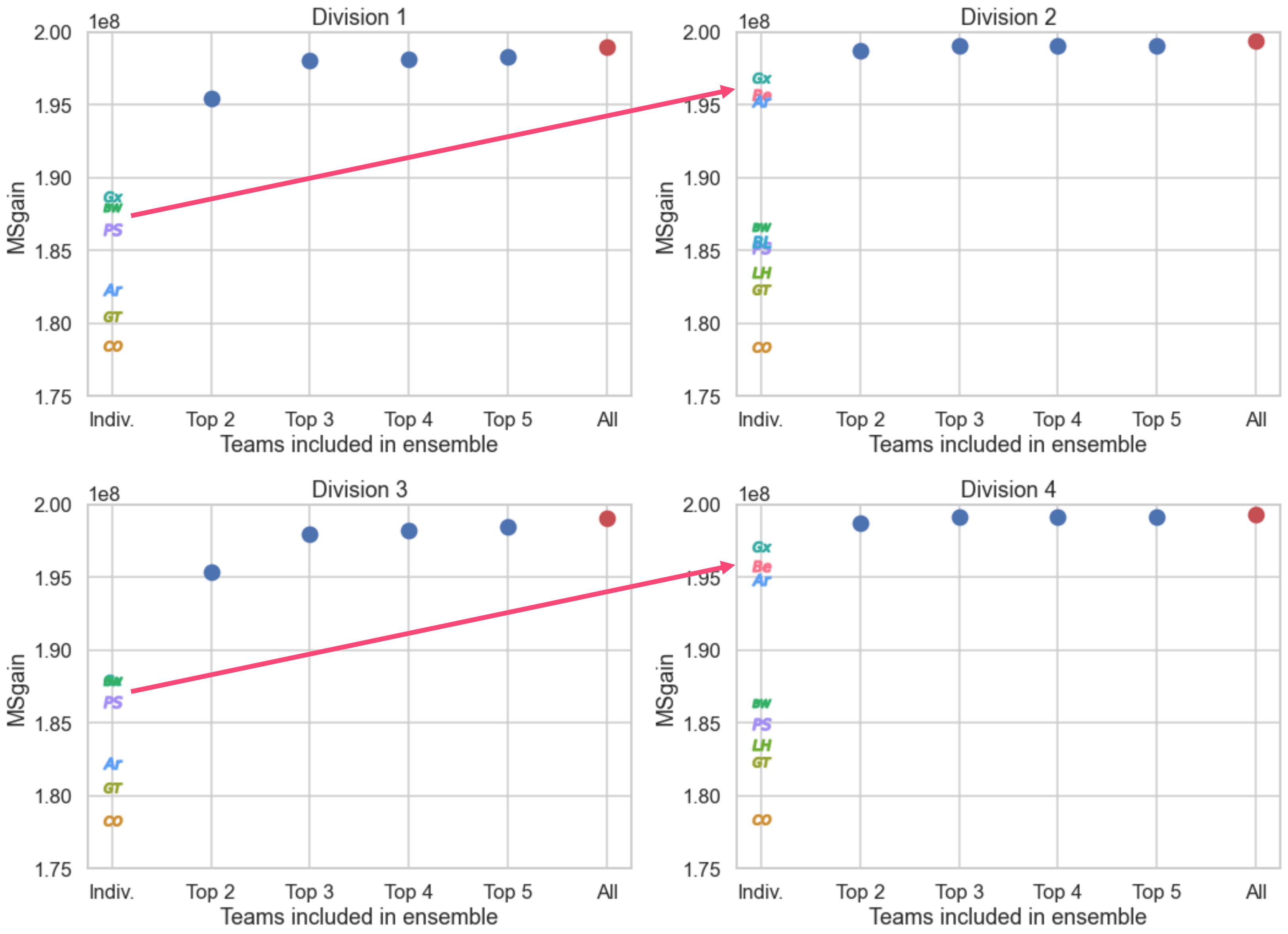
$$T_i = T_i^*$$

Modification:

$$T_i \geq T_i^* - 0.01$$
$$T_i \leq T_i^* + 0.01$$

Ensemble scores of the top 2/3/4/5 teams

- The overall ensemble score is almost equal in each division.
- But individual teams still benefitted from additional time in Div. 2 and 4.
- Algorithm approach is more important when time is more limited.



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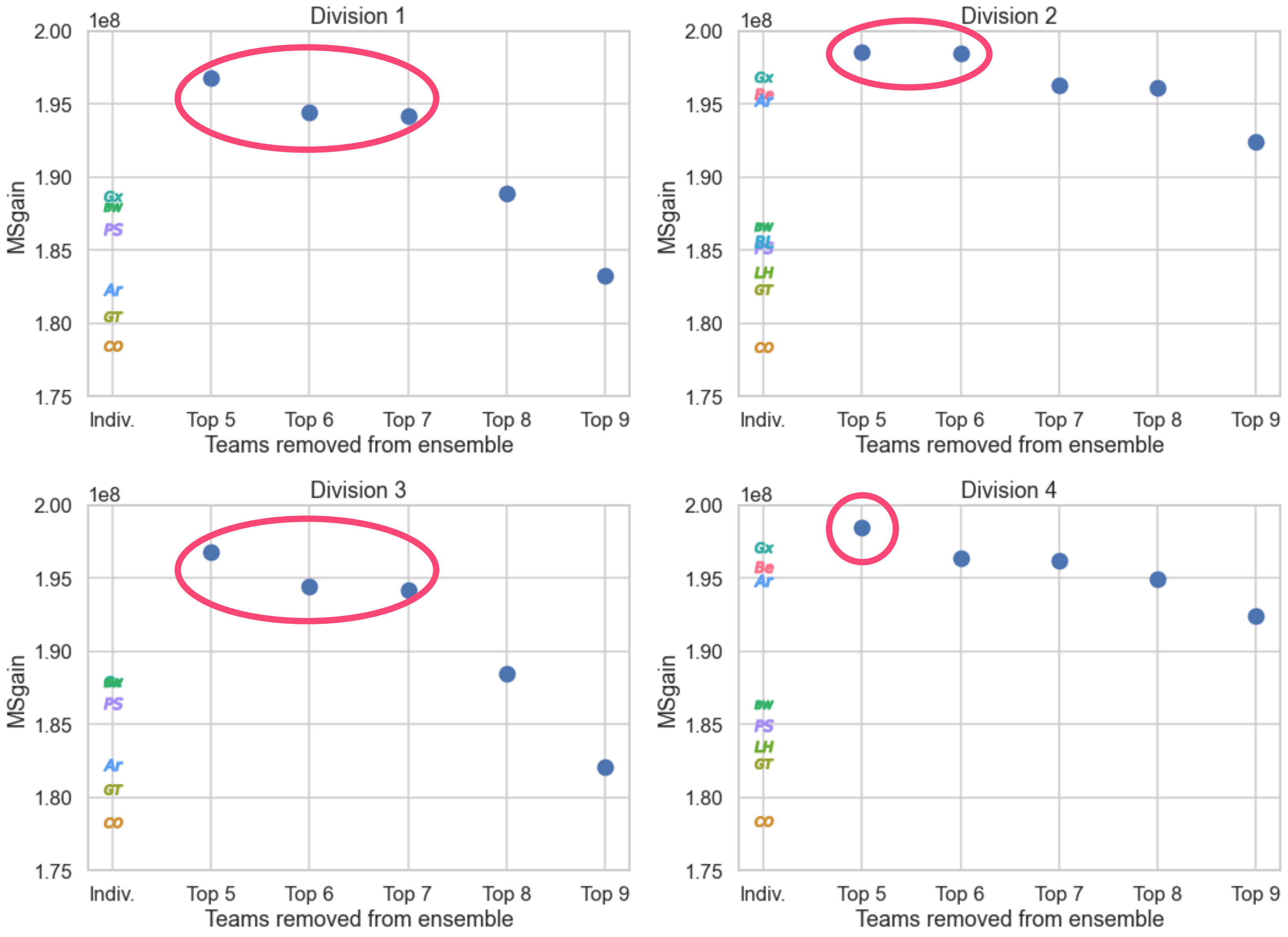
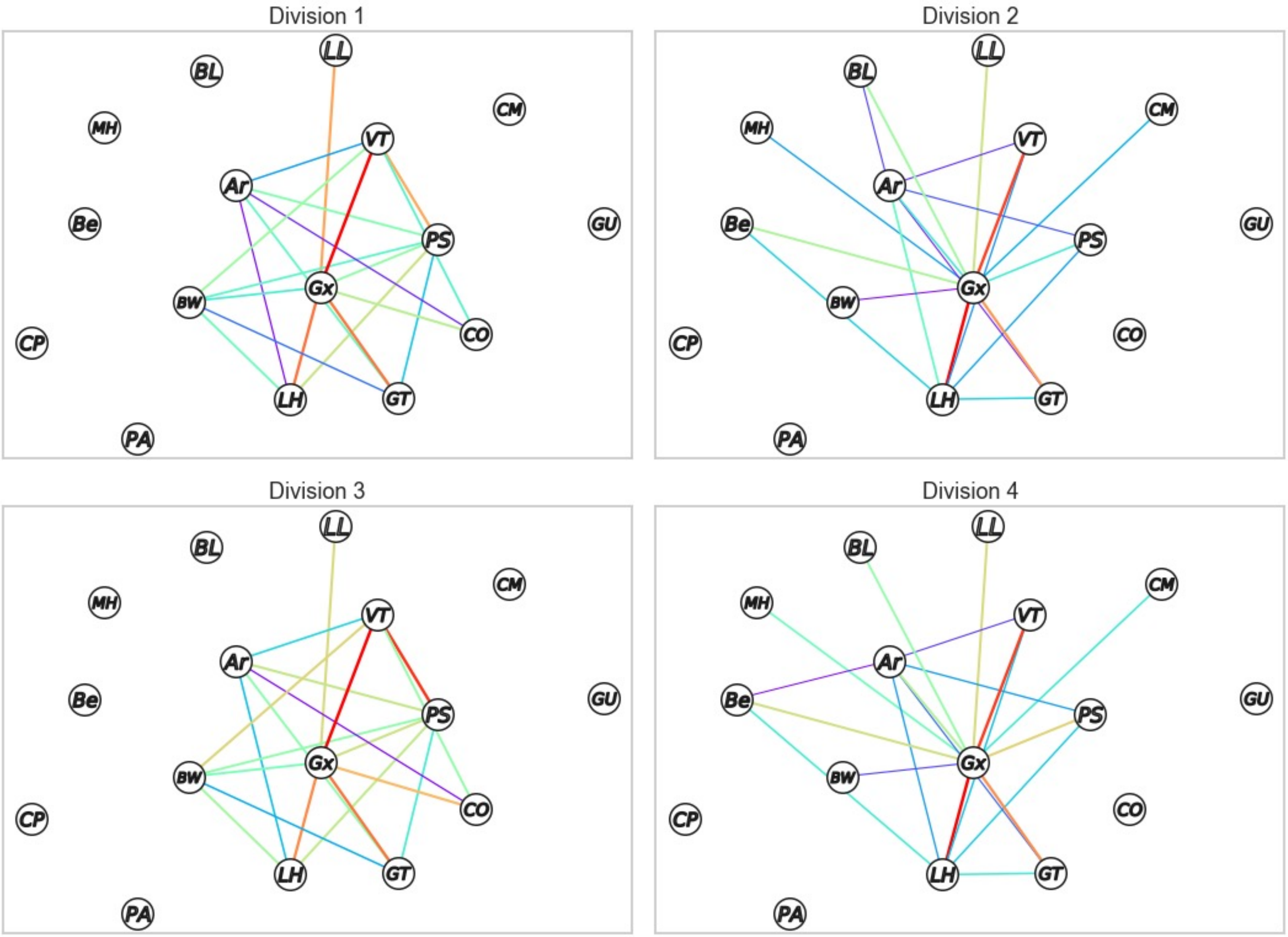
Ensemble scores with top teams removed

- An ensemble without any of the top 5 teams still would have won each division.
- Lower scoring teams were still able to find high-quality solutions, but not consistently.



Pairwise ensembles (best in parallel)

- The top-scoring teams almost always scored high on the same cases.
  - Almost no benefit to combining solutions from the top teams
- Best pairings are GravityX with one of the VaTech, GaTech, or Lehigh teams



Twenty highest-scoring pairs are colored in (red=highest).

Transmission switching results

- Overall, very few attempts
  - Only five of the 16 teams attempted transmission switching.
  - Total 205 solutions with switches, but only 18 with solution improvement > 1%.
  - High risk, low reward: ***reduced*** teams' Division 4 scores in most (57%) of the attempts.
- Most switching improvements occurred in networks with < 10,000 busses.

Team	(a) # cases with switches	(b) # base switches	(c) # contin. switches	(d) (D4-D2)/D2 > 0.01	(d ÷ a) % success
Benchmark	19	16	0	5	26.3%
Bigwood	5	3	0	1	20.0%
LBNL	90	171	19,825	7	7.8%
Artelys	88	370	14,986	5	5.7%
GERS	3	0	~40,000	0	0.0%

Impact of high-performance computing resources

- Most teams used full HPC resources.
  - 6 nodes w/ 144 cores. Exceptions:
  - Bigwood: 1 node / 24 cores
  - Colorado: 3 nodes / 72 cores
  - VaTech: 6 nodes / 24 cores
- No apparent advantage or disadvantage to HPC.

Team Name	Total Prize, FE+T3 ($k)	# nodes	# cores
GravityX	730	6	144
NU_Columbia_Artelys	530	6	144
GOT-BSI-OPF (Bigwood)	420	1	24
Pearl Street Technologies	340	6	144
Electric Stampede (Colo.)	140	3	72
GMI-GO (GaTech)	120	6	144
Monday Mornings (LBNL)	60	6	144
GO-SNIP (Lehigh)	30	6	144
Gordian Knot (VaTech)	30	6	24
ARPA-e Benchmark	N/A	6	144

Conclusions

- GO Competition depends on selecting appropriately difficult cases.
  - a priori hardness metrics are challenging, especially for cases with large potential improvement.
  - Safdarian *et al.* describes industry/synthetic difference in more detail.
- No evidence that penalties were a major influence in final scores/rankings.
- Flexible demand was necessary for solver performance.
- Shorter time limits led to more competition between solvers.
  - Bottom-ranked ensembles outperformed each individual team.
  - Best pairwise ensembles came from top individual team + mid-ranked teams.
- Few attempts at transmission switching.
  - Inclusive: problem too hard? network dependence? did cases reflect real-world?

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Thank you