Demand Response Can Improve the Emission Benefits of Wind

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Disclaimer

The opinions expressed and conclusions reached are solely those of the authors and do not represent the official position of Pacific Gas and Electric Company.

Renewable Growth

- Tremendous growth in renewable deployment in the past decade
- Mostly wind (*e.g.*, 238 GW wind and 67 GW of PV by end of 2011 [IEA13])
- Many motivations:
    - Sustainable energy supply
    - More cost competitive with alternatives
    - Supply diversification
    - Climate change
    - Other environmental and emissions impacts of conventional alternatives

Those Emissions

- Renewables displace fossil fueled-generation and their emissions
- Net effect is more nuanced, due to resource variability and uncertainty

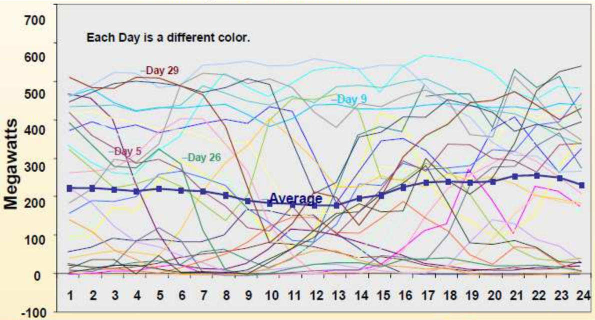

Figure: Tehachapi Wind Generation in April 2005
Source: California ISO

- Need some mixture of supply- and demand-side flexibility to operate system reliably
- Currently use supply-side solutions (*i.e.*, partially load generators to provide ramping and reserves)

Why Renewable Integration Matters

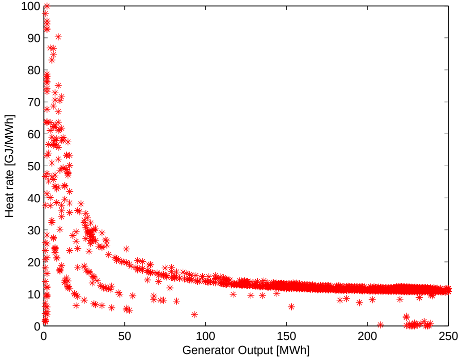

Figure: Measured Heat Rate of Wolf Hollow I CCGT *Source: US EPA CEMs*

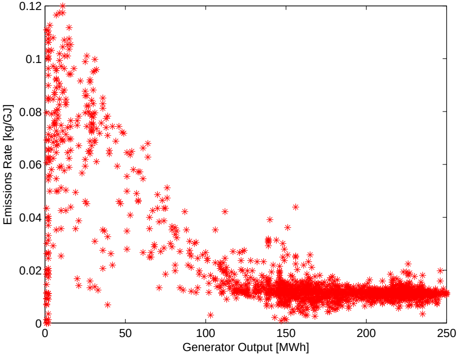

Figure: Measured NO_x Rate of Wolf Hollow I CCGT *Source: US EPA CEMs*

- You can get hit with double-whammy of higher heat rates and less effective emissions controls when units are partially loaded

Net Emissions Gain?

- Katzenstein and Apt [KA09] study these interactions
- Assume an NG unit follows output of a single wind plant to balance its real-time output
- Use five-minute wind data to simulate NG dispatch
- Combine with CEMs data to estimate CO_2 and NO_x emissions
    - CO_2 emissions go down, but by less than back of the envelope ‘displacement’ analysis predicts
    - NO_x emissions sensitive to type of controls—net **increase** if NG plant uses dry control technology

What We Do

- Use a case study based on ERCOT (Texas) system to:
  1. Revisit wind emissions analysis to determine what happens with a full wind and conventional portfolio and real system operating rules
  2. Examine effects of using supply-side measures (RTP) to accommodate wind variability and uncertainty and emissions impacts
- We find:
  1. Wind decreases system-wide conventional generator efficiency and increases marginal emissions rates (partial loading effect)
  2. Net CO_2, SO_2, and NO_x reductions, since displacement outweighs efficiency impacts
  3. RTP increases emissions due to rebound effect and changed diurnal load profiles, but decreases costs associated with wind uncertainty and variability
  4. Taking these two effects together, RTP delivers better bang for the buck (more emissions abatement per dollar of wind-integration cost)

Two Effects of Wind

- Short-run analysis, with fixed conventional generation mix
- Two short-run effects that we focus on:
  1. Cost
     - Although zero marginal cost, wind imposes external costs
     - Have to commit excess capacity and dispatch it in real-time to balance variable output
  2. Emissions
     - Displacement of fossil-fueled generators
     - Efficiency effects of partial loading

Model Overview

- Model operations with unit commitment and economic dispatch models
- Stochastic unit commitment model determines which generators to startup and run day-ahead, accounting for future wind uncertainty
- Deterministic real-time model determines generator dispatch based on actual wind
- ‘Fast start’ units can be committed in real-time, if needed
- Cases with RTP model demand response as a dispatchable resource, determine how much load to serve and how to serve it to maximize social welfare (based on assumed inverse demand function)
- All models operate at hourly timesteps and optimize operations in a rolling fashion

Day-Ahead Stochastic Unit Commitment

- Day-ahead model has a two-stage scenario tree structure
- Scenarios represent possible wind realizations
- Stochastic model commits a mix of units that can feasibly serve load under a range of possible wind scenarios ($\xi \in \Xi$)
- Generator commitments ($u_{g,t}$, $s_{g,t}$, and $h_{g,t}$) determined in first stage and are scenario-independent

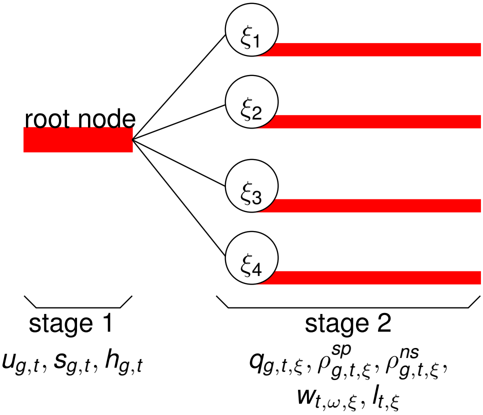

Figure: Scenario Tree Schematic

Day-Ahead Stochastic Unit Commitment

- Generator dispatch and reserves ($q_{g,t,\xi}$, $\rho^{sp}_{g,t,\xi}$, and $\rho^{ns}_{g,t,\xi}$), wind generation ($w_{t,\omega,\xi}$), and load served ($l_{t,\xi}$) determined in second stage and are scenario-dependent
- Objective function maximizes expected social welfare (integral of inverse demand function, less generation cost)
- Includes load-balance, spinning and non-spinning reserve, ramping, minimum up- and down-time constraints

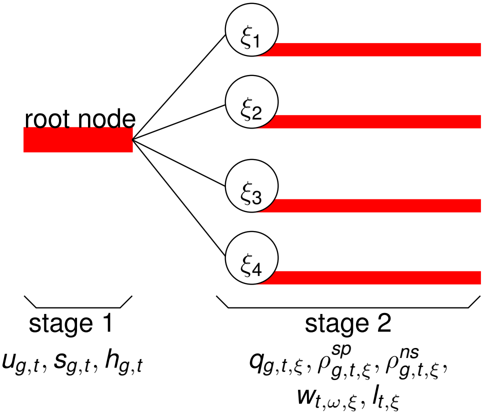

Figure: Scenario Tree Schematic

Model Formulation

Real-Time Economic Dispatch

- Deterministic model, has same model structure (*i.e.*, maximize expected social welfare subject to same constraint types)
- Use actual wind availability
  - Generally different than any of the scenarios modeled day-ahead
- Generator commitments fixed based on day-ahead solution
- 'Fast start' units can be started up, if needed
- Determines actual generator dispatch and load served, based on actual wind and day-ahead commitment

Emissions Estimation

- Translate generator commitment and dispatch into fuel use, based on heat rates
- Use input-based emissions rate estimates
- Constant CO_2 rates, since these are uncontrolled
- Non-parametric estimates of SO_2 and NO_x rates, based on CEMs data

Non-Parametric Emissions Estimate

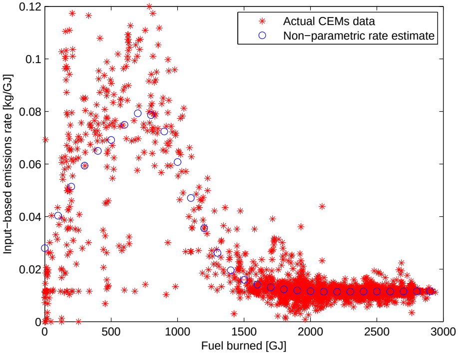

Figure: Non-parametric Estimate of NO_x Rate of Wolf Hollow I CCGT *Source: US EPA CEMs*

Case Study

- Based on the ERCOT system, used in previous wind-integration studies [SS09, Sio10, MS13a, MS13b]
- Use 2005 conventional generator and load data
- Model a high-wind case with 14 GW of wind (14% of generating capacity)

Table: Conventional Generation Mix [%]

Type	Capacity	Base Case Generation
Natural Gas	75	41
Coal	19	45
Nuclear	6	14

Case Study

Demand Response

- Model demand response as a dispatchable resource the system operator can use to balance the system
- Use an inverse demand function to represent willingness to pay for energy
- Calibrate demand function in each hour by assuming an own-price elasticity (cross-price elasticities assumed to be zero) and fixing:

$$p_t(l_t) = p^{ret},$$

  where:
  - l_t is historical demand
  - p^{ret} is historical retail electricity electricity price
- Load fixed and equal to l_t in fixed-load cases

Case Study

Wind Modeling

- 14 GW of wind based on sites built through end of 2011
- Modeled actual wind availability (used in real-time dispatch model) from NREL's Western Wind Resources Dataset (WWRD)
  - Wind generators are associated with locations in WWRD
  - Actual wind modeled as:

$$\Omega_\omega \cdot \phi_{\omega,t},$$

    where:
    - Ω_ω is nameplate capacity
    - $\phi_{\omega,t} \in [0, 1]$ is fraction available in hour t

Case Study

Wind Modeling

- Day-ahead wind forecasts are generated by adding a forecast error term to actual wind availability:

$$\phi_{\omega,t} + \epsilon_t,$$

- Assume a serially autocorrelated error structure [LH07]:

$$\epsilon_t = \nu_t + \zeta \cdot \epsilon_{t-1}$$

  where ν_t is hour-t innovation, with unbiased truncated Gaussian distribution

- Randomly generate 1000 sample paths and use SCENRED to reduce to four scenarios [DGKR03]

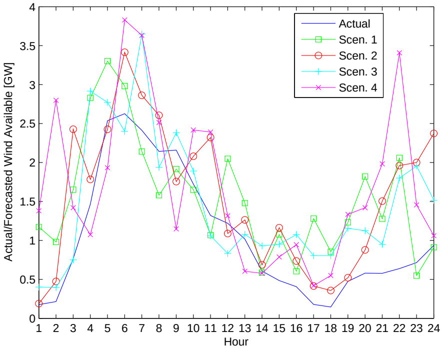

Figure: Modeled Day-Ahead Wind Forecasts and Actual Wind

Cases Modeled

- Compare system costs and emissions in five cases to determine effects of wind
- Cases with ‘perfect foresight’ assume wind availability is known day-ahead, no forecast or scenario tree used

Table: Cases Modeled

Case	Wind	DA Wind	Loads
`Base`	None	n/a	Fixed
`Wind Fore`	High	Forecast	Fixed
`Wind PF`	High	Perfect Foresight	Fixed
`DR Fore`	High	Forecast	Price-Responsive
`DR PF`	High	Perfect Foresight	Price-Responsive

Emissions Effects of Wind

Fixed Load Case

- Emissions in `Base` and `Wind Fore` cases
- ≈43 TWh of conventional generation (27% coal) displaced by wind
- Emissions reductions, increasing in forecast error variance

Table: Annual Generation and Generator Emissions

Wind Forecast Error Variance	Generation [TWh] Coal	Generation [TWh] NG	Emissions CO_2 [Mt]	Emissions SO_2 [kt]	Emissions NO_x [kt]
No Wind	134.8	122.8	198.5	451.2	140.4
0.0025	122.9	91.0	172.1	400.7	124.2
0.0100	122.7	91.1	171.9	399.7	124.0
0.0225	122.5	91.4	171.8	398.8	123.8

Emissions Effects of Wind

Fixed Load Case

- Higher variance means less accurate forecasts
- Day-ahead wind scenarios are more variable, requiring greater ramping
- Commit more NG units (in place of coal), shifting load to them
- NG units are more lightly loaded, giving lower heat rates and less efficient SO_2 and NO_X control

Table: Average Natural Gas Plant Loading and Emissions Rates

Wind Forecast Error Variance	Plant Loading [%]	Emissions Rates [g/MWh] SO_2	NO_x
0.0025	34.1	3.59	349.5
0.0100	30.2	3.59	350.3
0.0225	28.1	3.61	350.6

Emissions Effects of Wind

NO_x Decreases

- NO_x decreases, despite wind variability and uncertainty (*contra* Katzenstein and Apt)
- Observe same loss of generator and emissions control efficiency
- Two important distinctions with their assumptions:
  - They implicitly assume 100% reserves for each wind plant (*i.e.*, model a dedicated NG plant following wind output); we use stochastic model to 'dynamically' determine reserve needs, exploit spatial smoothing of wind availability
  - Don't capture effect of wind on mix of committed generators (*i.e.*, shift away from coal to NG, due to ramping needs)

Emissions Effects of Wind

Price-Responsive Load Case

Table: Annual Emissions Increase (Between `DR Fore` and `Wind Fore` Cases) [%]

Wind Forecast Error Variance	Demand Elasticity -0.1 CO_2	SO_2	NO_x	Demand Elasticity -0.3 CO_2	SO_2	NO_x
0.0025	0.9	3.0	0.5	2.3	7.3	0.7
0.0100	0.9	3.1	0.6	2.3	7.5	0.8
0.0225	0.9	3.1	0.6	2.3	7.6	0.9

- Emissions increase when RTP is introduced
- Primarily due to a change in the diurnal load pattern—off-peak energy is relatively cheap, loads shift toward those hours
- Coal generation is marginal during off-peak hours (coal increases from 57% to 60% of thermal generation)
- Also have a rebound effect—wind suppresses real-time prices, giving overall demand increase

Cost Effects of Wind

- Wind has an ancillary cost effect, due to variability and uncertainty
- We measure this 'wind-uncertainty cost' as difference between operating cost with wind forecasts to counterfactual case with perfect foresight [DGMS05, SMDP07, DJK+07]
- In fixed load case, this is welfare loss between `Wind PF` and `Wind Fore` cases
- With price-responsive loads, compare `DR PF` and `DR Fore` cases

Table: Wind-Uncertainty Cost [$/MWh of Wind]

Wind Forecast Error Variance	Demand Elasticity Fixed Load	-0.1	-0.3
0.0025	1.81	0.25	0.02
0.0100	3.79	0.99	0.02
0.0225	6.11	1.89	0.04

The 'Bottom Line' of Wind

- Wind has two primary ancillary effects on the power system:
  1. External uncertainty cost
  2. Emissions abatement
- Capture the two by computing emissions averted per dollar of wind-uncertainty cost incurred
- Although RTP errodes some emissions benefits of wind, the lower wind-uncertainty cost more than makes up for this
- Less accurate wind forecasting is a costly means of reducing emissions

Table: Annual Emissions Averted Per Dollar of Wind-Uncertainty Cost

Wind Forecast Error Variance	Without RTP			With RTP		
	CO_2 [t/$]	SO_2 [kg/$]	NO_x [kg/$]	CO_2 [t/$]	SO_2 [kg/$]	NO_x [kg/$]
0.0025	3	6	0	23–232	35–216	1–10
0.0100	2	3	0	6–228	9–215	0–11
0.0225	1	2	0	3–125	5–119	0–6

To Summarize

- We explore interactions between wind and demand response in energy systems, with focus on emissions
- Revisit some counterintuitive findings regarding net emissions impacts of wind
- Show that when the total power system 'portfolio' and operating practices are accounted for, wind delivers overall emissions reductions
- Demand response is a cost- and emissions-effective way of accommodating wind variability and uncertainty
- Reduced wind-integration costs due to demand response may also lower technical and financial barriers to entry
- Demand response can also reduce wind curtailment, when that becomes an issue [LCR03, DM07, SS09, TO11]

Caveats and Future Work

- Short-run analysis only, not much detailed work examining long-term investment and issues or benefits from demand response
- Unclear how other renewables (*e.g.*, solar) may benefit from demand response
- Differences possible due to diurnal and seasonal solar patterns being so different to wind

Questions?

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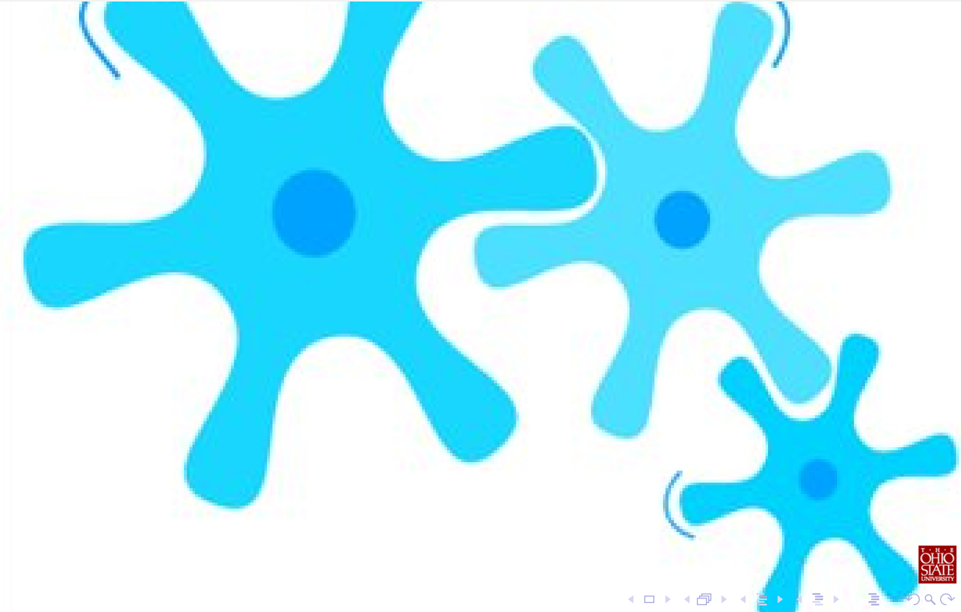
Modeling Details



Day-Ahead Stochastic Unit Commitment

Model Formulation

$$\max \sum_{\xi \in \Xi} \sum_{t \in T} \pi_\xi \cdot \left\{ \int_0^{l_{t,\xi}} p_t(x)dx - \sum_{g \in G} \left[c_g^v(q_{g,t,\xi}) + c_g^n \cdot u_{g,t} + c_g^s \cdot s_{g,t} \right] \right\};$$

$$\text{s.t. } l_{t,\xi} = w_{t,\xi} + \sum_{g \in G} q_{g,t,\xi}; \qquad \forall\, t \in T, \xi \in \Xi;$$

$$\sum_{g \in G} \rho_{g,t,\xi}^{sp} \geq \eta^{sp} \cdot l_{t,\xi}; \qquad \forall\, t \in T, \xi \in \Xi;$$

$$\sum_{g \in G} (\rho_{g,t,\xi}^{sp} + \rho_{g,t,\xi}^{ns}) \geq (\eta^{sp} + \eta^{ns}) \cdot l_{t,\xi}; \qquad \forall\, t \in T, \xi \in \Xi;$$

$$K_g^- \cdot u_{g,t} \leq q_{g,t,\xi}; \qquad \forall\, g \in G, t \in T, \xi \in \Xi;$$

$$q_{g,t,\xi} + \rho_{g,t,\xi}^{sp} \leq K_g^+ \cdot u_{g,t}; \qquad \forall\, g \in G, t \in T, \xi \in \Xi;$$

Day-Ahead Stochastic Unit Commitment

Model Formulation

$$q_{g,t,\xi} + \rho^{sp}_{g,t,\xi} + \rho^{ns}_{g,t,\xi} \leq K^{+}_{i}; \qquad \forall\, g \in G, t \in T, \xi \in \Xi;$$

$$0 \leq \rho^{sp}_{g,t,\xi} \leq \bar{\rho}^{sp}_{g} \cdot u_{g,t}; \qquad \forall\, g \in G, t \in T, \xi \in \Xi;$$

$$0 \leq \rho^{ns}_{g,t,\xi} \leq \bar{\rho}^{ns}_{g}; \qquad \forall\, g \in G, t \in T, \xi \in \Xi;$$

$$R^{-}_{g} \leq q_{g,t,\xi} - q_{g,t-1,\xi}; \qquad \forall\, g \in G, t \in T, \xi \in \Xi;$$

$$q_{g,t,\xi} - q_{g,t-1,\xi} + \rho^{sp}_{g,t,\xi} + \rho^{ns}_{g,t,\xi} \leq R^{+}_{g}; \qquad \forall\, g \in G, t \in T, \xi \in \Xi;$$

$$\sum_{y=t-\tau^{+}_{g}}^{t} s_{g,y} \leq u_{g,t}; \qquad \forall\, g \in G, t \in T;$$

$$\sum_{y=t-\tau^{-}_{g}}^{t} h_{g,y} \leq 1 - u_{g,t}; \qquad \forall\, g \in G, t \in T;$$

$$s_{g,t} - h_{g,t} = u_{g,t} - u_{g,t-1}; \qquad \forall\, g \in G, t \in T;$$

Day-Ahead Stochastic Unit Commitment

Model Formulation

$$0 \le w_{t,\xi} \le \bar{w}_{t,\xi}; \qquad \forall\, t \in T, \xi \in \Xi;$$

$$l_{t,\xi} \ge 0 \qquad \forall\, t \in T, \xi \in \Xi; \text{ and}$$

$$u_{g,t}, s_{g,t}, h_{g,t} \in \{0, 1\}; \qquad \forall\, g \in G, t \in T.$$

Model Overview

Emissions Estimation

Non-Parametric Estimate

- Estimate emissions rate as a function of fuel use based on US EPA CEMs data
- Emissions rate of species p estimated as:

$$\phi_{g,p}(f) = \frac{\sum_{n=1}^{N} K\left(\frac{f - f_g^n}{h}\right) \phi_{g,p}^n}{\sum_{n=1}^{N} K\left(\frac{f - f_g^n}{h}\right)},$$

where:

- $\phi_{g,p}^n$ and f_g^n are emissions rate and fuel use in CEMs data
- $K(\cdot)$ is a kernel function, taken to be Gaussian density
- h is bandwidth

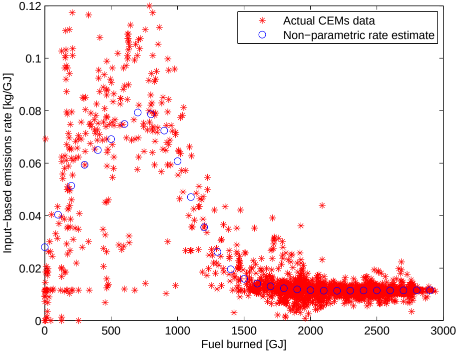


Figure: Non-parametric Estimate of NO_x Rate of Wolf Hollow I CCGT *Source: US EPA CEMs*

Emissions Estimation