Evaluating the Impact of Real-Time Pricing on the Cost and Value of Wind Generation

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Problem Background

- Wind generation and resource forecasting errors introduce operational challenges and costs to power systems:
  - Incorrect wind resource forecasts day-ahead can cause suboptimal unit commitments
  - These can also result in costly redispatch and deployment of ancillary services in real-time
  - Very poor forecasts can require load to be shed if insufficient capacity is available in real-time
- Many studies focus on the impacts of wind uncertainty on day-ahead and real-time dispatch, and suggest this timeframe is a major cost of wind integration
  - Fabbri *et. al.* (2005) show wind forecast error costs can be up to 10% of wind revenues
  - DeMeo *et. al.* (2005) and Smith *et. al.* (2007) survey wind integration studies and show costs of up to $5/MWh of wind
  - CEC (2007) and CAISO (2007) have both estimated need for more ancillary services and real-time redispatch to integrate wind into California's power system

Introducing Demand Response

- Real-time pricing (RTP) can help alleviate these costs of wind by using price signals to get demand to follow the supply of wind:
    - If wind forecasts turn out to be too high, the high real-time price of energy and ancillary service deployments will reduce real-time demand for energy
    - This demand reduction can also prevent the need for load curtailments if forecast errors are very high
- RTP can also increase the social value of wind
    - Sioshansi and Short (2009) have shown RTP can reduce the need to curtail wind due to conventional generator or power system constraints
    - RTP has been shown to increase social welfare compared to fixed retail rates
    - These two effects can work in concert with one another, giving superadditive surplus gains
- We show that RTP can noticeably reduce these costs and increase the value of wind

- We use a unit commitment model to represent day-ahead (DA) operations and a dispatch model for real-time (RT) dispatch
    - DA model uses forecasts of wind availability
    - RT model uses actual wind availability and fixed commitments from DA model (except quick-start units, which are allowed to be started) to serve load
- We simulate operations in ERCOT for an entire year
    - To model a high wind scenario, we use system data (loads, conventional generator set, generation costs) from 2005, but include all wind plants slated to be installed by 2011
        - Amounts to over 18 GW of wind, or 18% of total capacity
    - Each day is modeled in sequence, with starting state of generators taken from previous day and ending state determined by next day's expected operations
- Cost of system operations is compared to a scenario with perfect foresight of wind resource availability

- Actual hourly wind availability is taken from mesoscale-model data compiled by 3TIER, based on geographic location of wind plants being modeled
- DA forecast of wind availability is simulated as being the actual wind availability plus a forecast error
- Empirical analysis of actual and forecasted wind data done by AWS Truewind and CAISO (2007) shows forecast error fits an unbiased second-order autocorrelated truncated normal distribution (TND)
- We simulate forecast errors from a TND, assuming an autocorrelation coefficient of 0.60 and a range of variances between 0.0049 and 0.0121 (which is consistent with CAISO's estimates)

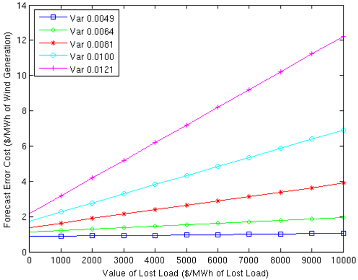
- Generation costs (consisting of startup, spinning no-load, and stepped marginal generation) computed based upon heat rate and fuel cost, VO&M, and emission price data from Platts Energy and Global Energy Decisions (GED)
- Generator constraint data also from GED
- Hourly load data from ERCOT
    - Models without RTP formulated to serve fixed load at minimum cost
    - Models with RTP formulated to maximize social welfare
        - Demand functions approximated as non-increasing step function with 100 steps
        - Assume demand exhibits own-price elasticity only, use a range of elasticities between -0.10 and -0.30
        - Functions calibrated to go through point defined by actual historical load and retail electricity rate

Wind Forecast Error Cost
With Fixed Loads

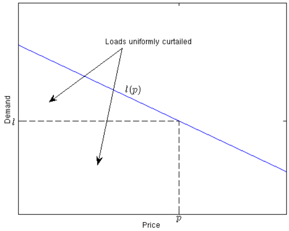
- Table summarizes annual increase in system operation costs with DA wind availability forecast errors and fixed loads, showing costs increase with higher forecast error variance (*i.e.* less accurate DA forecasts)

Forecast Error Variance	Forecast Error Cost ($/MWh Wind Generation)
0.0049	0.868
0.0064	1.109
0.0081	1.385
0.0100	1.744
0.0121	2.172

- One cost not included in previous table is value of lost load
- With fixed loads high wind forecast errors can cause loss of load if there's insufficient capacity available in real-time
- Figure shows forecast error cost with lost load included, as a function of VOLL
  - These costs can be substantial with high forecast error variance



- When comparing cost of wind forecast errors with RTP, it is more appropriate to measure social welfare losses
  - Comparing cost alone does not capture consumer surplus losses from curtailing load in response to reduced wind availability
  - When computing surplus losses without RTP, we assume there is a demand function $l(p)$, which is not expressed due to fixed retail rate. Lost load is valued using willingness to pay assuming random curtailment



Wind Forecast Error Cost

With RTP: Elasticity -0.1

- Table summarizes social welfare losses ($/MWh of wind generation) with DA wind availability forecast errors if actual demand elasticity is -0.1, showing RTP can reduce losses by up to 80%

Forecast Error Variance	Without RTP	With RTP
0.0049	0.889	0.310
0.0064	1.209	0.380
0.0081	1.682	0.477
0.0100	2.355	0.539
0.0121	3.361	0.661

- Table summarizes social welfare losses ($/MWh of wind generation) with DA wind availability forecast errors if actual demand elasticity is -0.2, showing RTP can reduce losses by up to 89%

Forecast Error Variance	Without RTP	With RTP
0.0049	0.879	0.133
0.0064	1.162	0.166
0.0081	1.543	0.212
0.0100	2.068	0.252
0.0121	2.804	0.302

Wind Forecast Error Cost

With RTP: Elasticity -0.3

- Table summarizes social welfare losses ($/MWh of wind generation) with DA wind availability forecast errors if actual demand elasticity is -0.3, showing RTP can reduce losses by up to 93%

Forecast Error Variance	Without RTP	With RTP
0.0049	0.875	0.081
0.0064	1.146	0.116
0.0081	1.497	0.134
0.0100	1.973	0.152
0.0121	2.618	0.171

Wind Forecast Error Cost

With RTP—Lost Load

- Another benefit of RTP is that there is no lost load
  - When wind forecasts are too high, the high cost of replacement energy reduces demand
- A secondary benefit of RTP is that the “least valuable” load is shed when wind availability is less than forecast
  - Without RTP, load curtailment may rely on inefficient means of rationing supply
  - We compare consumer surplus losses (per MWh of curtailed load) from “random” load curtailment as opposed to curtailing consumers with the lowest willingness to pay

	Demand Elasticity		
Forecast Error Variance	-0.1	-0.2	-0.3
0.0049	995.59	497.80	331.86
0.0064	1038.13	519.07	346.04
0.0081	979.91	489.95	326.64
0.0100	1006.80	503.40	335.60
0.0121	976.31	488.15	325.44

Value of Wind with RTP

- RTP has been shown to have multiple welfare benefits
  - Borenstein (2002) and Borenstein and Holland (2005) are two papers showing RTP increases short-run social welfare from electricity use
  - We've shown RTP increases use of wind and decreases social surplus losses from wind forecast errors
- Wind provides a costless source of energy in the short-run, which will increase social welfare
- We use our model to see if these two effects together result in superadditive surplus gains
  - We examine four different scenarios:
    1. no RTP, no wind generators;
    2. no RTP, wind generators;
    3. RTP, no wind generators; and
    4. RTP, wind generators.
  - If we let σ_i denote social welfare under scenario i, then if $\sigma_4 - \sigma_1 > \sigma_3 + \sigma_2 - 2\sigma_1$, there are superadditive welfare gains from introducing both wind and RTP

Value of Wind with RTP
Example

- Table below demonstrates these welfare gains with a forecast error variance of 0.0049.
- Values are annual social surplus gains ($ million)

	Demand Elasticity		
	-0.1	-0.2	-0.3
Adding wind generation	2,658	2,658	2,658
Adding RTP	190	355	489
Sum of surplus gains	2,848	3,013	3,147
Adding wind and RTP	2,924	3,131	3,298

- Comparing last two rows shows surplus gains from introducing wind and RTP together

- Table summarizes social welfare gains from adding wind and RTP, as a percentage of sum of welfare gains from introducing each independently (*i.e.* $\frac{\sigma_4-\sigma_1}{\sigma_3+\sigma_2-2\sigma_1}$)

Forecast Error Variance	Demand Elasticity -0.1	-0.2	-0.3
0.0049	2.7	3.9	4.8
0.0064	2.9	4.3	5.1
0.0081	3.2	4.6	5.5
0.0100	3.7	5.1	6.0
0.0121	4.2	5.7	6.6

Conclusions

- Day-ahead uncertainty in and forecast errors of wind resource availability can lead to suboptimal unit commitments, costly real-time system dispatch, and even lost load
  - As expected, these costs rise as forecasts become more inaccurate (variance rises)
- Introducing demand response/RTP allows the load to more closely follow supply of wind generation, and reduces wind integration costs
  - The cost reduction becomes more pronounced with more elastic demand
- RTP also eliminates lost load events, which would otherwise occur with fixed loads
- The combination of RTP and wind result in superadditive surplus gains compared to introducing these individually