A Comparative Study of Stochastic and Security Constrained Unit Commitment Using High Performance Computing

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Outline

Motivation and Research Objective

- Increased need for systematic approach to committing day-ahead reserves due to:
  - Renewable penetration
  - Demand response integration
- Four paradigms for systematic day-ahead scheduling:
  - Stochastic optimization
  - Security constrained optimization
  - Robust optimization
  - Probabilistically constrained optimization
- Our objective:
  - Compare relative performance of SUC and SCUC
  - Demonstrate benefits of parallel computation

Systematic Approaches to Unit Commitment

- Stochastic UC (Takriti 1996): minimize expected cost over weighted set of scenarios
  - Difficulty: scenario selection and probability assignment
  - Common solution approach: Lagrangian relaxation
- Security constrained UC: minimize no-contingency cost while withstanding failures without shedding load
  - (Wang 2008): exogenous reserve criteria, Benders
  - (Wu 2007): blend failures with scenarios, LR
- Robust UC (Jiang 2012, Bertsimas 2013): minimize cost of operation against worst-case uncertainty
  - Limited information about uncertainty required
  - Consistent with paradigm of system operators
- UC with probabilistic constraints (Ozturk 2004, Vrakopoulou 2013)
  - Limited information about uncertainty required

Parallel Computing Literature in Power Systems

- Monticelli et al. (1987): Benders decomposition algorithm for SCOPF
- Pereira et al. (1990): Applications of parallelization in various applications including SCOPF, composite (generator, transmission line) reliability, hydrothermal scheduling
- Falcao (1997): Survey of HPC applications in power systems
- Kim, Baldick (1997): Distributed OPF
- Bakirtzis, Biskas (2003) and Biskas et al. (2005): Distributed OPF

PSR Cloud

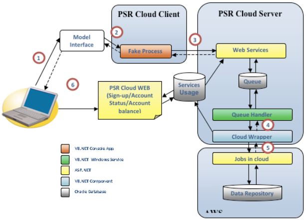
Industry practice for hydrothermal scheduling

PSR Case Study: Amazon Web Services

http://aws.amazon.com/solutions/case-studies/psr/

- Authorization Module - Authenticates each request and authorizes the user to proceed with the requested operation.
- Queuing Module - Queues the authorized requests for asynchronous processing.
- Cloud Wrapping Module - Executes each service in the queue by allocating the resources needed for the computations. This component uses the Software Development Kits (SDKs) offered by AWS.

The PSR architecture is depicted in the following diagram:



Since moving to the cloud, PSR has recorded impressive results. Mr. Pereira explains: "AWS is important to our consulting services in order to run our mathematical models in tolerable execution times, as well as for our customers when they buy our models to run them on their own. Internal measurements have been taken and the expected power of the cloud was proven to be the right direction. As an example, a glance of AWS usage in October 2010 revealed over 44,000 processor hours were carried out, which would have required 76 days to be handled using the local available

Unit Commitment Model

- Domain $\mathcal{D}$ represents min up/down times, ramping rates, thermal limits of lines, reserve requirements, import constraints

$$(UC) : \min \sum_{g \in G} \sum_{t \in T} (K_g u_{gt} + S_g v_{gt} + C_g p_{gt})$$

$$s.t. \sum_{g \in G_n} p_{gt} = D_{nt}$$

$$P_g^- u_{gt} \leq p_{gt} \leq P_g^+ u_{gt}$$

$$e_{kt} = B_k(\theta_{nt} - \theta_{mt}), k = (m, n)$$

$$(\mathbf{p}, \mathbf{e}, \mathbf{u}, \mathbf{v}) \in \mathcal{D}$$

Stochastic Unit Commitment Model

$$(SUC): \min \sum_{g \in G} \sum_{s \in S} \sum_{t \in T} \pi_s (K_g u_{gst} + S_g v_{gst} + C_g p_{gst})$$

$$s.t. \sum_{g \in G_n} p_{gst} = D_{nst},$$

$$P^-_{gs} u_{gst} \leq p_{gst} \leq P^+_{gs} u_{gst}$$

$$e_{kst} = B_{ks}(\theta_{nst} - \theta_{mst}), k = (m, n)$$

$$(\mathbf{p}, \mathbf{e}, \mathbf{u}, \mathbf{v}) \in \mathcal{D}_s$$

$$u_{gst} = w_{gt}, v_{gst} = z_{gt}, g \in G_s$$

1. First stage: DA market realization for slow generators G_s
2. Renewable supply, line / generator outages
3. Second stage: RT market realization

Scenario-Based Security Constrained Unit Commitment

$$(SCUC): \min \sum_{g \in G} \sum_{s \in S} \sum_{t \in T} \pi_s (K_g u_{gst} + S_g v_{gst} + C_g p_{gst})$$

$$s.t. \sum_{g \in G_n} p_{gst} = D_{nst}$$

$$P^-_{gs} u_{gst} \leq p_{gst} \leq P^+_{gs} u_{gst}, g \in G$$

$$e_{kst} = B_{ks}(\theta_{nst} - \theta_{mst}), k = (m, n)$$

$$(\mathbf{p}, \mathbf{e}, \mathbf{u}, \mathbf{v}) \in \mathcal{D}_s$$

$$p_{lst} = 0, l \in L, s \in S, t \in T$$

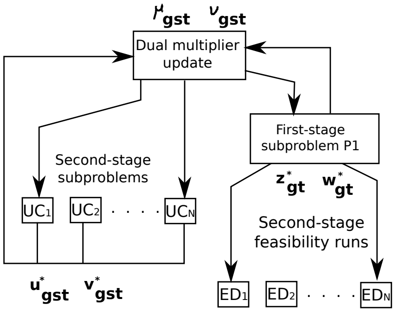
$$u_{gst} = w_{gt}, v_{gst} = z_{gt}, g \in G_s$$

- May not have feasible second-stage response

Scenario Selection [1 - 3]

- Stochastic UC: scenario selection algorithm inspired by importance sampling
  1. Generate a sample set $\Omega_S \subset \Omega$, where $M = |\Omega_S|$ is adequately large. Calculate the cost $C_D(\omega)$ of each sample $\omega \in \Omega_S$ against the best deterministic unit commitment policy and the average cost $\bar{C} = \sum_{i=1}^{M} \frac{C_D(\omega_i)}{M}$.
  2. Choose N scenarios from Ω_S, where the probability of picking a scenario ω is $C_D(\omega)/(M\bar{C})$.
  3. Set $\pi_s = C_D(\omega)^{-1}$ for all $\omega^s \in \hat{\Omega}$.
- Security Constrained UC:
  1. S is Cartesian product of renewable supply with no contingency and worst single-element contingencies
  2. Equal $\pi_s > 0$ for no-contingency scenarios, $\pi_s = 0$ for single-element contingency scenarios

Lagrange Relaxation for SUC [1 - 3]

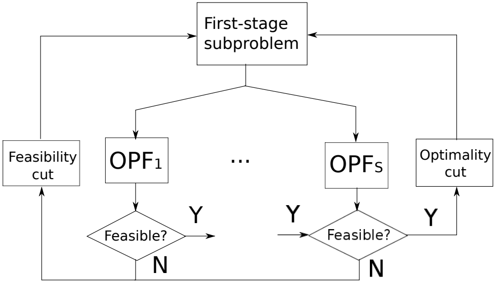


$$\mathcal{L} = \sum_{g \in G} \sum_{s \in S} \sum_{t \in T} \pi_s (K_g u_{gst} + S_g v_{gst} + C_g p_{gst})$$
$$+ \sum_{g \in G_s} \sum_{s \in S} \sum_{t \in T} \pi_s (\mu_{gst} (u_{gst} - w_{gt}) + \nu_{gst} (v_{gst} - z_{gt}))$$

Benders Decomposition for SCUC

- Motivation:
  - Good feasibility cuts can be generated by severe contingencies
  - Optimality cuts can be rapidly computed in parallel
- Assumptions
  - Convexity of value function: unit commitment has to be fixed in the first stage for all generators
  - Ramping: assume away ramping constraints in order to decompose second-stage domain by time period, $\mathcal{D}_{st}$

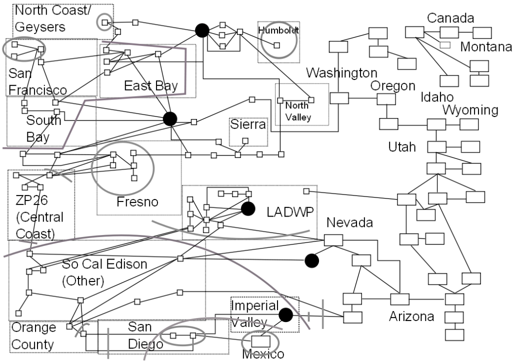
Benders Decomposition for SUC



- In order to avoid stall of standard feasibility cuts (Van-Slyke, Wets, 1969), pass entire set of power flow equations $\mathcal{D}_{st}$ for most severe contingency

WECC Model

- 130 units, 225 buses, 375 transmission lines



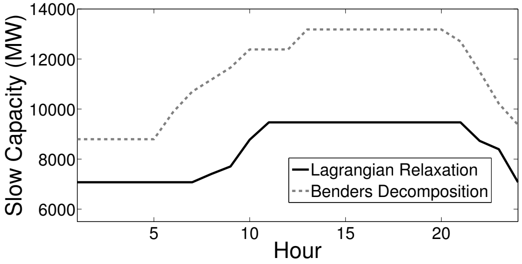
Unit Characteristics

Type	No. of units	Capacity (MW)
Nuclear	2	4,499
Gas	94	20,595.6
Coal	6	285.9
Oil	5	252
Dual fuel	23	4,599
Import	22	12,691
Hydro	6	10,842
Biomass	3	558
Geothermal	2	1,193
Wind (deep)	10	14,143
Fast thermal	88	11,006.1
Slow thermal	42	19,225.4

Implementation

- Lawrence Livermore National Laboratory
  - 8 CPUs per node, 2.4 GHz and 10 GB per node
  - MPI calling on CPLEX Java callable library
- 30 scenarios:
  - SUC: importance sampling
  - SCUC: Cartesian product of ten renewable production scenarios with no-contingency case and two most severe contingencies (Diablo and San Onofre nuclear plants)
- 1,000 Monte Carlo outcomes
  - Spring weekdays (calibrated against NREL wind data)
  - 1% generator failure probability
  - 0.1% line failure probability

Unit Commitment Schedules



- Conservative commitment of SCUC driven by assumption that all generators are slow.

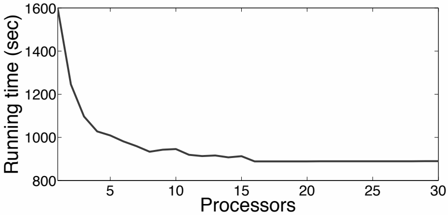
Performance

Table: Daily cost breakdown ($)

	Startup	Min. load	Load shed	Fuel	Total
SCUC	66.5	1,205.3	0	4,687.3	5,959.1
SUC	106.0	699.4	0.3	4,831.5	5,637.2

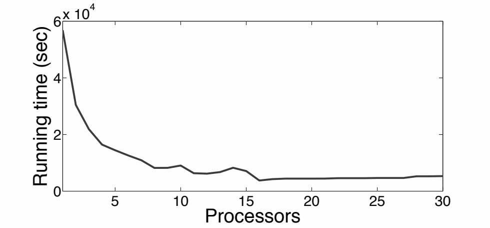
- SCUC is more reliable, at the expense of a 5.4% cost increase.

Running Time of Benders Decomposition



- Algorithm converged to optimal solution in 31 iterations. First feasible UC schedule detected in iteration 19.
- Marginal benefits vanish beyond 15 processors. Fully serial: 26.6 minutes. Fully parallel: 14.8 minutes.
- Approach is not scalable as number of scenarios increases (due to growth of first-stage subproblem).

Running Time of Lagrangian Decomposition



- Algorithm ran for 80 iterations. Lower bound: \$5.868M. Upper bound: \$5.911M.
- Marginal benefits vanish beyond 15 processors. Fully serial: 15.8 hours. Fully parallel: 47.7 minutes.
- Approach is scalable as number of scenarios increases.

Conclusions and Perspectives

- **Tradeoffs:** The SCUC model achieves greater reliability at the expense of a 5.4% cost increase
- **Parallelism:** Lagrange relaxation algorithm benefits more from parallelism
  - Second-stage problems of SUC are more difficult to solve
  - First-stage problem of SCUC is not decomposable
- **Future work:** Improve feasibility cuts in Benders algorithm in order to scale for larger number of scenarios

Thank you

Questions?

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References

[1] A. Papavasiliou, S. S. Oren, *Multi-Area Stochastic Unit Commitment for High Wind Penetration in a Transmission Constrained Network*, Operations Research, vol. 61, no. 3, pp. 578-592, May/June 2013.

[2] A. Papavasiliou, S. S. Oren and R. O'Neill, *Reserve Requirements for Wind Power Integration: A Scenario-Based Stochastic Programming Framework*, IEEE Transactions on Power Systems, Vol. 26, No. 4, November 2011.

[3] A. Papavasiliou, S. S. Oren, B. Rountree, *Applying High Performance Computing to Multi-Area Stochastic Unit Commitment for Renewable Penetration*, under review in IEEE Transactions on Power Systems.

Lagrangian Decomposition Algorithm

- Past work: (Takriti et al., 1996), (Carpentier et al., 1996), (Nowak and Römisch, 2000), (Shiina and Birge, 2004)
- Key idea: relax non-anticipativity constraints on both unit commitment and startup variables
  1. Balance size of subproblems
  2. Obtain lower and upper bounds at each iteration

  Lagrangian:

$$\mathcal{L} = \sum_{g \in G} \sum_{s \in S} \sum_{t \in T} \pi_s (K_g u_{gst} + S_g v_{gst} + C_g p_{gst}) + \sum_{g \in G_s} \sum_{s \in S} \sum_{t \in T} \pi_s (\mu_{gst}(u_{gst} - w_{gt}) + \nu_{gst}(v_{gst} - z_{gt}))$$