Multi-Area Stochastic Unit Commitment for High Wind Penetration in a Transmission Constrained Network

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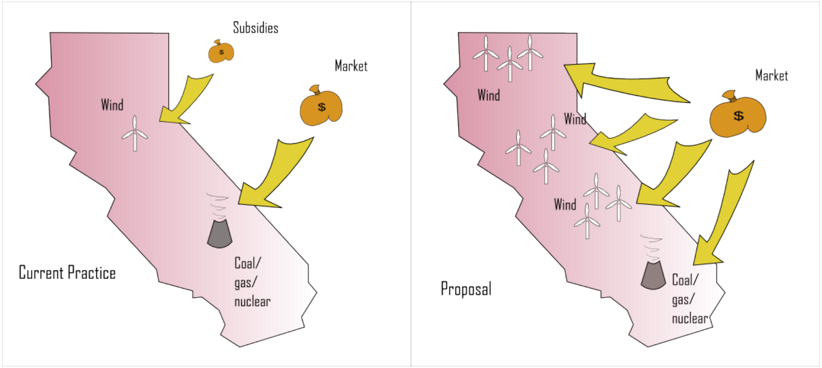
A Vision for Renewable Energy



Renewable resources can become economically competitive by targeting flexible consumers

Research Objective

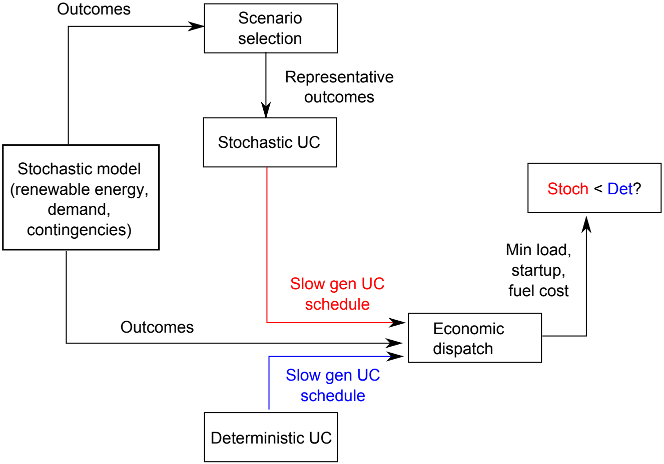
In order to assess the economic implications of large-scale renewable integration, we seek to quantify:

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

Stochastic unit commitment an appropriate model:

- Quantifies renewable energy utilization (decision variable)
- Quantifies operating costs (objective function)
- Endogenously determines reserves (as opposed to ad hoc rules)

Validation of Stochastic Unit Commitment Model



Outcomes

Scenario selection

Representative outcomes

Stochastic UC

Stochastic model (renewable energy, demand, contingencies)

Stoch < Det?

Min load, startup, fuel cost

Slow gen UC schedule

Outcomes

Economic dispatch

Slow gen UC schedule

Deterministic UC

Unit Commitment and Economic Dispatch

- Deterministic model (Sioshansi and Short, 2009)
  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: $w_{gt} = w_{gt}^{\star}, g \in G_s$

Two-Stage Stochastic Unit Commitment

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

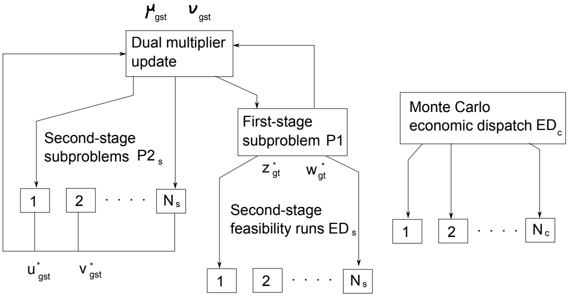
- Past work: (Takriti et al., 1996), (Carpentier et al., 1996), (Nowak and Römisch, 2000), (Shiina and Birge, 2004)
- Key idea: relax non-anticipativity constraints on both unit commitment and startup variables
  1. Balance size of subproblems
  2. Obtain lower and upper bounds at each iteration

  Lagrangian:

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

Parallelization

- Second-stage subproblems, second-stage feasibility runs and economic dispatch simulations can be parallelized
- Implemented in MPI, CPLEX



μ_{gst} ν_{gst}

Dual multiplier update

Second-stage subproblems $P2_s$

1 2 · · · · N_s

u^*_{gst} v^*_{gst}

First-stage subproblem P1

z^*_{gt} w^*_{gt}

Second-stage feasibility runs ED_s

1 2 · · · · N_s

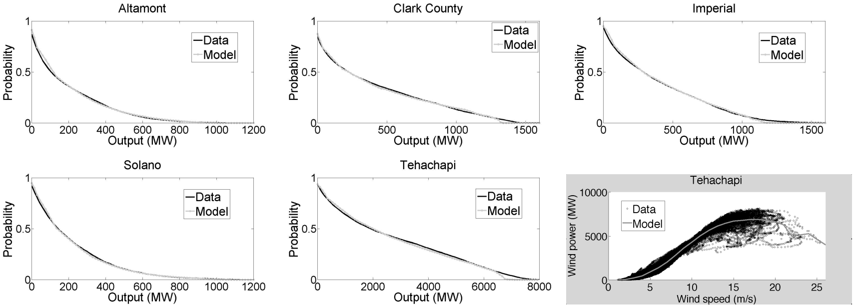
Monte Carlo economic dispatch ED_c

1 2 · · · · N_c

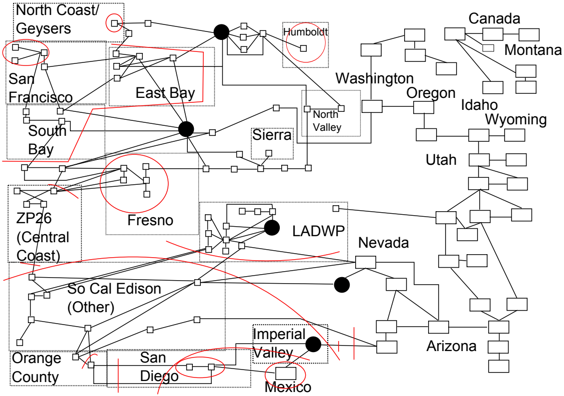
Scenario Selection for Wind Uncertainty and Contingencies

- Past work: (Gröwe-Kuska et al., 2002), (Dupacova et al., 2003), (Heitsch and Römisch, 2003), (Morales et al., 2009)
- 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 determinstic 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 $\omega^s \in \hat{\Omega}$.

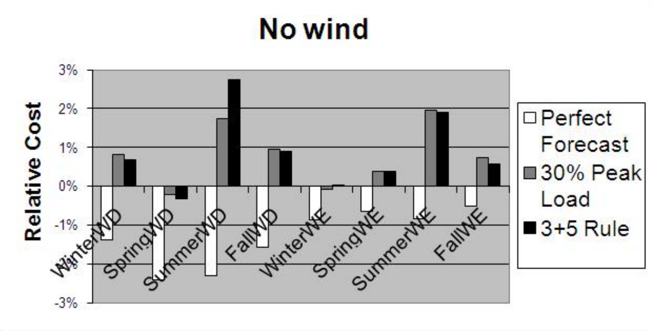
Multi-Area Wind Model



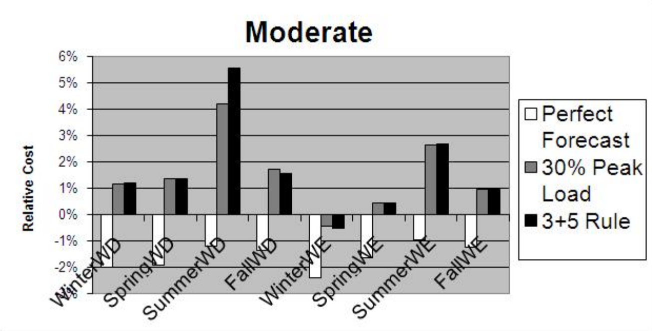
WECC Model


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

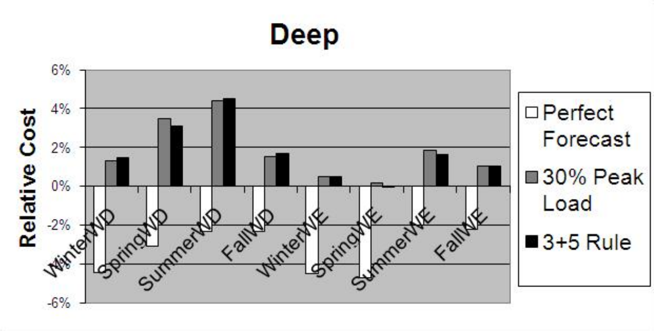
Policy Comparison - No Wind Integration



Policy Comparison - Moderate Integration



Policy Comparison - Deep Integration



Summary

	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

Conclusions and Perspectives

- **Consistent performance of scenario selection:** Stochastic unit commitment policy yields 32.4% - 46.7% of potential benefits of perfect foresight over various types of uncertainty
- **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
- **New frontiers for renewable integration studies**
  - Sub-hourly resolution and ramp rates
  - Detailed models of system resources (demand response, CCGTs, nuclear, hydro)
  - Parallel computing