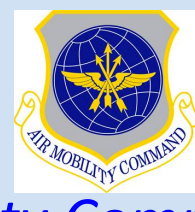


Split-and-Merge Method for Accelerating Convergence of Stochastic Linear Programs

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MOTIVATION



US Air Mobility Command Mission:
Optimally schedule 1300 aircraft for
 Cargo shipment
 Personnel movement
 Distinguished visitor support
 Air refueling

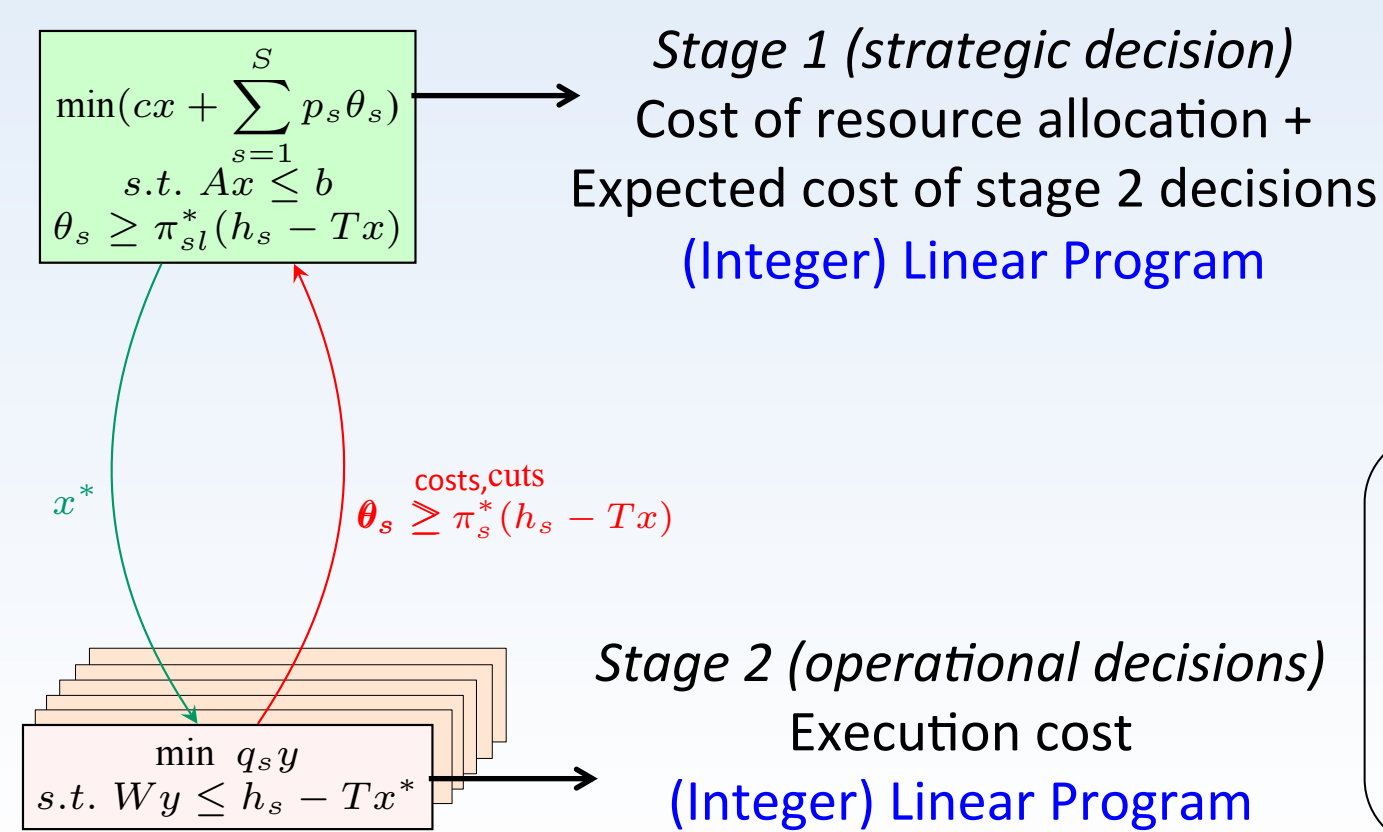


CHALLENGE
Mission requirements subject to enormous uncertainty, even in peacetime

- Demand delays
- Demand changes
- Aircraft breakdown
- Weather events
- Natural disaster
- Conflicts



STOCHASTIC OPTIMIZATION OVERVIEW

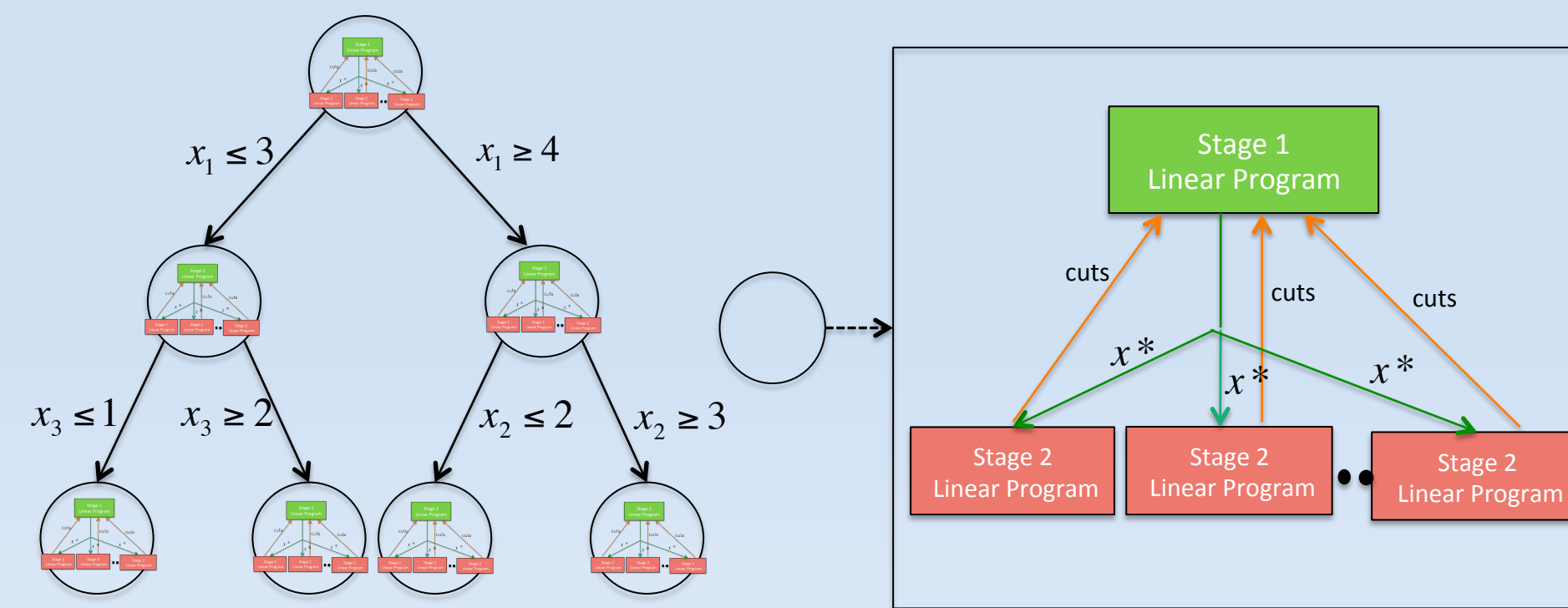


Planning Stage: Makes decision about known parameters

Execution stage: Assumes probabilistic distribution of uncertain parameters is known and evaluates them for the stage 1 decision

NESTED BRANCH-AND-BOUND PARALLELISM

Relax integer program to linear program → Each vertex is a stochastic linear program

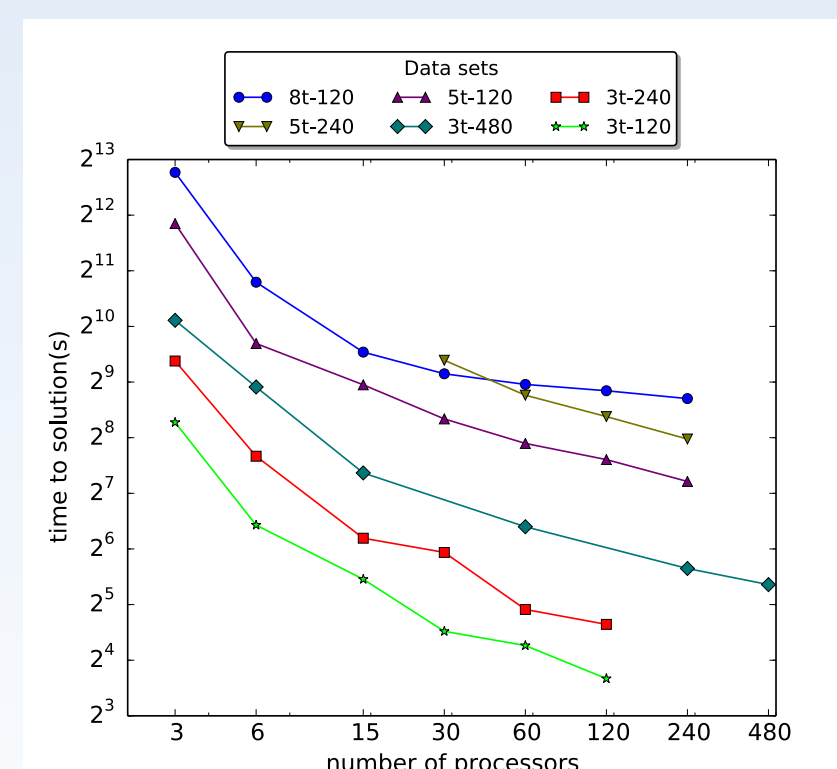


Nested Parallelism

- Parallel exploration of tree vertices
- Simultaneous evaluation of scenarios

PERFORMANCE COMPARISON WITH COMMERCIAL SOLVERS

Scaling



SIPS Performance
1.96x speedup from 3 to 480 cores

VS

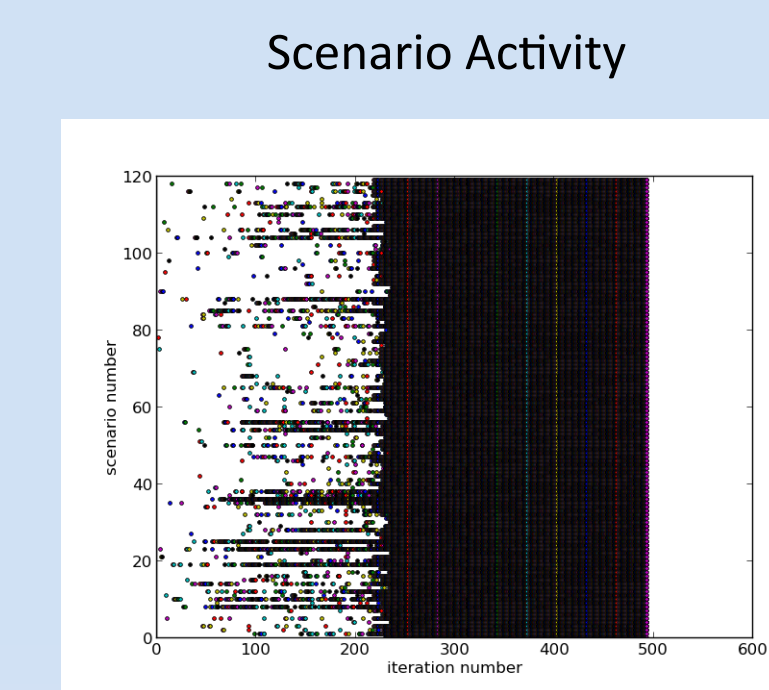
Gurobi Optimization Performance
Typical parallel efficiency of just 0.1 at 32 cores

Challenge

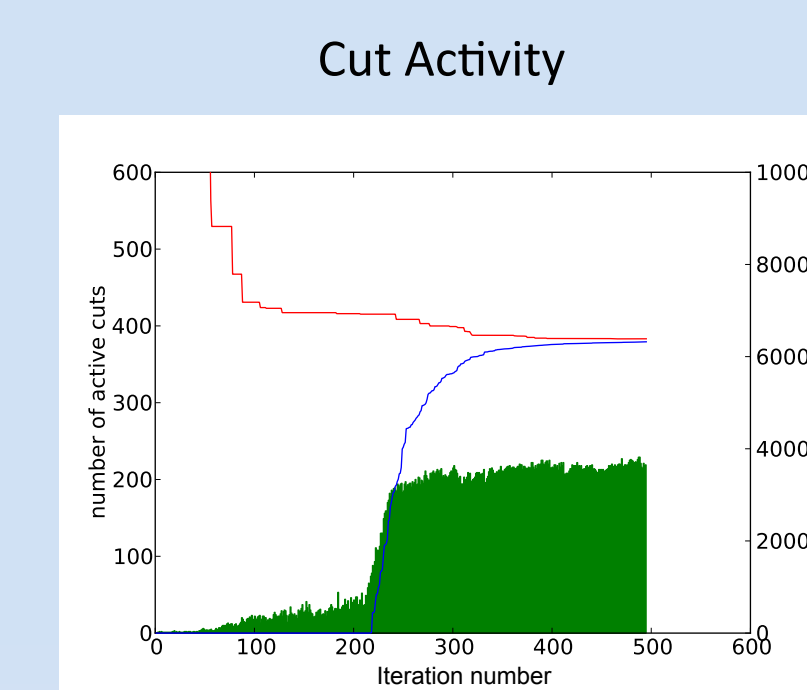
Root vertex solve is a bottleneck, when #scenarios are large

RESULTS

Multicut Benders method



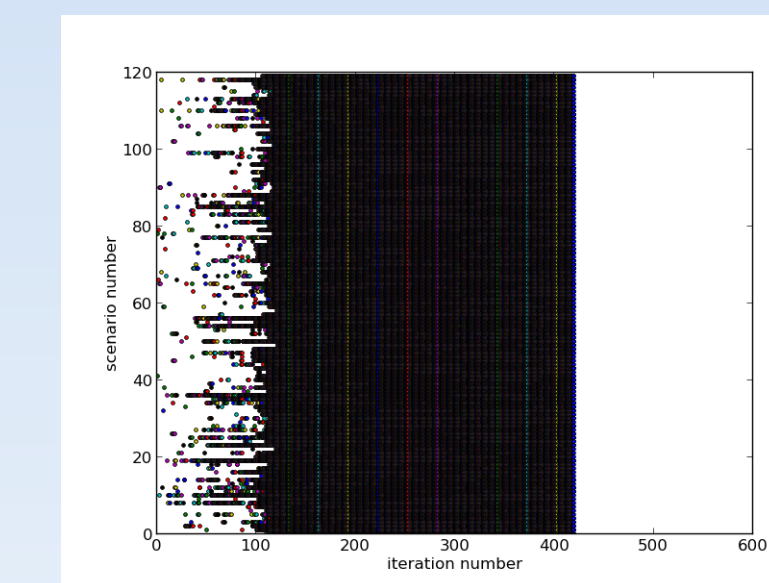
Total Iterations = 495



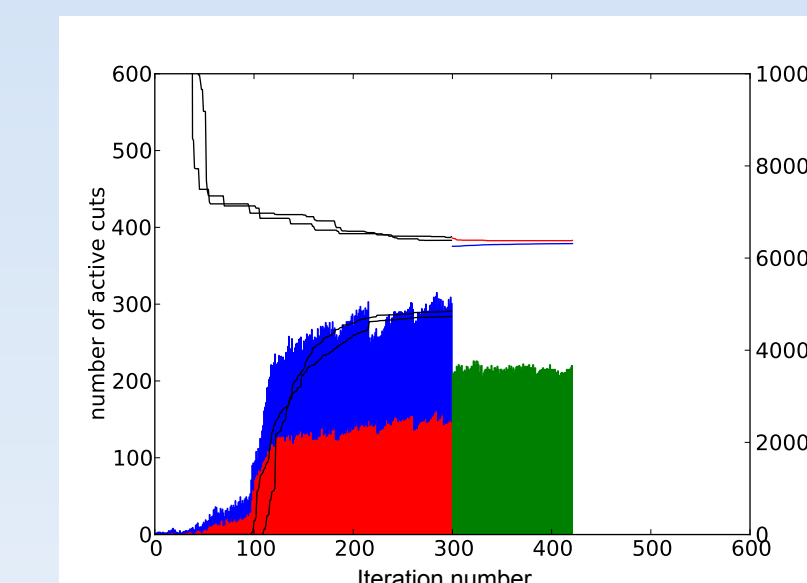
Time to Solution = 1190s

SAM method

34% improvement in time



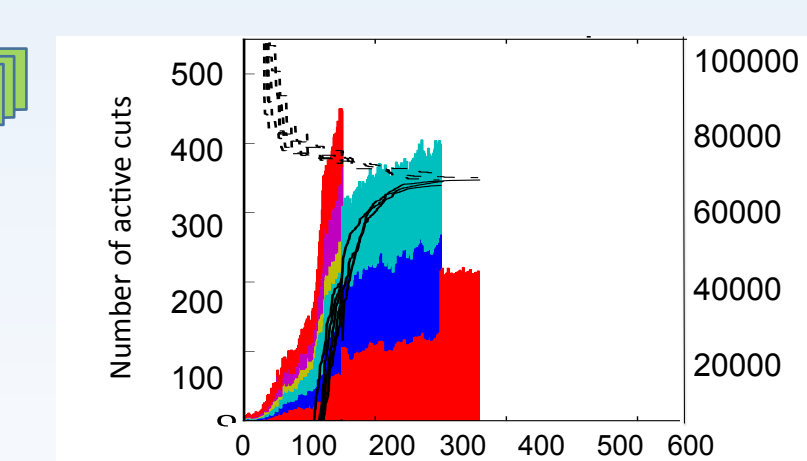
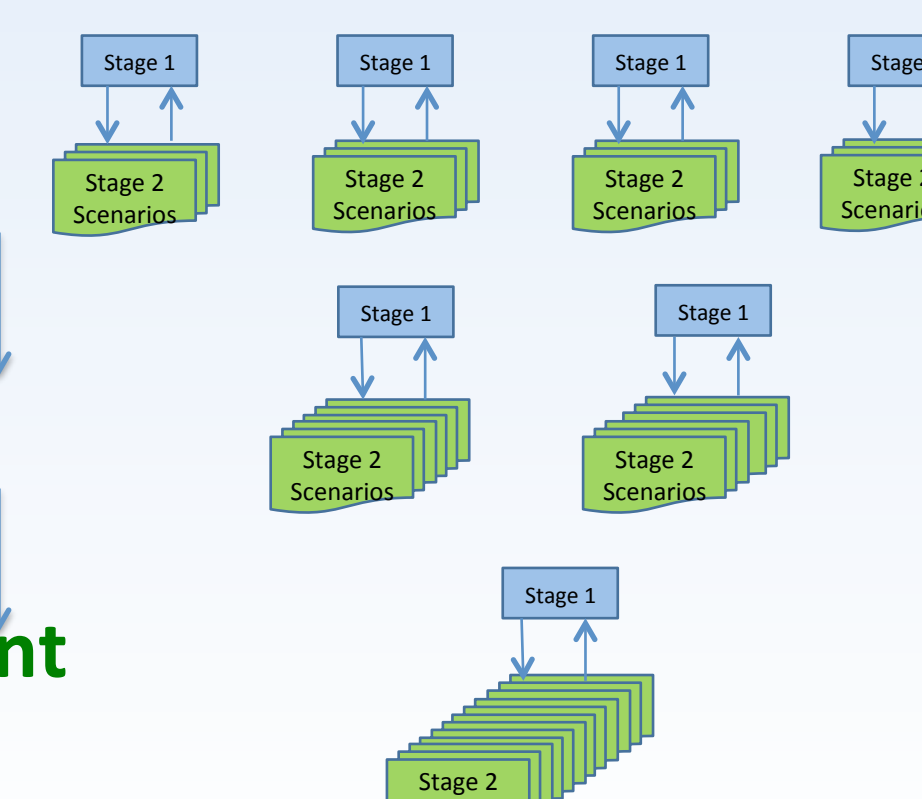
Total Iterations = 415



Time to Solution = 784s

Hierarchical Split-and-Merge Method

58% improvement in time



Total Iterations = 360
Time to Solution = 507s

APPLICATIONS

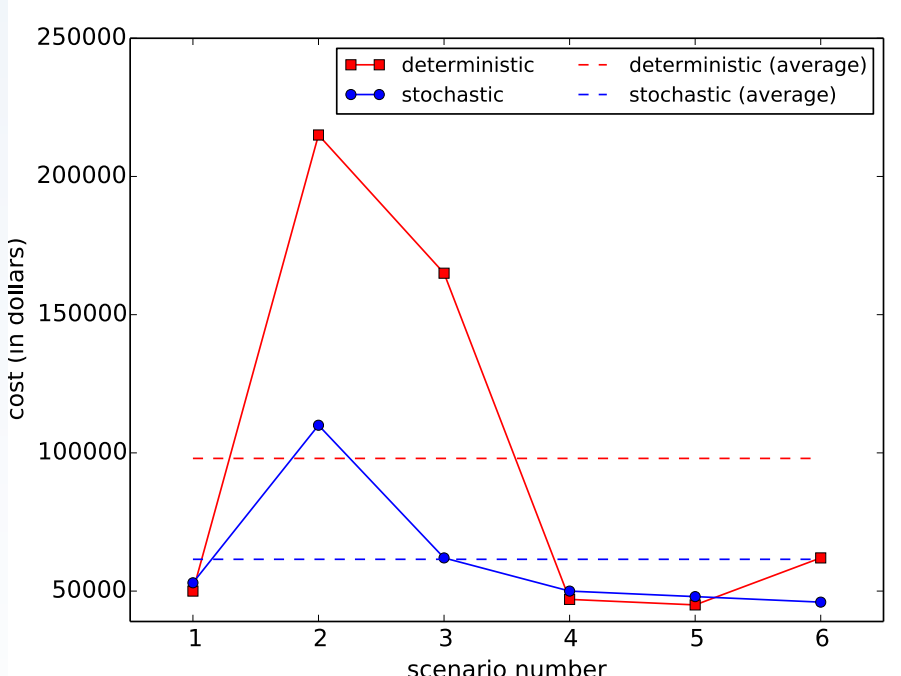


STATE-OF-THE-ART CANNOT SOLVE LARGE PROBLEMS TO OPTIMALITY

What is new that we are doing?

- Combine stochastic programming with high performance computing
- Facilitates reconciliation of myriad possible outcomes in a timely manner
- Makes it feasible to solve integer programs

CASE STUDY: US MILITARY AIRCRAFT ALLOCATION PROBLEM



US AMC yearly expenses: ~USD 4 Billion
 Average cost benefit: 35%
 Robustness: 66% reduction in variance

RELATED WORK

- Magnanti and Wong, 1981
- Add only dominating cuts
- Requires solving additional optimization problems
- Linderoth et al, 2003
- Requires solving additional optimization problems to determine usability of cuts
- Trust Region, Ruszczyński, 1886 and Linderoth et al, 2003
- Add objective term to minimize movement of candidate solution
- Requires doing several minor iterations between major iterations
- Progressive Hedging Algorithm, 1991
- Requires search for optimal Lagrangean multiplier which can be prohibitive

PROPOSED SPLIT-AND-MERGE (SAM) METHOD

Split original problem into many small subproblems each with a subset of scenarios

Input: S (set of scenarios), Original Stochastic Program (P)
 Divide S into n clusters, S_1, S_2, \dots, S_n
 Generate n stochastic programs, P_1, P_2, \dots, P_n , with scenarios from S_1, S_2, \dots, S_n , respectively
 Scale scenario probabilities in each of these subproblems such that they sum up to 1

Perform stochastic linear optimization of subproblems (in parallel) until converged or until a specified number of iterations

```
#pragma omp parallel for
for i in range(1,n):
    scostsi = [] #scenario costs
    cutsi = [] #scenarios cut constraints
    while ri < r or hasConverged(i):
        xi = solveStage1(Pi, scostsi, cutsi)
        scostsi, cutsi = solveStage2(xi)
        ri = r + 1
    end while
```

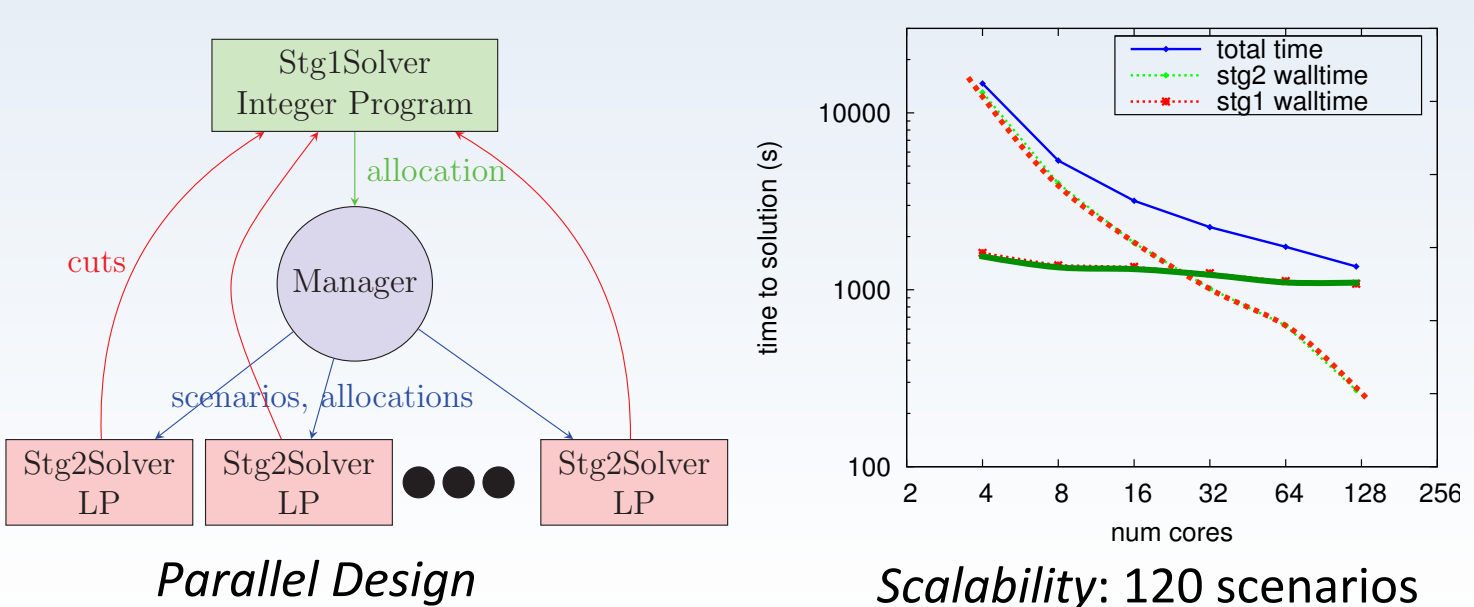
Merge cuts from subproblems

```
#wait until all the subproblems have returned
cuts = []
scosts = []
for i in range(1,n):
    cuts.add(getCutConstraints(Pi))
```

Solve original problem with collected cuts

```
#now solve the original problem
while not hasConverged(P):
    x = solveStage1(P, scosts, cuts)
    scosts, cuts = solveStage2(x)
end while
```

LIMITATIONS OF NAÏVE PARALLELIZATION



Scalability limited by #scenarios
 Stage 1 bottleneck
 Parallel efficiency decreases with increase in Stage 1 size

SAM BENEFITS

- Higher cut activity from initial iterations of Benders method
- Reduced Stage 1 bottleneck size
- Increased Parallelism in Stage 1
- Reduced total iterations and time to solution
- 58% improvement in time to solution compared with Benders method

FUTURE WORK

- Further exploration of HSAM method
- Automated determination of split-phase duration
- Determining optimal subproblem size

TAKEAWAYS

- Accelerated convergence by problem decomposition
- Enabled large-scale stochastic optimizations leading to robust planning of US AMC operations
- Reduced time to solution
- Asynchronous parallel programming model for maximum productivity and performance

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- Akhil Langer, Ramprasad Venkataraman, Udatta Palekar, and Laxmikant V. Kale. "Parallel branch-and-bound for two-stage stochastic integer optimization." In *High Performance Computing (HPC), 2013 20th International Conference on*, pp. 266-275. IEEE, 2013. **Best Paper Award**. **HPCC 2012 Finalist**.
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