Managing the Uncertainty of Renewable Resources in Power System Operations

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About Me

Assistant Professor, Engie Chair
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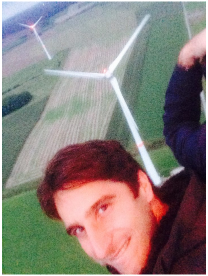
Research interests: renewable integration, demand response, market design, stochastic programming, resource planning, parallel computing



M.Sc. (2007) and Ph.D. (2011) in Industrial Engineering and Operations Research (2011)
University of California at Berkeley, USA
B.Sc. in Electrical and Computer Engineering (2006)
National Technical University of Athens, Greece

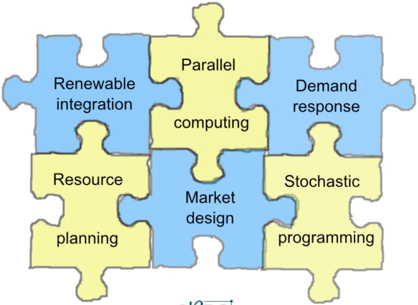
Solving the Sustainability Puzzle

Engie Chair research problems and methodology

Lawrence Livermore National Laboratory

ENGIE

High-fidelity economic dispatch and unit commitment



Electrabel GDF SUEZ

ColorPower: residential demand response business models based on quality differentiated service

CREG

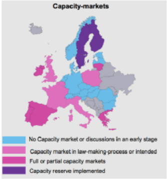
Rewarding flexible capacity in the Belgian electricity market

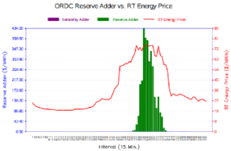
Ongoing Projects

ColorPower: residential DR aggregator business models

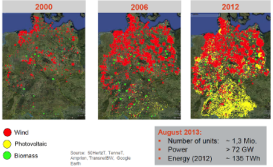
Green = price responsive
Yellow = reserve
Red = unavailable

Remuneration of flexibility in electricity markets





Application of HPC to renewable energy integration



Renewables Making Headlines

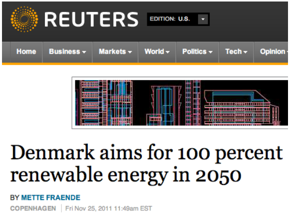
BBC NEWS EUROPE

30 May 2011 Last updated at 12:25 GMT

Germany: Nuclear power plants to close by 2022

COMMENTS (542)

Germany saw mass anti-nuclear protests in the wake of the Fukushima disaster

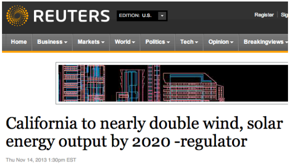


REUTERS

Denmark aims for 100 percent renewable energy in 2050

BY METTE FRAENDE

COPENHAGEN | Fri Nov 25, 2011 11:49am EST

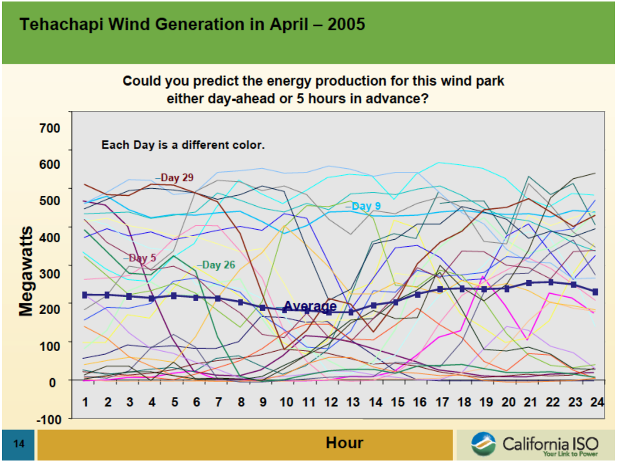


REUTERS

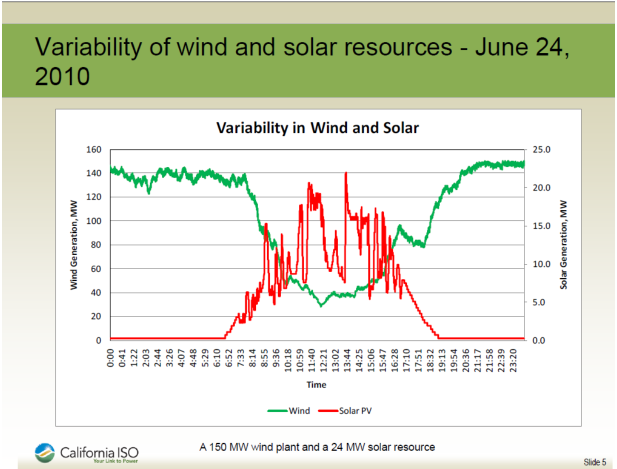
California to nearly double wind, solar energy output by 2020 -regulator

Thu Nov 14, 2013 1:30pm EST

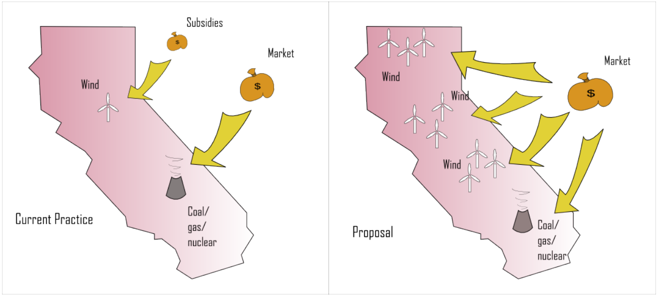
Uncertainty



Variability



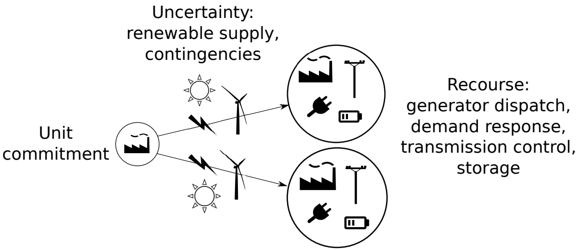
A Vision for Renewable Energy



Stochastic unit commitment appropriate for quantifying:

- Renewable energy utilization
- Cost of unit commitment and economic dispatch
- Capital investment in generation capacity

Unit Commitment under Uncertainty



Appropriate for modeling various balancing options:

- Demand (deferrable, price responsive, wholesale)
- Storage (pumped hydro, batteries)
- Transmission control (FACTS, tap changers, switching)

Unit Commitment

- Objective: $\min \sum_{g,t}(K_g u_{gt} + S_g v_{gt} + C_g p_{gt})$
- Load balance: $\sum_{g \in G} p_{gt} = D_t, \forall t$
- Min / max capacity limits: $P_g^- u_{gt} \leq p_{gt} \leq P_g^+ u_{gt}, \forall g, t$
- Ramping limits: $-R_g^- \leq p_{gst} - p_{gs,t-1} \leq R_g^+, \forall g, t$
- Min up times: $\sum_{q=t-UT_g+1}^{t} v_{gq} \leq u_{gt}, \forall g, t \geq UT_g$
- Min down times: $\sum_{q=t+1}^{t+DT_g} v_{gq} \leq 1 - u_{gt}, \forall g, t \leq N - DT_g$
- State transition: $v_{gt} \geq u_{gt} - u_{g,t-1}, \forall g, t$
- Integrality: $v_{gt}, u_{gt} \in \{0, 1\}, \forall g, t$
- Kirchhoff voltage/current laws
- Transmission line thermal constraints

The Real Thing

pjm

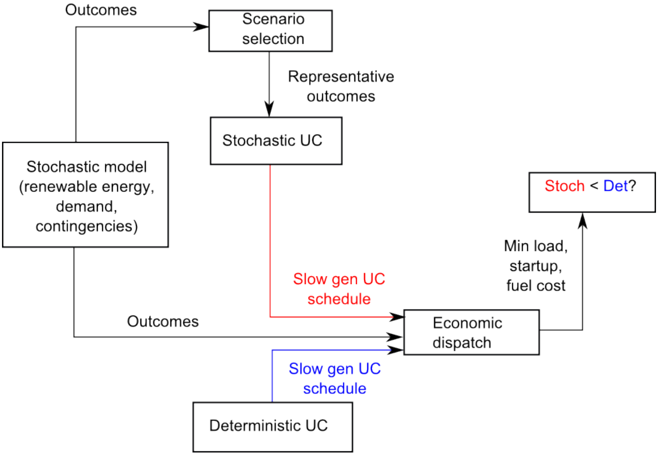
Day-ahead Market – Average Daily Volumes

- 1,210 generators, 3 part offers (startup, no load, 10 segment incremental energy offer curve)
- 10,000 - Demand bids – fixed or price sensitive
- 50,000 - Virtual bids / offers
- 8,700 - eligible bid/offer nodes (pricing nodes)
- 6,125 - monitored transmission elements
- 10,000 - transmission contingencies modeled

Relevant Literature

- Wind integration studies based on stochastic unit commitment: (Bouffard, 2008), (Wang, 2008), (Ruiz, 2009), (Tuohy, 2009), (Morales, 2009), (Constantinescu, 2011)
  - **Contribution:** coupling scenario selection inspired by importance sampling with dual decomposition algorithm
- Integrating demand response with unit commitment: (Sioshansi, 2009), (Sioshansi, 2011)
  - **Contribution:** simultaneous modeling of uncertainty and DR
- Parallel computing in power system operations: (Monticelli, 1987), (Pereira, 1990), (Falcao, 1997), (Kim, 1997), (Bakirtzis, 2003), (Biskas, 2005)
  - **Contribution:** application to short-term scheduling

Validation Process



Unit Commitment and Economic Dispatch

- Deterministic model
  1. Reserve requirements

$$\sum_{g \in G} s_{gt} + \sum_{g \in G_f} f_{gt} \geq T_t^{\mathrm{req}}, \sum_{g \in G_f} f_{gt} \geq F_t^{\mathrm{req}}, t \in T$$

  2. Import constraints

$$\sum_{l \in IG_j} \gamma_{jl} e_{lt} \leq IC_j, j \in \mathcal{IG}, t \in T$$

- Slow generator schedules are fixed in economic dispatch model: $w_{gt} = w^{\star}_{gt}, g \in G_s$

Two-Stage Stochastic Unit Commitment

Used to simulate ideal two-settlement system

1. In the first stage we commit slow generators: $u_{gst} = w_{gt}, v_{gst} = z_{gt}, g \in G_s, s \in S, t \in T$ (corresponds to day-ahead market)
2. Uncertainty is revealed: net demand D_{nst}, line availability B_{ls}, generator availability P^+_{gs}, P^-_{gs}
3. Fast generator commitment and production schedules are second stage decisions: $u_{gst}, g \in G_f$ and $p_{gst}, g \in G_f \cup G_s$ (corresponds to real-time market)
4. Objective:

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

Lagrangian Decomposition Algorithm

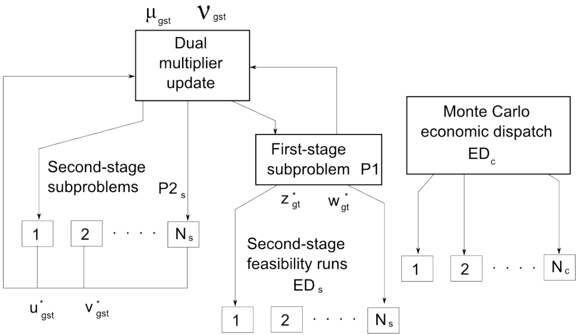
- Decomposition methods: (Nowak, 2000), (Takriti, 1996), (Carpentier, 1996), (Redondo, 1999), (Bertsimas, 2013)
- **Contribution:** relax non-anticipativity constraints on both unit commitment and startup variables
  1. Feasible solution at each iteration
  2. Optimality gap at each iteration

  Lagrangian:

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

Parallelization

- Lawrence Livermore National Laboratory Hera cluster: 13,824 cores on 864 nodes, 2.3 Ghz, 32 GB/node
- MPI calling on CPLEX Java callable library

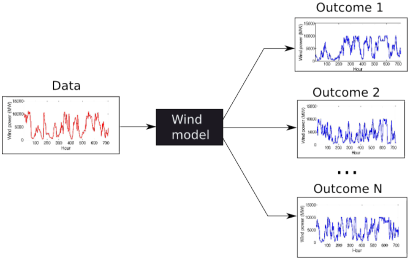


Scenario Selection for Wind Uncertainty and Contingencies

- Past work: (Gröwe-Kuska, 2002), (Dupacova, 2003), (Heitsch, 2003), (Morales, 2009)
- **Contribution:** 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 $C_D(\omega)/\bar{C}$.
  3. Set $\pi_s = C_D(\omega)^{-1}$ for all $\omega^s \in \hat{\Omega}$.

Wind Model Data Source

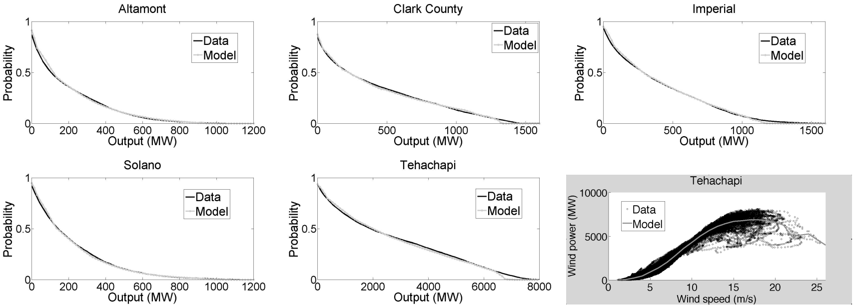
- 2 wind integration cases: moderate (7.1% energy integration, 2012), deep (14% energy integration, 2020)
- California ISO interconnection queue lists locations of planned wind power installations
- NREL Western Wind and Solar Interconnection Study archives wind speed - wind power for Western US



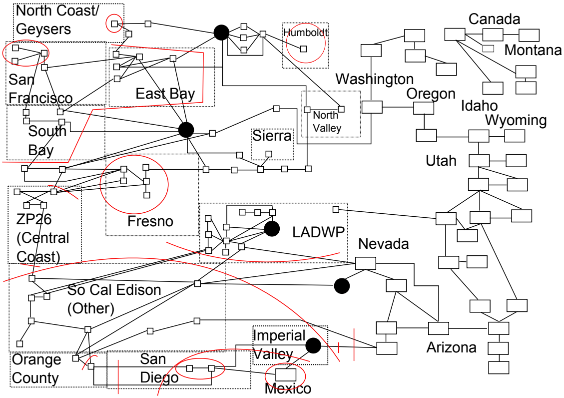
Calibration

- Relevant literature: (Brown, 1984), (Torres, 2005), (Morales, 2010)
- Calibration steps
  1. Remove systematic effects:
  $$y_{kt}^{S} = \frac{y_{kt} - \hat{\mu}_{kmt}}{\hat{\sigma}_{kmt}}.$$
  2. Transform data to obtain a Gaussian distribution:
  $$y_{kt}^{GS} = N^{-1}(\hat{F}_k(y_{kt}^{S})).$$
  3. Estimate the autoregressive parameters $\hat{\phi}_{kj}$ and covariance matrix $\hat{\Sigma}$ using Yule-Walker equations.

Data Fit


Altamont
Clark County
Imperial
Solano
Tehachapi
Tehachapi
Probability
Output (MW)
Data
Model
Wind power (MW)
Wind speed (m/s)

WECC Model


North Coast/ Geysers
Humboldt
Canada
Montana
San Francisco
East Bay
Washington
Oregon
Idaho
North Valley
Wyoming
South Bay
Sierra
Utah
Fresno
ZP26 (Central Coast)
LADWP
Nevada
So Cal Edison (Other)
Imperial Valley
Arizona
Orange County
San Diego
Mexico

Model Summary

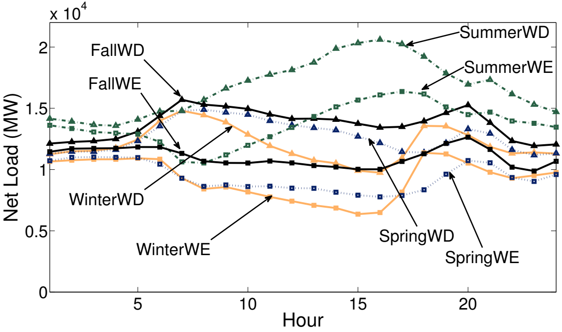
- System characteristics
  - 124 units (82 fast, 42 slow)
  - 53665 MW power plant capacity
  - 225 buses
  - 375 transmission lines
- **Four studies**
  - Deep (14% energy integration) without transmission constraints, contingencies
  - With transmission constraints, contingencies:
    - No wind
    - Moderate (7.1% energy integration, 2012)
    - Deep (14% energy integration, 2020)

Competing Reserve Rules

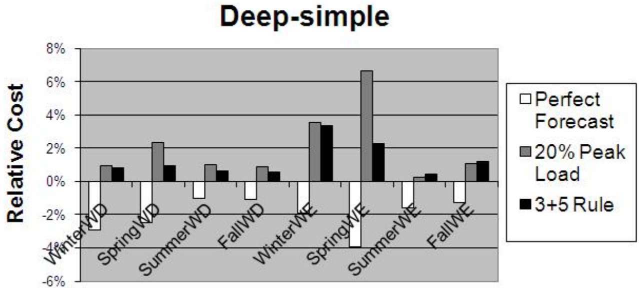
- Perfect foresight: anticipates outcomes in advance
- Percent-Of-Peak-Load rule: commit total reserve T_{req} at least x% of peak load, $F_{\mathrm{req}} = 0.5T_{\mathrm{req}}$
- 3+5 rule: commit fast reserve F_{req} at least 3% of hourly forecast load plus 5% of hourly forecast wind, $T_{\mathrm{req}} = 2F_{\mathrm{req}}$

Day Types

- 8 day types considered, one for each season, one for weekdays/weekends
- Day types weighted according to frequency of occurrence

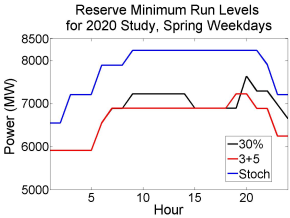


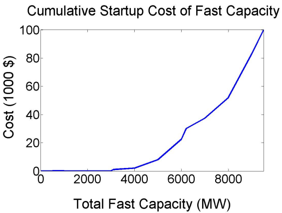
Policy Comparison - Deep Integration, No Transmission, No Contingencies



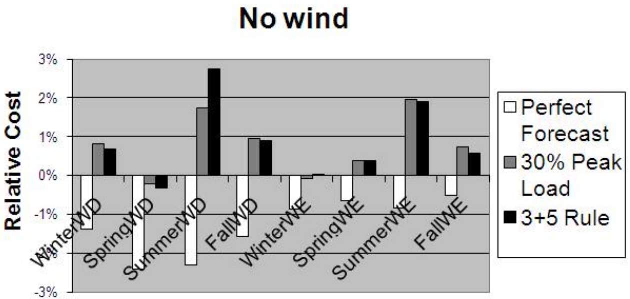
Explanation of SUC Superior Performance

- When reserve constraints are binding, deterministic policy overcommits.
- When reserve constraints are not binding, deterministic policy underestimates value of protecting against adverse wind outcomes.

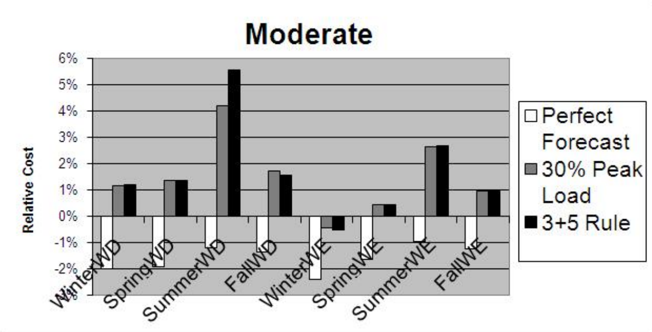




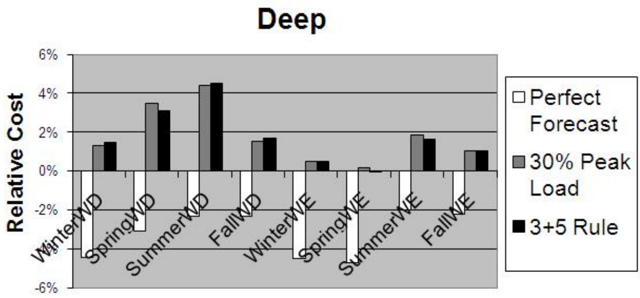
Policy Comparison - No Wind Integration



Policy Comparison - Moderate Integration



Policy Comparison - Deep Integration



Summary[1]

	Deep-S	No Wind	Moderate	Deep
RE daily waste (MWh)	100	0	890	2,186
Cost ($M)	5.012	11.508	9.363	7.481
Capacity (MW)	20,744	26,377	26,068	26,068
Daily savings ($)	38,628	104,321	198,199	188,735
Forecast gains (%)	32.4	35.4	41.9	46.7

[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, **INFORMS award for best publication in energy (2015)**.

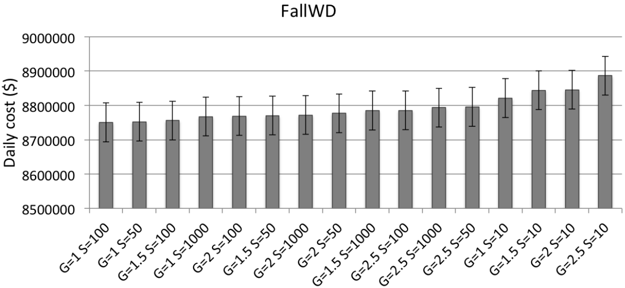
Model Size

How Many Scenarios? Do we want to solve a more representative problem less accurately or a less representative problem more accurately?

Model	Gens	Buses	Lines	Hours	Scens.
CAISO1000	130	225	375	24	1000
WILMAR	45	N/A	N/A	36	6
PJM	1011	13867	18824	24	1

Model	Integer var.	Cont. var.	Constraints
CAISO1000	3,121,800	20,643,120	66,936,000
WILMAR	16,000	151,000	179,000
PJM	24,264	833,112	1,930,776

Gaps Versus Number of Scenarios



A large number of scenarios:

- results in a more accurate representation of uncertainty
- increases the amount of time required in each iteration of the subgradient algorithm

Conclusions

- **Consistent performance of scenario selection:**
  - Stochastic unit commitment yields 32.4%-46.7% of benefits of perfect foresight over various types of uncertainty
  - Favorable performance relative to Sample Average Approximation with 1000 scenarios.
- **Insights from parallel computing[2]:**
  - Reducing the duality gap seems to yield comparable benefits relative to adding more scenarios
  - All problems solved within 24 hours (operationally acceptable), given enough processors.

[2] A. Papavasiliou, S. S. Oren, B. Rountree, *Applying High Performance Computing to Multi-Area Stochastic Unit Commitment for Renewable Penetration*, IEEE Transactions on Power Systems, vol. 30, no. 3, pp. 1690-1701, May 2015.

Conclusions (II)

- **Transmission constraints and contingencies strongly influence results - need for advanced optimization**
  - Overestimation of capacity credit from 1.2% of installed wind capacity to 39.8% for deep integration
  - Underestimation of daily operating costs from 7.481 $M to 5.102 $M for deep integration
- **First steps towards integrating deferrable demand models with renewable supply uncertainty[3]:** Deferrable demand imposes no additional capacity requirements, coupling results in 3.06% - 8.38% operating cost increase

[3] A. Papavasiliou, S. S. Oren, *Large-Scale Integration of Deferrable Electricity and Renewable Energy Sources in Power Systems*, IEEE Transactions on Power Systems, vol. 29, no. 1, pp. 489-499, January 2014.

Perspectives

- Model refinements
  - Sub-hourly time scales (15’, 5’)
  - Rolling horizon simulation
  - Conventional and storage resources
    - Nuclear swings
    - CCGT and coal startup/shutdown profiles
  - Solar power
- Computation
  - Asynchronous subgradient methods
  - Primal recovery heuristics
  - Fast convergence to ‘good-enough’ solutions
- Demand response
  - Bottom-up modeling of demand elasticity
  - Assessment of renewable integration limits

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, **INFORMS award for best publication in energy (2015)**.
2. A. Papavasiliou, S. S. Oren, B. Rountree, *Applying High Performance Computing to Multi-Area Stochastic Unit Commitment for Renewable Penetration*, IEEE Transactions on Power Systems, vol. 30, no. 3, pp. 1690-1701, May 2015.
3. A. Papavasiliou, S. S. Oren, *Large-Scale Integration of Deferrable Electricity and Renewable Energy Sources in Power Systems*, IEEE Transactions on Power Systems, vol. 29, no. 1, pp. 489-499, January 2014.

Thank you

Questions?

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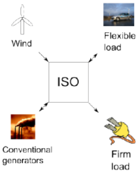
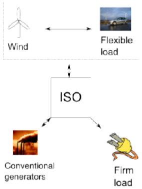
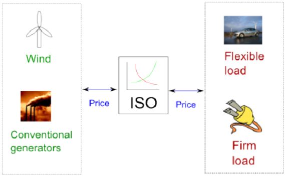
Demand Response Results

	Daily Cost ($)	Daily Load Shed (MWh)
No wind	**9,012,031**	17.301
Centralized Moderate	**8,677,857**	1.705
Bids Moderate	211,010	609.914
Coupled Moderate	265,128	2.217
Centralized Deep	**8,419,322**	10.231
Bids Deep	578,909	1221.492
Coupled Deep	705,497	112.452

Load Flexibility







System operator control

Coupling renewables with deferrable demand

Price-responsive demand

Centralized → Decentralized

Demand Response Study

	Zero	Moderate	Deep
Wind capacity (MW)	0	6,688	14,143
DR capacity (MW)	0	5,000	10,000
Daily wind energy (MWh)	0	46,485	95,414
Daily DR energy (MWh)	0	40,000	80,000
DR/firm energy (%)	0	6.1	12.2

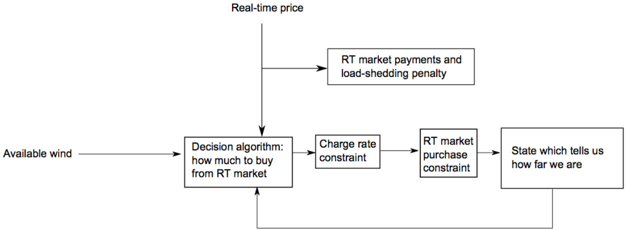
Centralized Load Dispatch

- Stochastic unit commitment with additional constraint:
$$\sum_{t=1}^{N} p_{gst} = R$$
- Assumptions of centralized load control:
  - Central co-optimization of generation and demand (computationally prohibitive)
  - Perfect monitoring and control of demand
- Centralized load control represents an idealization that can be used for:
  - Quantifying the cost of decentralizing demand response
  - Estimating the capacity savings of deferrable demand

Demand Bids

- Based on retail consumer model of (Borenstein and Holland, 2005), (Joskow and Tirole, 2005), (Joskow and Tirole, 2006)
- State contingent demand functions used in economic dispatch $D_t(\lambda_t; \omega) = a_t(\omega) - \alpha b \lambda^R - (1 - \alpha) b \lambda_t$
- Note that the demand function model has to:
  - Be comparable to the deferrable demand model in terms of total demand R
  - Be consistent with the observed inflexible demand in the system

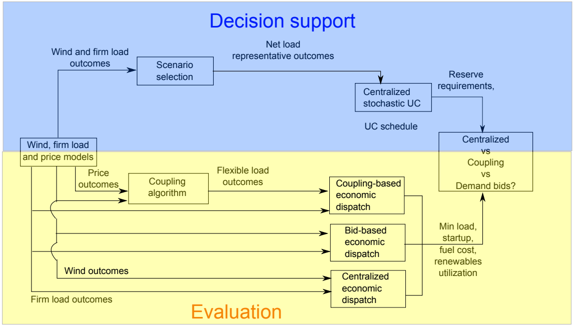
Coupling



$$\min_{\mu_t(x_t)} \mathbb{E}[\sum_{t=1}^{N-1} \lambda_t(\mu_t(x_t) - s_t)^+]\Delta t + \rho r_N]$$

$$\mu_t(x) \leq C, (\mu_t(x) - s_t)^+ \leq M_t, r_{t+1} = r_t - u_t$$

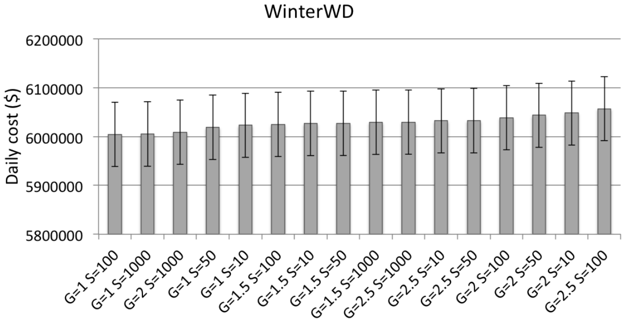
Integrating Demand Response in Stochastic Unit Commitment



Running Times

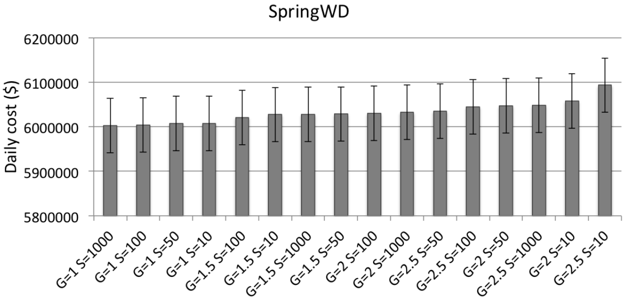
- CPLEX 11.0.0
- DELL Poweredge 1850 servers (Intel Xeon 3.4 GHz, 1GB RAM)
- $(P1), (P2_s)$ run for 120 iterations, (ED_s) run for last 40 iterations
- Average running time of 43776 seconds on single machine
- Average MIP gap of 1.39%

Cost Ranking: Winter Weekdays



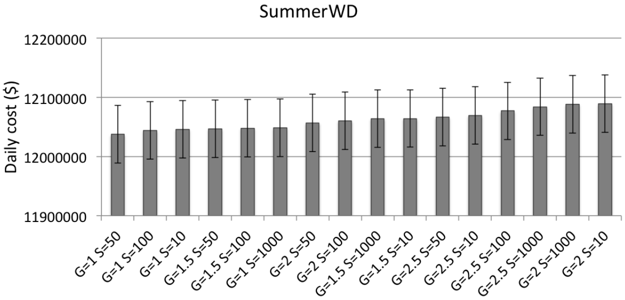
- $S = 1000$ corresponds to Shapiro's SAA algorithm
- Average daily cost and one standard deviation for 1000 Monte Carlo outcomes

Cost Ranking: Spring Weekdays



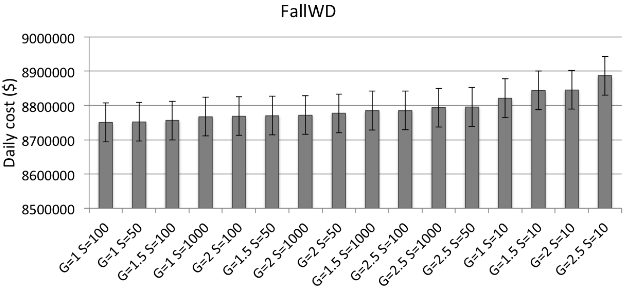
- $S = 1000$ corresponds to Shapiro's SAA algorithm
- Average daily cost and one standard deviation for 1000 Monte Carlo outcomes

Cost Ranking: Summer Weekdays



- $S = 1000$ corresponds to Shapiro's SAA algorithm
- Average daily cost and one standard deviation for 1000 Monte Carlo outcomes

Cost Ranking: Fall Weekdays



- $S = 1000$ corresponds to Shapiro's SAA algorithm
- Average daily cost and one standard deviation for 1000 Monte Carlo outcomes

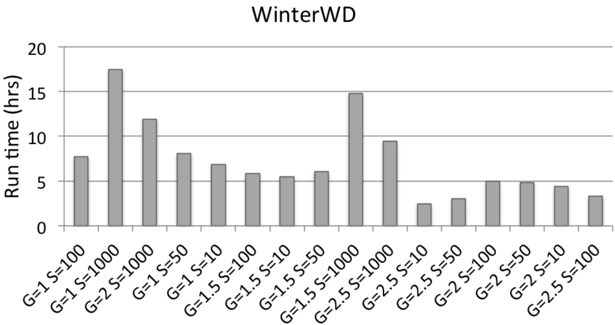
Influence of Duality Gap

- Among three worse policies in summer, $S = 1000$ with G = 2%, 2.5%
- Best policy for all day types has a 1% optimality gap ($S = 1000$ only for spring)
- For all but one day type the worst policy has $G = 2.5\%$
- For spring, best policy is $G = 1, S = 1000$
- For spring, summer and fall the worst policy is the one with the fewest scenarios and the greatest gap, namely $G = 2.5, S = 10$

Validation of Scenario Selection Policy

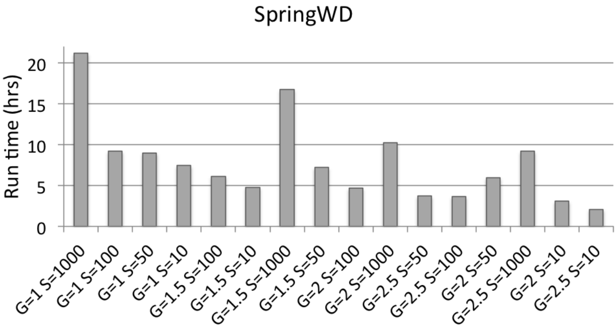
- Top performance for winter, summer and fall is attained by proposed scenario selection algorithm based on importance sampling
- For all day types, the importance sampling algorithm results in a policy that is within the top 2 performers
- Satisfactory performance (within top 3) can be attained by models of moderate scale (S50), provided an appropriate scenario selection policy is utilized

Run Time Ranking: Winter Weekdays



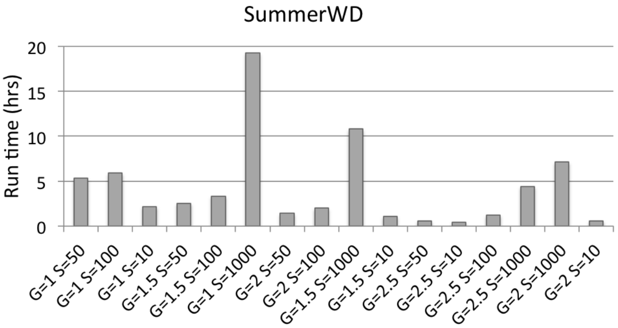
- Best-case running times ($S = P$)

Run Time Ranking: Spring Weekdays



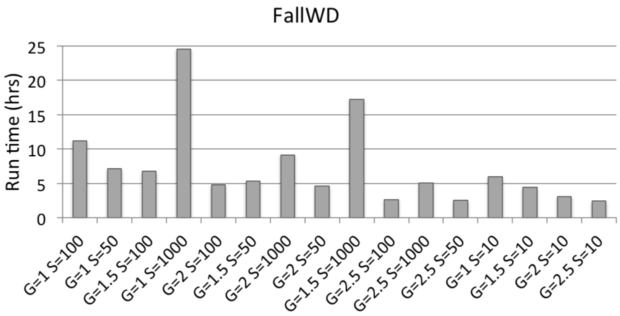
- Best-case running times ($S = P$)

Run Time Ranking: Summer Weekdays



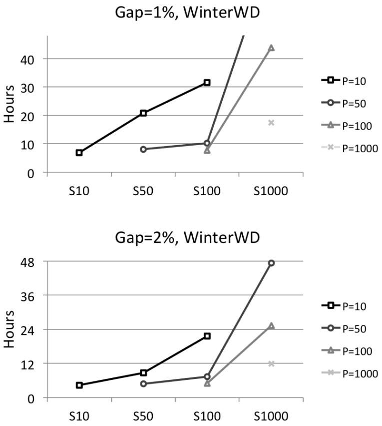
- Best-case running times ($S = P$)

Run Time Ranking: Fall Weekdays

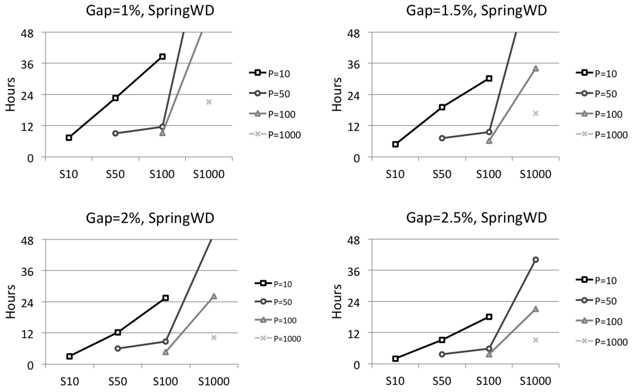


- Best-case running times ($S = P$)

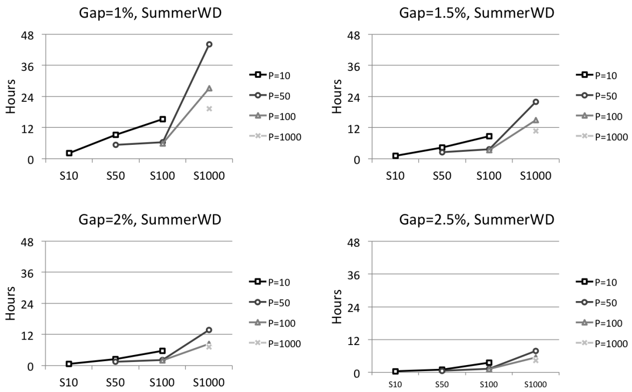
Running Times: Winter Weekdays



Running Times: Spring Weekdays



Running Times: Summer Weekdays



Running Times: Fall Weekdays