`mpi-sppy`: Optimization Under Uncertainty for Pyomo

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Introduction

`mpi-sppy` provides support for *scenario-based* optimization under uncertainty with support for

- massive parallelism
- convergence based on multiple upper and lower bounds.

`mpi-sppy`:

- “mpi” – we utilize MPI functions through `mpi4py`
- “sp” – Stochastic Programming
- “py” – Implemented in Python

Basic requirements:

- Deterministic-equivalent Pyomo model
- Function to create a scenario instance of said Pyomo model
- See David Woodruff’s talk in TD34 for a how-to
- `mpi4py` with an MPI implementation to utilize most functionality

Available: http://github.com/Pyomo/mpi-sppy

Overview

1 Architecture

2 Algorithms & Cylinders

3 Case Study

4 Conclusion

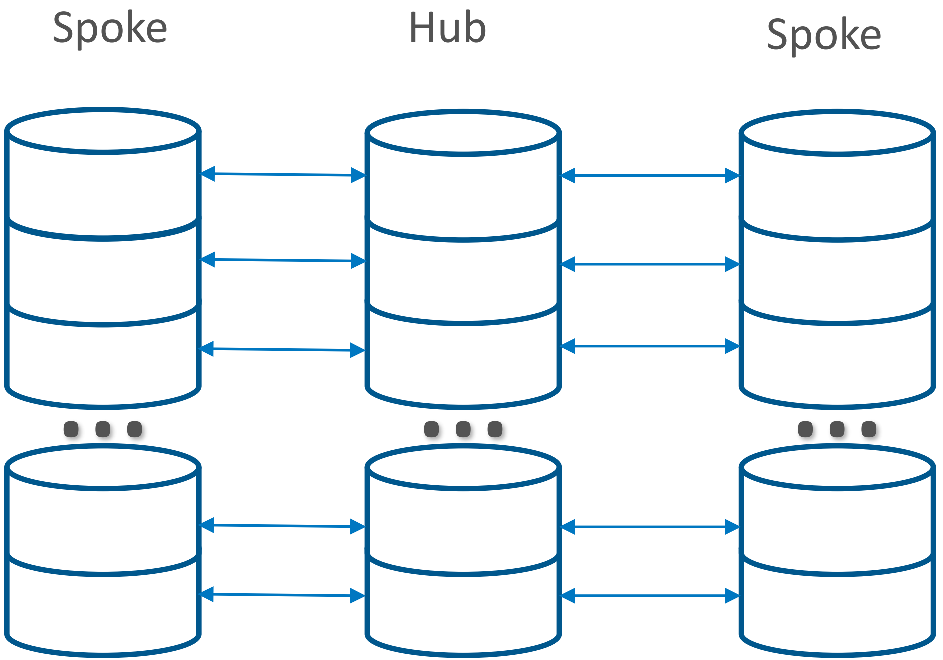
Architecture

The `mpi-sppy` architecture is divided into *cylinders* of compute units

– Typically synchronous communication within a cylinder
– Asynchronous communication between cylinders

The “Hub” cylinder carries out some iterative algorithm, and the “Spoke” cylinder(s) help the hub

– Bound computation
– Cutting planes



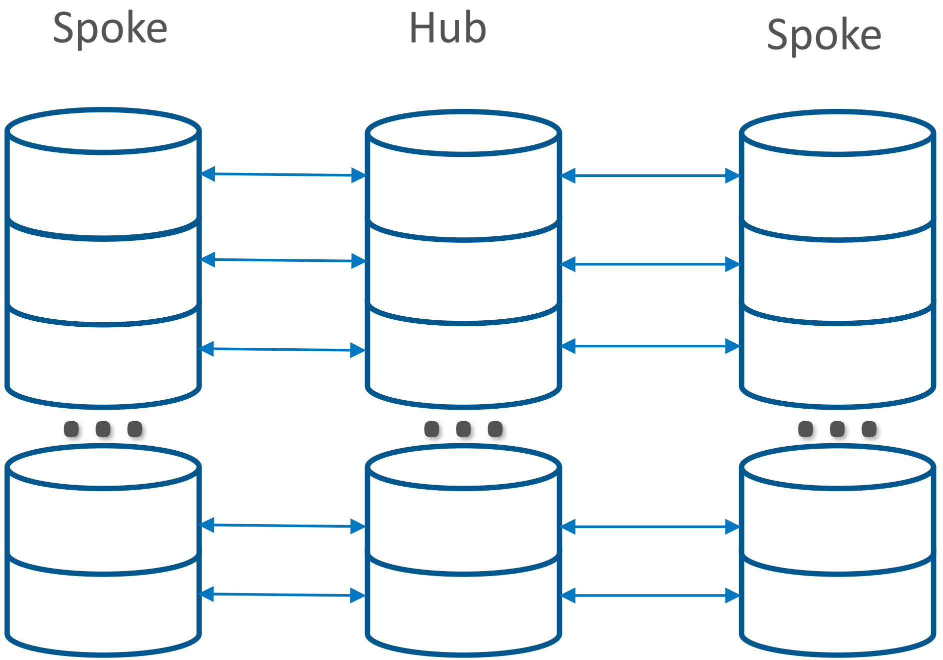
Architecture

One-to-one correspondence between a hub rank and its associated spoke rank(s), collectively called *strata*

- Within a strata, the hub and spoke ranks process the same scenarios

Two types of convergence:

- Traditional termination or convergence of Hub algorithm
- Inner and outer bounds as computed by Spokes is sufficiently small



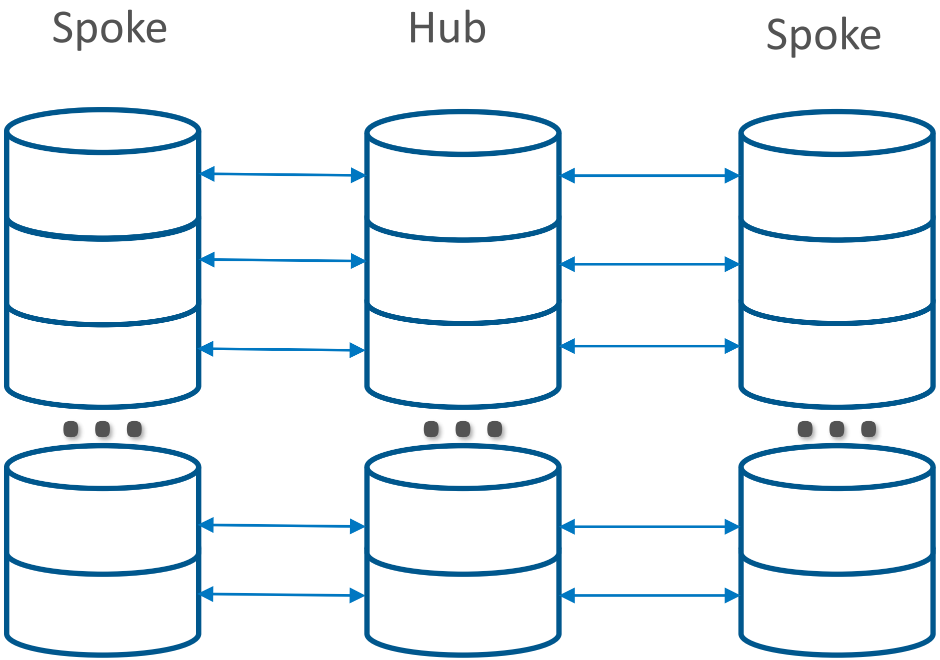
Architecture

Intra-cylinder communication is done through MPI reductions

- `mpi-sspy` utilizes the combined functionality of `mpi4py` and `numpy` such that the reductions occur on C arrays for speed and efficiency

Intra-strata (inter-cylinder) communication utilizes MPI Window objects for one-sided communication

- Passing happens using C arrays
- Generally non-blocking
- Spokes can read new information from hub when ready
- Hub acts on new information from spokes when ready



Algorithms & Cylinders

Hub Algorithms

- Progressive Hedging
- Asynchronous Projective Hedging
- L-Shaped Method[1]

Spoke Algorithms

- Frank-Wolfe Progressive Hedging[1] (dual bound)

Spoke Helpers

- Lagrangian (dual bound)
  - Uses subgradiants on non-anticipatory constraints computed by PH
- Lagranger (dual bound)
  - Computes subgradiants separately from PH
- Xhatters (primal bound)
  - Use non-anticipative decisions from Hub algorithms
  - Xhat-Specific, Xhat-Shuffle[1], Xhat L-Shaped[1]
- Slam Heuristics[1] (primal bound, PH)
  - Slam non-anticipative decisions to max/min of scenario solutions
- Cross-scenario Cuts[1] (PH)

[1] Two-stage problems only

Case Study

Stochastic Unit Commitment

- Schedule thermal generators (on/off) to meet uncertain load and supply from wind generators.
- Two-stage:
  - Stage 1: determine on/off status of thermal generators
  - Stage 2: dispatch thermal/wind generators for realized load and wind availability

Case Study

Stochastic Unit Commitment

- Thermal fleet based on WECC-240
  - 85 thermal generators
  - 48-hour time-horizon
- 1,000 aggregated wind scenarios based on CAISO data
  - Created using `mape_maker` (https://github.com/mape-maker/mape-maker)
  - Wind as percentage of load: 0-46%; maximal single-period difference: 45%
- Deterministic equivalent problem formulated using EGRET's unit commitment models (https://github.com/grid-parity-exchange/Egret)
  - 61833 constraints, 54805 variables (20533 binary), 226235 non-zeros
  - 4080 binary first-stage (non-anticipative) variables

Case Study

Stochastic Unit Commitment

- Full scenario decomposition using PH as Hub algorithm
  - 1 subproblem : 1 scenario
  - PH “Fixer” extension (fixed “converged” non-anticipative variables)
  - custom rho setter
- XhatShuffleLooper Spoke: discover incumbent solutions
- Lagrangian Spoke: Dual bounds from PH-calculated subgradients (Gade et al. 2016)
- FW-PH Spoke: Dual bounds using the method from Boland et al. (2018)
- 1000 subproblems with 4 cylinders: utilize up to 4000 MPI ranks

Case Study

Stochastic Unit Commitment

- Tested on NREL's HPC platform Eagle
- 36 cores per node; 223 nodes
- 4000 MPI ranks; 1000 per cylinder
- Subproblem solver Xpress (limited to 2 threads)
  - Using 8000 cores of the 8028 available
- 100 PH iterations (fixed by negative convergence criterion)

Case Study

```
[    0.00] Initializing mpi-sppy
[   36.07] Start SPBase.__init__
[   39.94] Start PHBase.__init__
[   40.02] Starting spcomm.main()
[   40.34] Creating solvers
[  177.43] Entering solve loop in PHBase.Iter0
[  187.54] Iter.            Best Bound  Best Incumbent      Rel. Gap        Abs. Gap
[  187.54]      1  L        47031.9895             inf           inf             inf
[  190.90]      2    X      47031.9895   51662636.7443   109745.7396   51615604.7547
[  193.53]      3    X      47031.9895      47300.5886        0.5711        268.5991
[  196.79]      4    X      47031.9895      47117.3894        0.1816         85.3999
[  199.46]      5    X      47031.9895      47111.5210        0.1691         79.5315
[  202.05]      6    X      47031.9895      47094.9459        0.1339         62.9564
[  204.85]      7           47031.9895      47094.9459        0.1339         62.9564
[  208.67]      8    X      47031.9895      47093.4180        0.1306         61.4285
[  210.47]      9           47031.9895      47093.4180        0.1306         61.4285
[  212.66]     10           47031.9895      47093.4180        0.1306         61.4285
[  214.00]     11           47031.9895      47093.4180        0.1306         61.4285
[  215.19]     12           47031.9895      47093.4180        0.1306         61.4285
                                 • • •
[  271.36]     96           47031.9895      47091.1755        0.1258         59.1860
[  271.93]     97           47031.9895      47091.1755        0.1258         59.1860
[  272.49]     98           47031.9895      47091.1755        0.1258         59.1860
[  273.06]     99           47031.9895      47091.1755        0.1258         59.1860
[  273.62]    100           47031.9895      47091.1755        0.1258         59.1860
[  274.10] Reached user-specified limit=100 on number of PH iterations
                                 • • •
[  274.23] Hub algorithm complete, waiting for termination barrier
[  310.03]
[  310.03] Statistics at termination
[  310.03] Iter.            Best Bound  Best Incumbent      Rel. Gap        Abs. Gap
[  310.03]    100           47031.9895      47091.1755        0.1258         59.1860
[  310.13] Windows freed
```

Warm-up to warm-down computation time: 97 sec.

Post warm-up time: 133 sec.

Total time: 310 sec.

Final gap: 0.1258%

Case Study

Stochastic Unit Commitment

- Same computation on LLNL's Quartz cluster
- 36 cores per node; 256 nodes
- 4000 MPI ranks; 1000 per cylinder
- Subproblem solver Gurobi (limited to 2 threads)
  - Using 8000 cores of the 9216 available
- 100 PH iterations (fixed by negative convergence criterion)

$\lvert S \rvert$	Time to PH iter. 0 solve loop (s)	Time to completion (s)	Δ	PH LB	PH UB
1000	69.49	182.92	113.43	47032.130	47097.578

Case Study

1000- vs. 3-scenario instance on Eagle

|S| (Iter)	1000 (0)	3 (0)	1000 (25)	3 (25)	1000 (50)	3 (50)	1000 (75)	3 (75)
Total iteration time	10.11 s	2.89 s	0.74 s	0.39 s	0.58 s	0.39 s	0.56 s	0.45 s
Pyomo & solver time	8.74 s	1.58 s	0.54 s	0.27 s	0.39 s	0.26 s	0.39 s	0.29 s
Difference	1.37 s	1.31 s	0.20 s	0.12 s	0.19 s	0.13 s	0.17 s	0.16 s

Very low additional inter-iteration overhead scaling from 3 scenarios on a single node to 1,000 scenarios on 200+ nodes

Conclusion

Available: http://github.com/Pyomo/mpi-sppy

Several examples (farmer, SSLP, unit commitment, network design, others) and documentation available:

– See David Woodruff's talk (TD34)

– UC driver used in the computation section can optionally use most of the functionality of mpi-sppy with progressive hedging; only ~400 lines of (unoptimized) Python over deterministic model.

– Easy to get started with existing two-stage PySP model

With enough compute power, `mpi-sppy` enables the solution of very large-scale stochastic optimization problems

Q&A

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