Uncertainty analysis of methane emissions from natural gas production

Stefan Schwietzke* [1], W. Michael Griffin[1,2], H. Scott Matthews[1,3]
*sschwiet@andrew.cmu.edu
[1]Department of Engineering and Public Policy, [2]Tepper School of Business, and [3]Department of Civil and Environmental Engineering at Carnegie Mellon University, Pittsburgh, PA

Introduction

Natural gas (NG) use is expected to increase significantly over the next decades in the U.S. and worldwide due to an unprecedented expansion of unconventional NG production: shale gas, coal-bed methane, and tight sands gas. For example, EIA expects global NG consumption to increase from currently 110 Tcf to about 170 Tcf in 2035. With this increase in NG production and the fact that many coal-fired power plants in the U.S. will need to be overhauled, replaced, or substituted with other sources within the next 10-20 years, EIA projects that over the next 30 years an additional 100 GW NG-fired net electricity capacity will be installed compared to only 5 GW for coal.

The U.S. electricity sector is responsible for about 40% of energy related CO_2 emissions. Transitioning from coal fired electricity generation towards a greater share of NG is perceived as a low cost alternative to decarbonizing the energy system. While many studies indicate associated reductions in GHG emissions, there are **significant uncertainties regarding the CH_4 emissions from NG leakage and venting**. Furthermore, some climate modeling studies suggest the distinct possibility that replacing coal with NG could lead to temporarily (decadal time scales) higher global warming due to increased emissions of 25 times more potent CH_4 in addition to greenhouse effects from CO_2 *(1)*. However, the uncertainty in the transient climate response – particularly in comparison to CH_4 uncertainty – remains to be quantified.

Research questions:

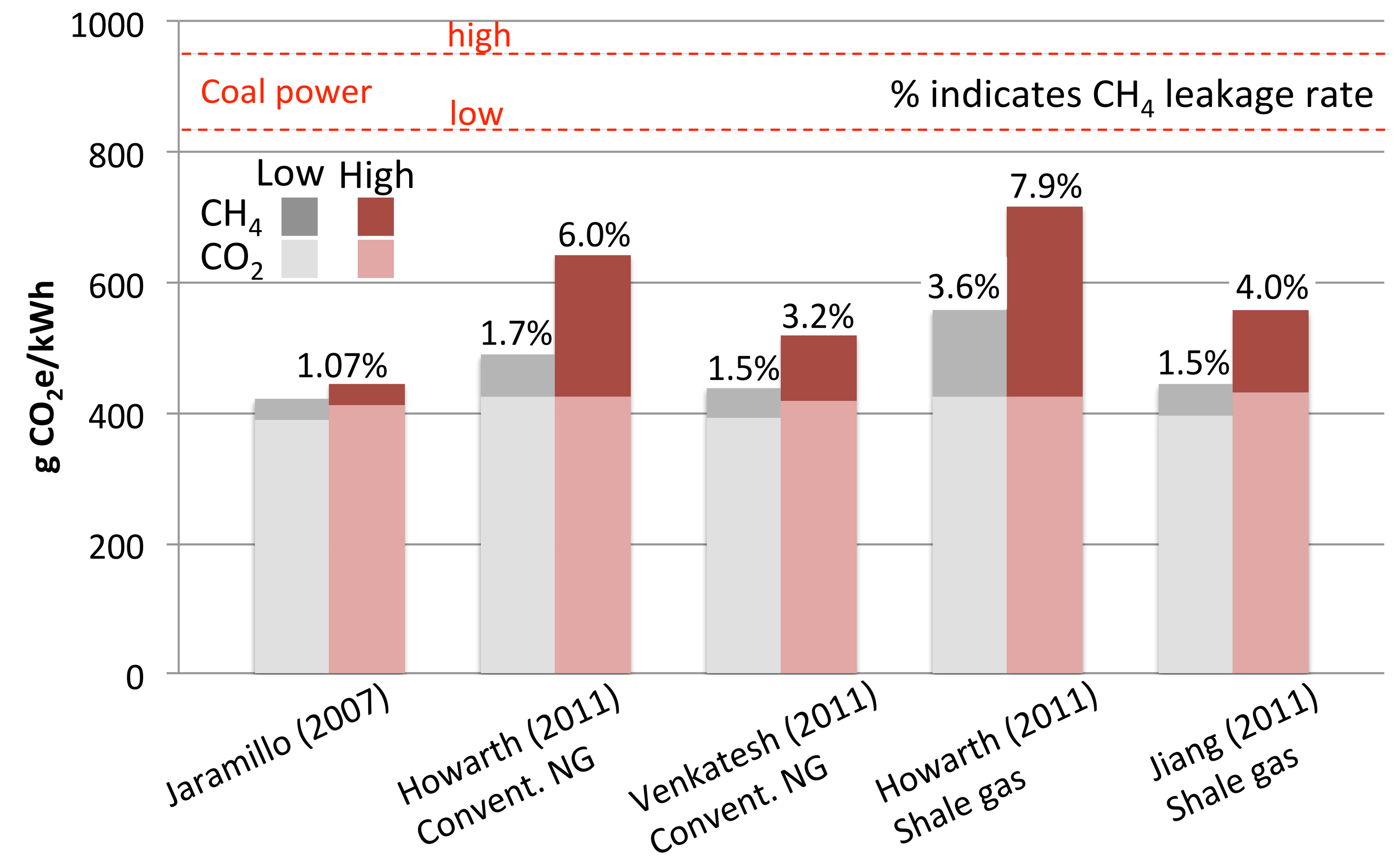
- After considering differences in GHG accounting among studies, what is the overall range of reported CH_4 emissions (g CH_4/kWh) from NG power?
- What is a reasonable range of CH_4 leakage from the NG power life cycle when taking into account analyses of atmospheric CH_4 measurements?

Life cycle CH_4 estimates (bottom-up approach)

The GHG emissions reductions from the coal-to-gas transition have been estimated using life cycle assessment (LCA), a widely used accounting tool, which compares technologies based on the GHG emissions over their life cycle. Results indicate that CH_4 leakage appears to be a major contributor to life cycle GHGs from NG power generation *(2-4)*. Methane leakage is defined as fugitive CH_4 emissions from sources such as equipment leaks, venting, and accidental leaks. Given its potency, it is also one of the most influential parameters in the GHG difference between power generation from NG and coal.

Overall GHG emissions from NG are highly uncertain, both on an absolute scale and compared to coal emissions uncertainty. Most fossil fuel technologies emit mainly CO_2, which are relatively easy to estimate from combustion and other processes. In contrast, **the fugitive CH_4 emissions from NG are difficult to quantify as monitoring and measuring data is often not available**. Values from the life cycle literature for NG lost during production, processing, transmission, and storage range from 1.1-6.0% and 1.5-7.9% of total NG produced for conventional and shale gas, respectively. Figure 1 summarizes the results of a literature review with values adjusted for the same functional unit, global warming potential, and power plant efficiencies. **Given the low and high leakage rate estimates, overall GHG reductions range from about 27-50% relative to coal (18-50% for shale gas).**

Figure 1: Literature review of life cycle GHG estimates from NG power generation. All data is adjusted to the same functional unit (kWh of generated power) and to include the same 100-yr global warming potentials (GWP) and power plant efficiencies. More sources to be added.



Atmospheric CH_4 inversions (top-down)

Methane emissions can also be estimated using atmospheric inversions, which is useful for validating life cycle estimates. **Inversion techniques are based on a combination of (i) measuring CH_4 concentrations from a global observation network, (ii) measuring CH_4 isotope ratios to distinguish emissions sources, (iii) prior bottom-up emissions inventories, and (iv) employing atmospheric emissions transport models *(5)*.** In this process, air flask samples are collected at least weekly from a global network of up to 68 observation towers at 15-500 m height, the $^{13}C/^{12}C$ isotope ratio of the sampled CH_4 is measured to distinguish emissions sources, such as NG production and wetlands, and inverse modeling is used to solve for spatial and temporal CH_4 distributions that give optimal agreement between observations and simulations. Analyzing top-down and bottom-up estimates, I will bound the uncertainty range of CH_4 leakage estimates by eliminating bottom-up leakage rates that appear incompatible with top-down inversions.

Preliminary results

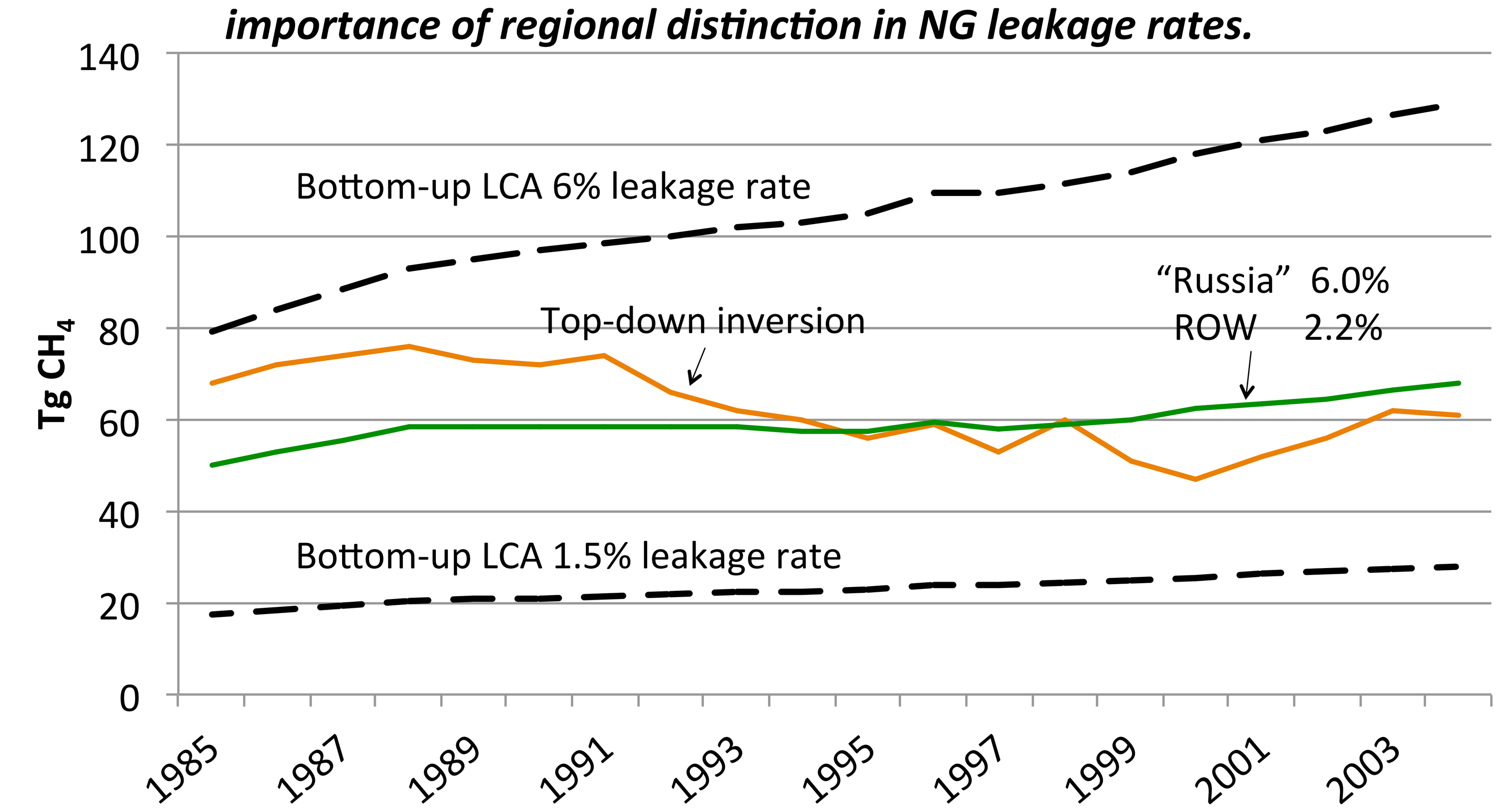
Figure 2 shows NG related CH_4 emissions trajectories using both bottom-up and top-down approaches. The orange line shows best estimate global mean top-down CH_4 emissions from NG leakage. Bottom-up estimates are shown in black, which are estimated from global NG production data and low and high leakage rate values from the literature. While my objective is to constrain the very large bottom-up uncertainty (factor of 4), top-down emissions are within this range, i.e., not contradicting the bottom-up range. During the late 1980s, observation supports high leakage rates. However, global CH_4 emissions decreased significantly after 1989, presumably due to collapsing production of high leakage NG in the former Soviet Union *(5)*. In contrast, observations during the early 2000s coincide better with the low end of the leakage rate spectrum. In fact, the higher bound leakage rate overestimates observations by 75-100%. Reduced CH_4 emissions may be the result of improved industry practices.

Further analysis will focus on reviewing the uncertainty in the top-down emissions estimates in order to evaluate whether or not top-down and bottom-up flux estimates truly do not overlap. Since the gap between low and high bottom-up estimates is wide (about 300% difference between low and high), it is likely that top-down estimates will be inconsistent with some of the bottom-up estimates.

I will gather two available global CH_4 inversions and evaluate the posterior uncertainties as provided from each inversion, and the prior flux estimates and atmospheric chemistry and transport characteristics for each inversion to evaluate whether there could be biases among the inversions due to these inputs to the inversions.

Finally, I will discriminate global average leakage rates among world regions, over time, and among NG sources (conventionally and unconventionally produced NG). These distinctions in bottom-up data will help better explain CH_4 observations, thereby leading to more certainty in leakage rates.

Figure 2: Preliminary bottom-up and top-down CH_4 emissions estimates from NG production. The green line illustrates the importance of regional distinction in NG leakage rates.



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Acknowledgements

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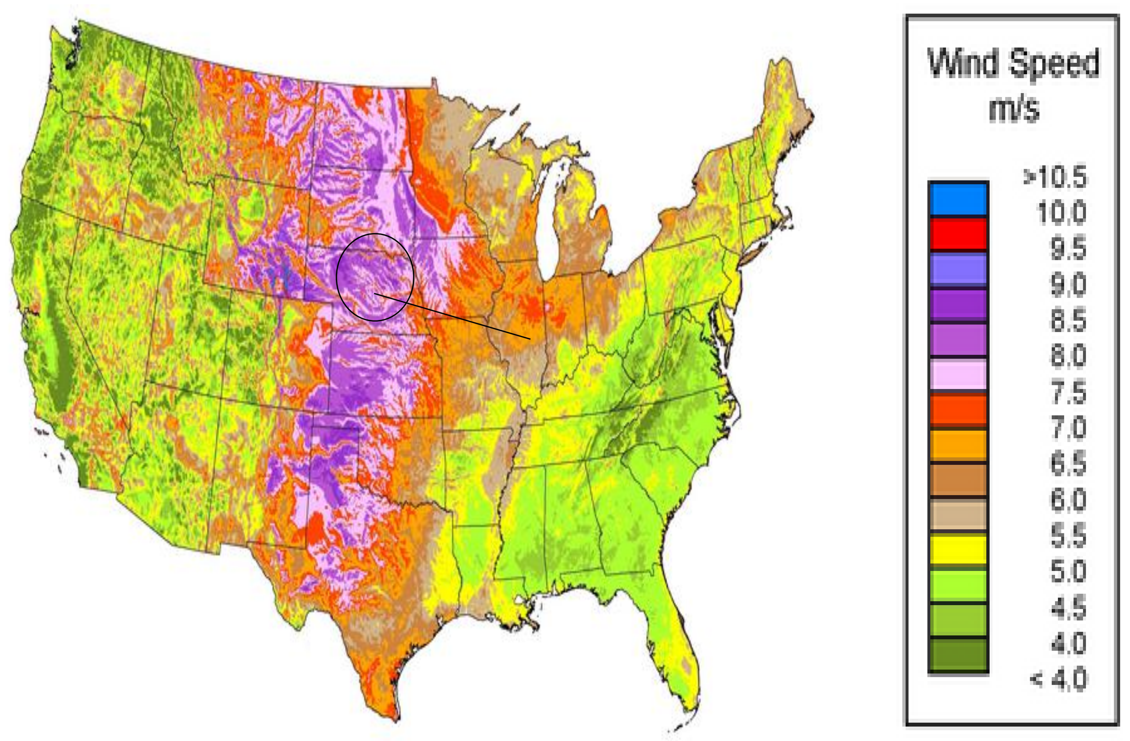
Integrating Remote Wind Resources: The Role of Energy Storage

Julian Lamy

Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, PA 15213

Main Issues Integrating Remote Wind

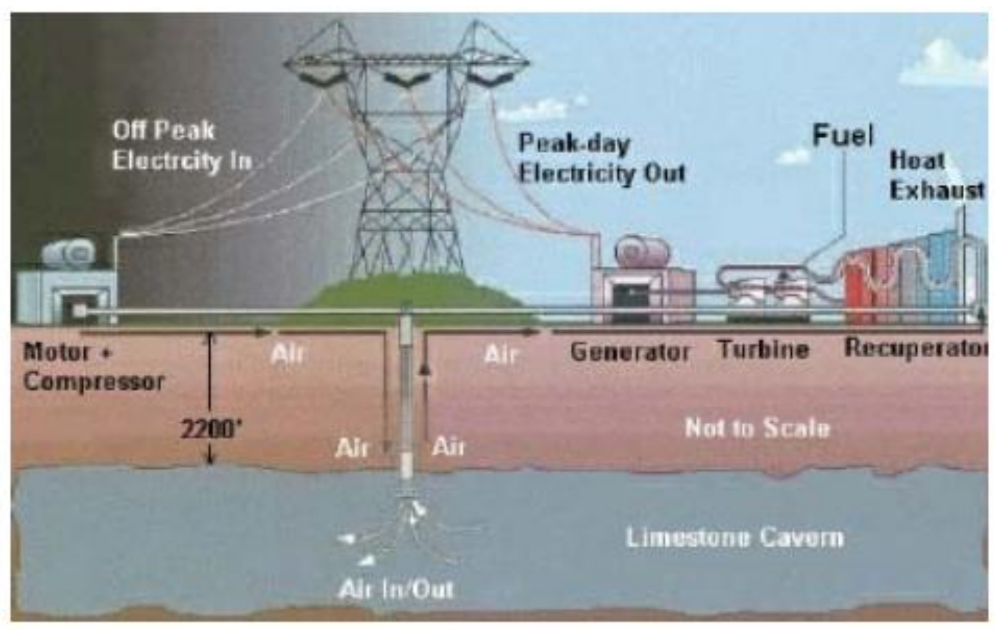
1. Wind suffers from intermittency and variability in generation output
2. variability of power varies greatly by location
3. Best wind resources are far from load centers where its needed
4. Transm. expansion is expensive and uncertain ($200-1000/MW-km)



Energy Storage Technologies

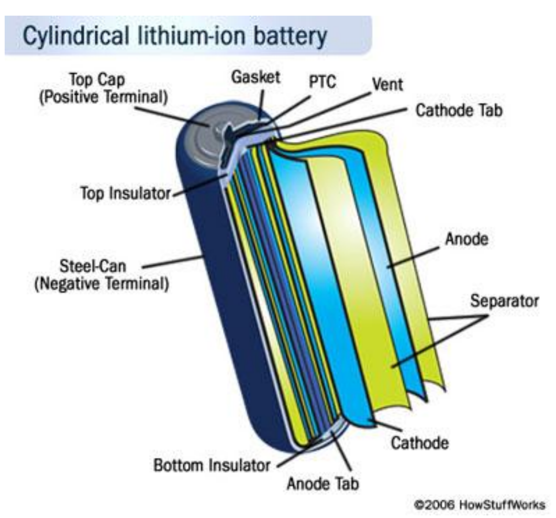
Compressed Air Energy Storage Technology

- 2 systems in operation: Germany, Alabama
- Most cost effective >400 MW, Big systems. $100-200/kwh
- Siting can be an issue, need appropriate geological structure



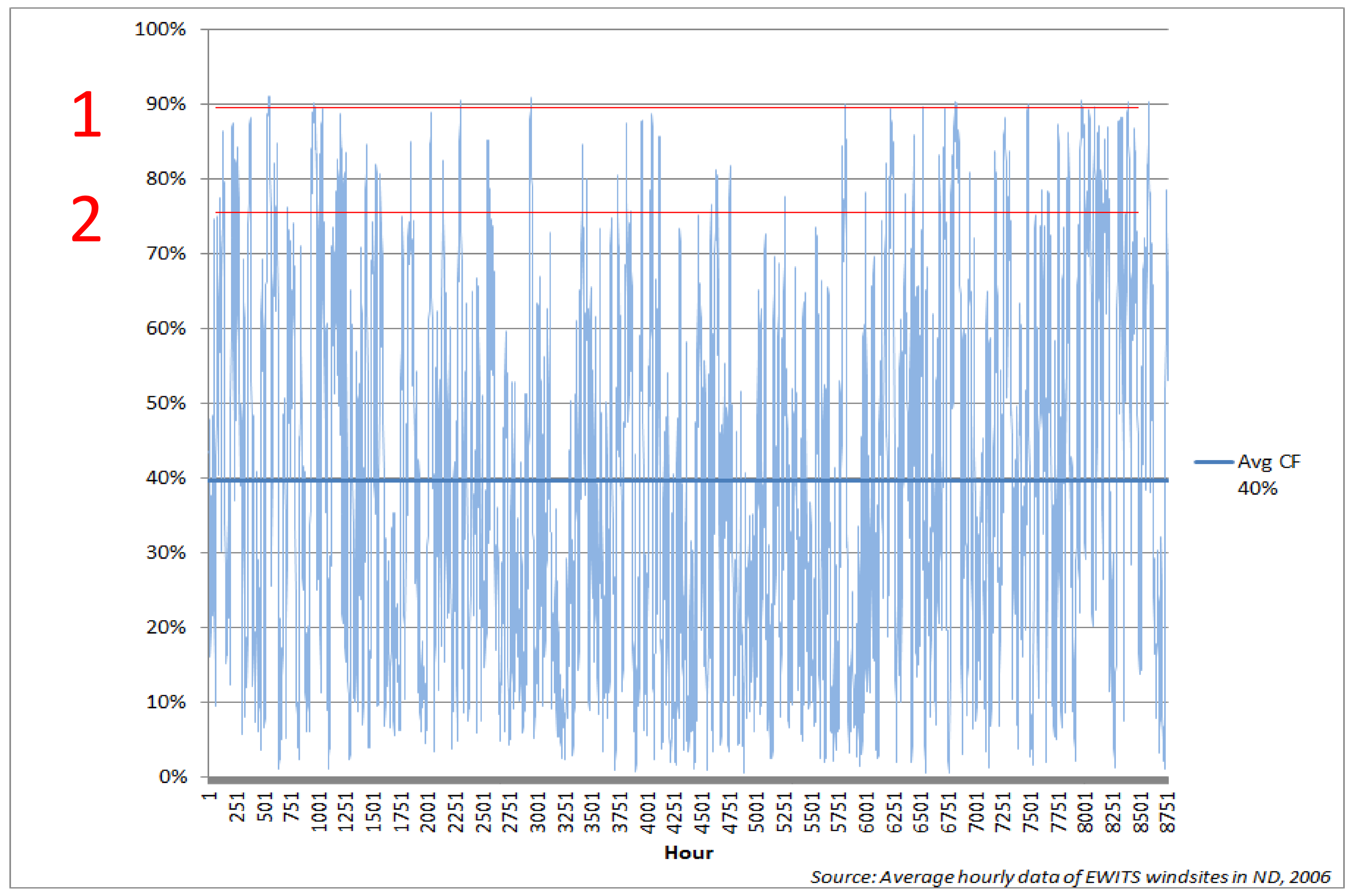
Li-Ion Batteries

- Small capacity. biggest grid-level is 12MW in Chile
- 300-$2000/kwh, $500/kwh is a standard benchmark
- Reused Li-ion batteries are also being considered for grid applications after use in PHEV. Preliminary costs for such batteries are $50-150/kWh



The Wind Investor's Decision

Suppose an investor is to build a large wind farm (1 GW) in a "good" wind location but also needs to build transmission to get it to load centers. How does the investor size the transmission line?



1 The investor could build transmission at 100% of the nameplate capacity of the wind farm to deliver all potential wind generation

2 Alternatively, he/she could decrease the transmission capacity to save in capital investment, but forgo revenues when wind generation is higher than the transmission capacity limit. Past research suggests that the optimal transmission capacity is 75% of the nameplate wind capacity (Pattanariyankool and Lave, 2010 ---P&L, 2010)

- 1600 km line, price $160/MWh, 40 yrs, 10.4% DR, 1GW wind

Potential For Energy Storage

What if one could store the power lost from 1 to 2? Does this change the optimal transmission capacity? How much storage capacity to build?

Break Even Cost For Added Capacity

Lifetime of added MW	$ MM	$/KWh
10 yr	$86	$440
15 yr	$70	$540
40 yr	$110	$700

**Using same cost assumptions as P&L, 2010*

Transmission costs (P&L) would total about <u>$750 MM</u>, far out of the range of break even costs displayed above. This suggests that adding cheaper capacity may be economical and even change the optimal transmission investment.

Research Objective

Estimate the optimal transmission and storage investment for a remote wind farm 500km + from a desired load center. Compare the optimal decisions for different storage technologies.

<u>Steps in this Optimization</u>

1) Fix transmission and storage capacity
2) Optimize the wind farm's operation to maximize profits
   - Phase 1: Use deterministic ELE prices and wind output
   - Phase 2: Use stochastic ELE prices and wind output
3) Repeat starting at 1) by changing the storage/trans capacity

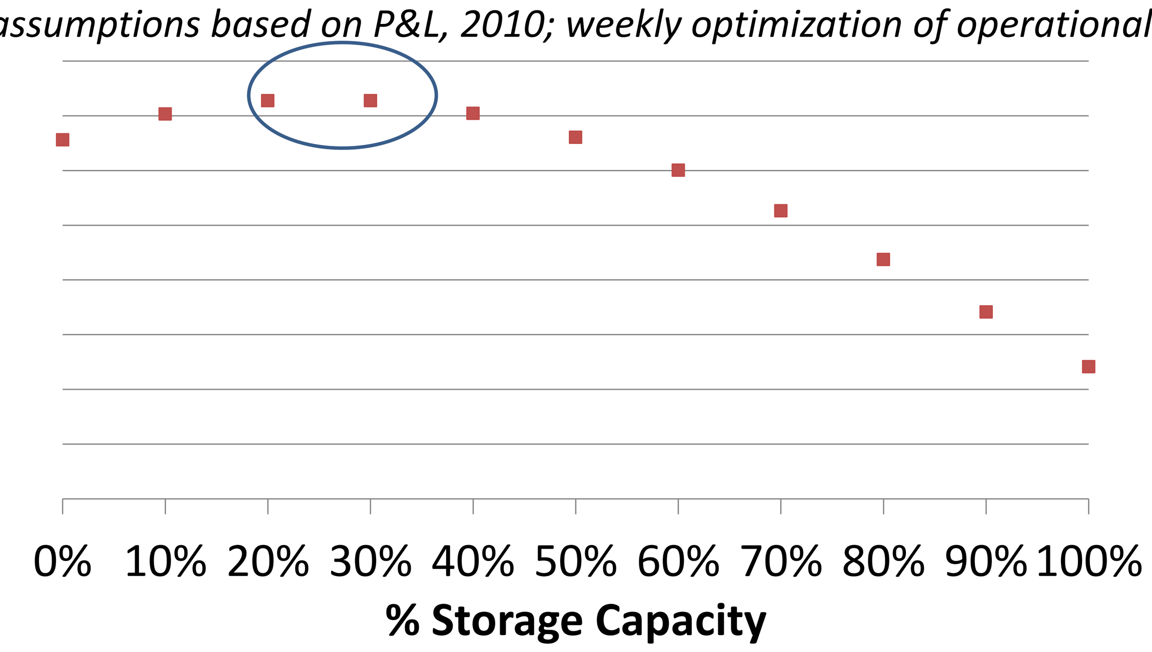
<u>Dynamic Programming Formulation</u>

For each hour t:

$$V_{t(a_t)} = pt * ct + Vt_{+1}(at_{+1})$$
$$st.\ \ at_{+1} = at + wt - ct - zt$$

.at	energy stored	<=Storage cap
.wt	wind output	Det/stoch.
.ct	energy transmitted	<=TRNS cap
.zt	wind curtailed	Det/stoch.

Results



Preliminary Findings

- Optimal storage capacity is 20-30% of nameplate wind capacity w/ 80% transm. capacity
- Even low % of storage can increase wind farm profits (>2%)

Next Steps

- Analysis is sensitive to input assumptions; more testing is needed
- Add stochasticity to state variables (price and wind output)
- Add storage technology specs and compare results across techs
- Consider existing transm. and integration with grid (MISO)

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The effect of long-distance interconnection on wind power variability

Emily Fertig, Jay Apt, Paulina Jaramillo, and Warren Katzenstein

Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, PA 15213

Motivation

- Most states now have Renewables Portfolio Standards, many of which are largely fulfilled by wind power
- Wind is variable and intermittent: high-frequency fluctuations increase the need for frequency regulation, and low-frequency (hourly to seasonal) fluctuations can change the capacity factors of baseload generators and in severe cases affect reliability
- Time scale is crucial to characterizing wind power variability: frequency domain analysis quantifies the variability at different time scales, but is seldom used in wind power integration studies

Previous work

- Sorensen et al. (2008) find that the smoothing effect of aggregating turbines within offshore wind plants is strongest at high frequencies
- Kempton et al. (2010) use offshore anemometer data (59% of which meets quality standards for inclusion in the study) and find that interconnection of wind sites would reduce variance, slow the rate of change, and eliminate hours of zero production in the study period
- Katzenstein et al. (2010) find that connecting just four wind plants in ERCOT reduces variability at an hourly frequency by 87 %, but that connecting more yields diminishing returns. At (12 h)$^{-1}$, connecting four wind plants reduces variability by only 30 %.

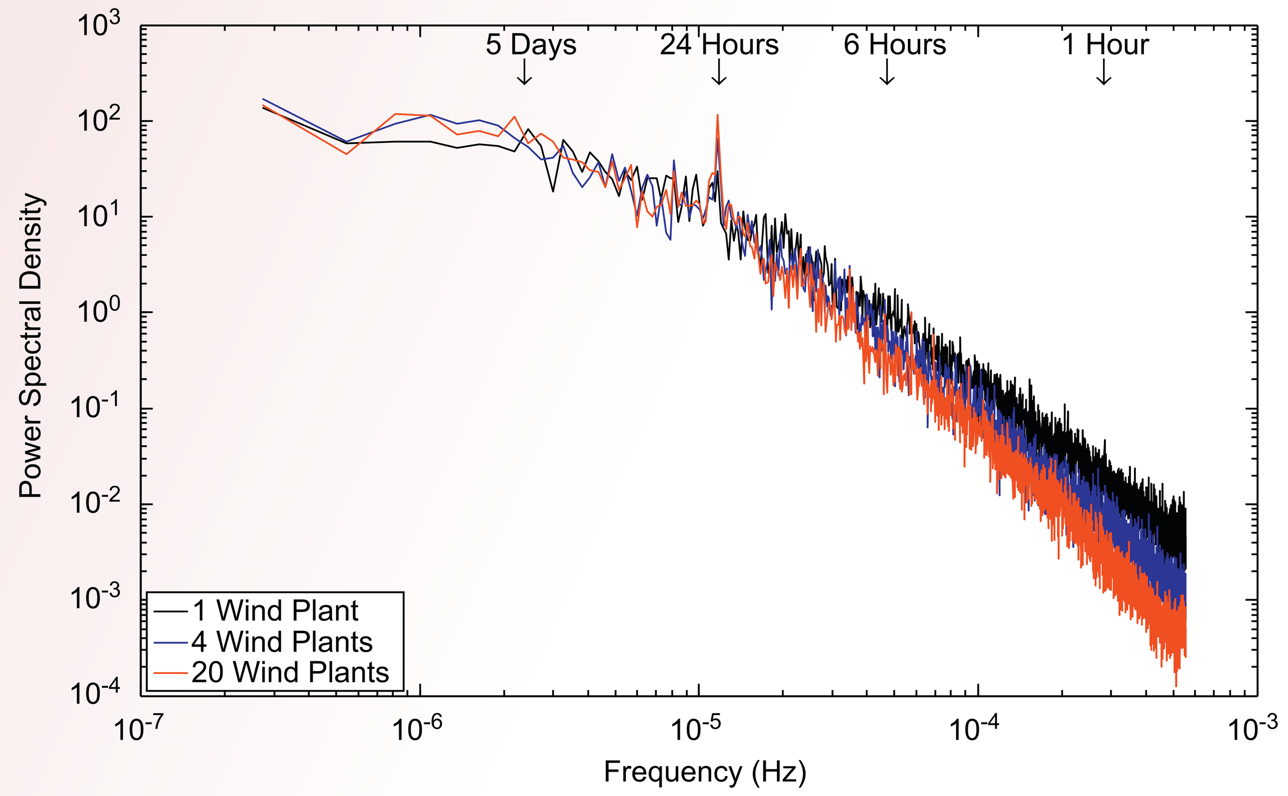

Figure 1. Power spectral density (8-segment averaging) for ERCOT wind (Katzenstein et al., 2010).

Geographic extent of wind data

We use hourly wind power data from Bonneville Power Authority (BPA), California ISO (CAISO), Electric Reliability Council of Texas (ERCOT), and Midwest ISO (MISO).

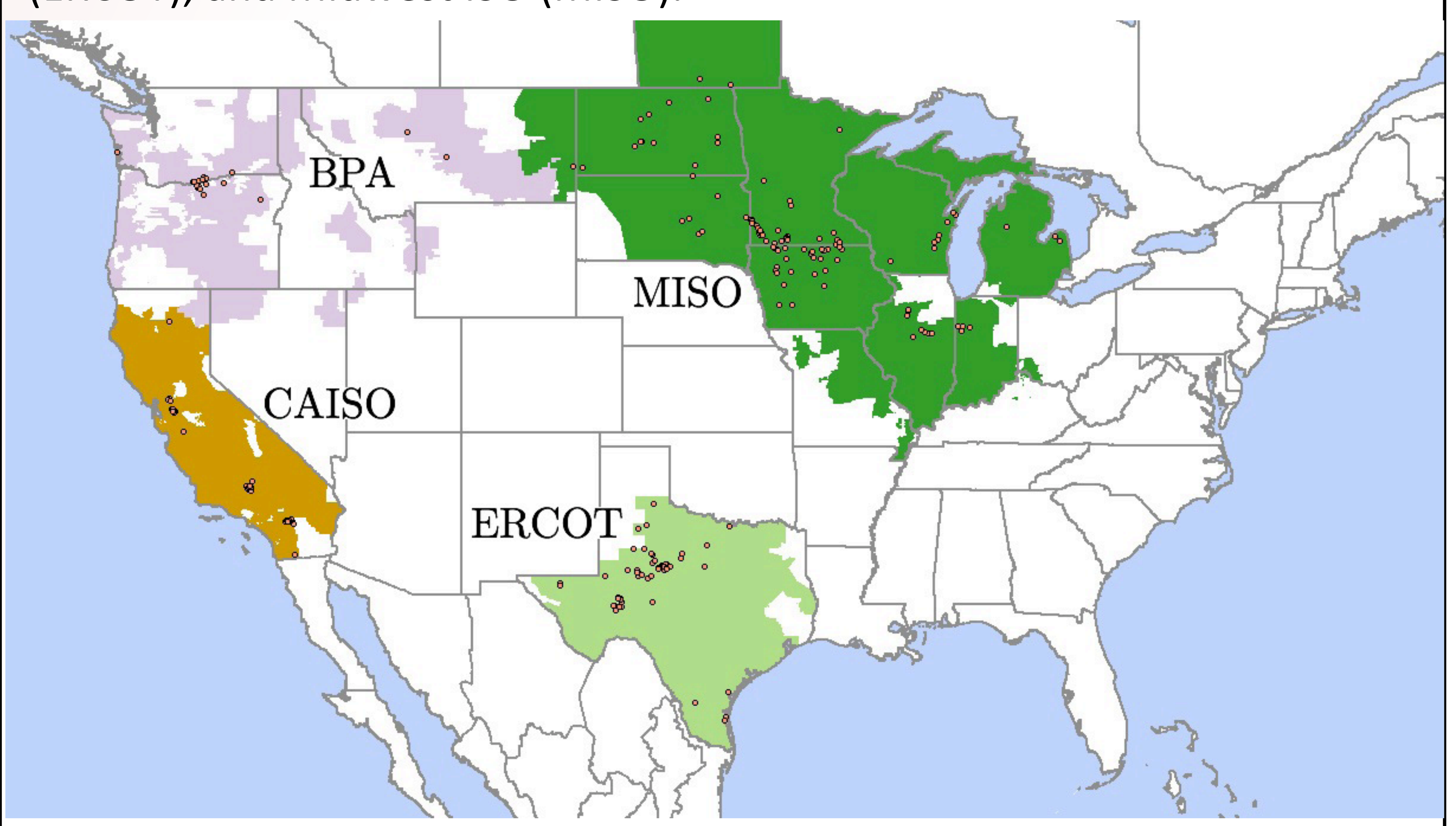

Figure 2. The area of each region and the wind plants it contains (pink dots).

Frequency domain analysis

The power spectral density (Figure 3a) gives the square amplitude of wind power fluctuations that occur at each frequency. Figure 3 shows that:

- Wind fluctuations are not white noise: low-frequency fluctuations have orders of magnitude higher amplitudes than high-frequency fluctuations. Therefore slow-ramping resources, such as coal plants, can compensate for most of the variability of wind power (Apt 2007).
- Although interconnecting wind plants within a single region reduces the ratio of high- to low-frequency variability (and thus the proportion of fast-ramping generators in the balancing portfolio), interconnection of aggregate regional wind power output provides no further reduction.
- Since the shapes of the PSD curves are similar, the log-linear distance between two curves approximates the ratio of the variances of the wind power time series. Although BPA and CAISO, for example, have similar mean wind power output, the PSD of CAISO lies substantially below that of BPA, implying greater wind power variability in BPA than in CAISO.

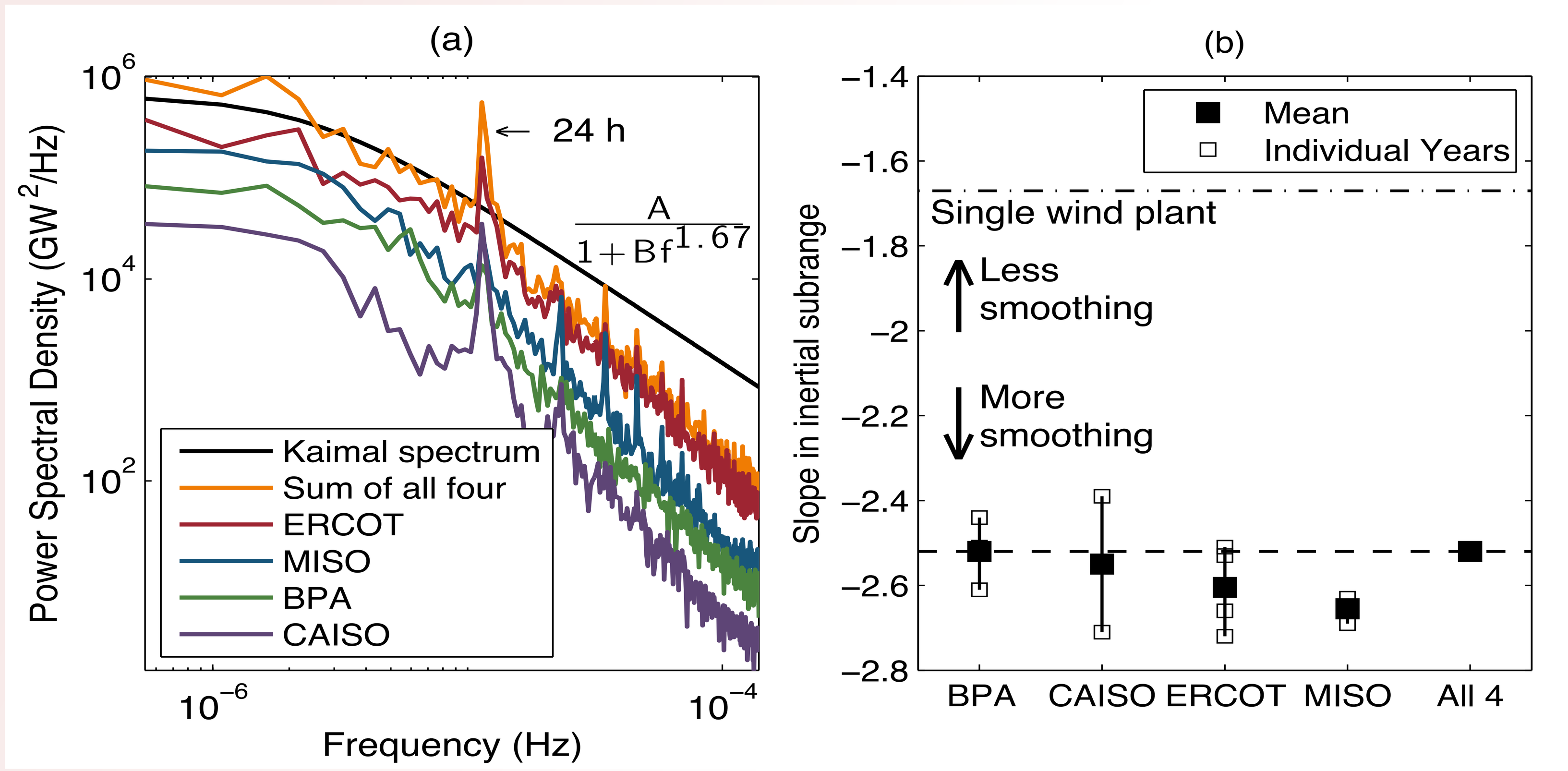

Figure 3: (a) PSDs for 2009 wind power output of each region and their sum. The displayed Kaimal spectrum equation approximates the PSD for a single wind plant fitted to the summed data (fitted parameters are A = 5.84 × 105 and B = 2.06 × 109). In the inertial subrange (frequencies higher than (24 h)$^{-1}$), the summed power output shows less variability than that of a single wind plant. (b) Slopes in the inertial subrange for each region and the interconnected regions for all years of available data and the means over time, which reflect the relative strength of high- and low-frequency variability in wind power output. The slope for the interconnected regions in 2009 is within the range of slopes for individual regions in other years for which data were available.

Step change analysis

Step changes are the fractional changes in power output over a time interval centered at t with length Δt, and can be expressed as:

$$\Delta P = \frac{P(t+\Delta t)-P(t)}{P_c}$$

P_c is the mean power output over the year.

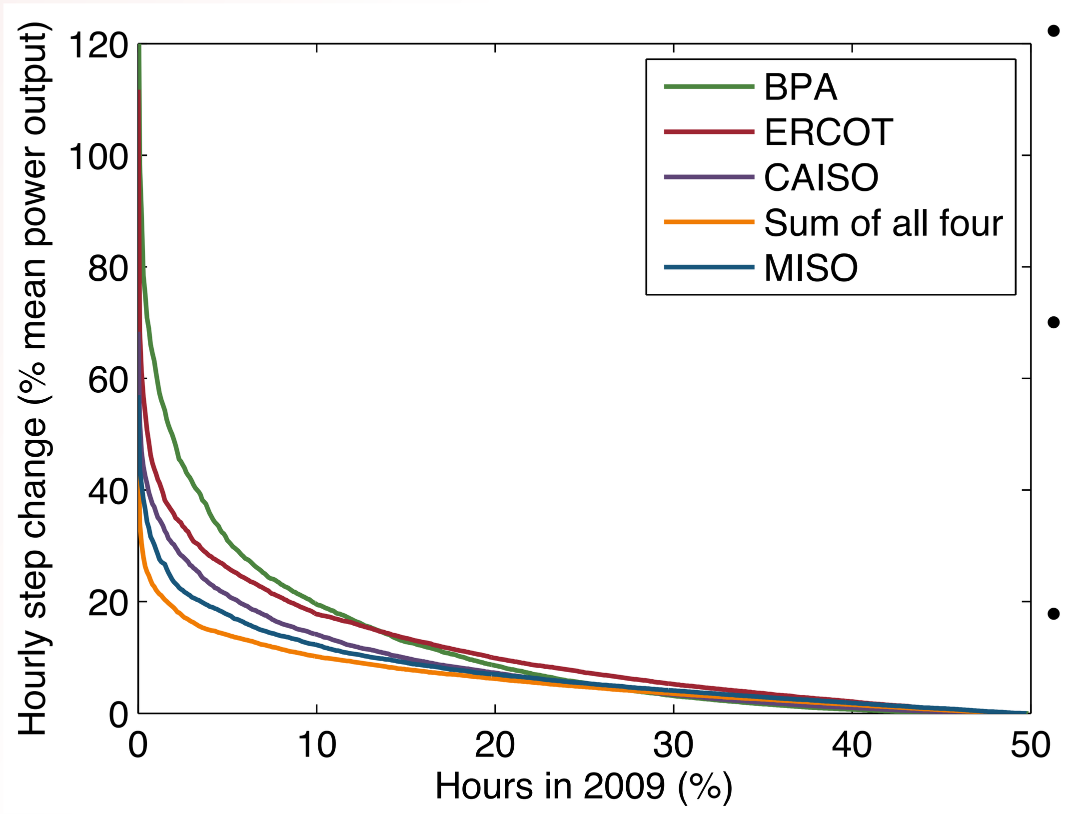

Figure 4: Duration curve for hourly step changes. For clarity, the curve shows only positive step changes; the negative portion of the curve is roughly symmetrical.

- Figure 4 shows a duration curve for hourly step changes, indicating the lower bound on step changes that occur with a given likelihood
- BPA and ERCOT are the most likely to have large hourly step changes, and MISO and the interconnected regions are the least likely.
- Interconnection of all four regions would reduce the magnitude of 99th percentile positive step changes by 8 to 40 percentage points compared with the individual regions

Wind power output duration curve

Figure 5 shows a duration curve for wind power output, indicating the minimum amount of capacity available a given percentage of the time

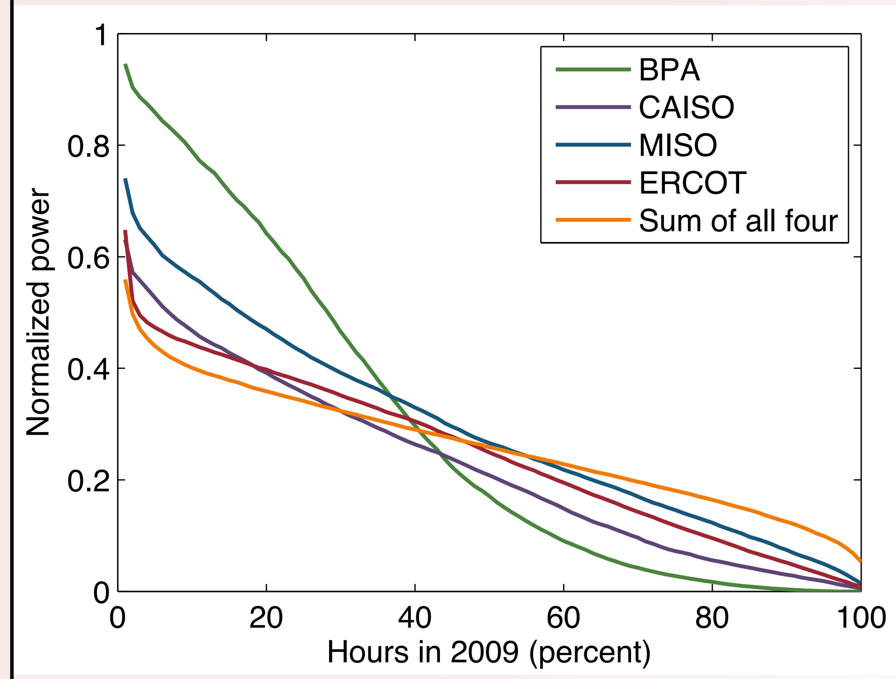

Figure 5: Duration curve for 2009 wind power output.

- The interconnected regions have the greatest amount of firm power (available 79 to 92% of the time).
- Interconnection would double the amount of firm power (available 92% of the time) compared with the maximum for the single regions

First-order cost analysis

We evaluate the cost-effectiveness of interconnecting wind plants to mitigate 99th percentile step changes in BPA and ERCOT (300 MW and 1.2 GW respectively). Using high cost assumptions and including emissions externalities, a natural gas plant this size would cost $380M (BPA) or $1.5B (ERCOT).

To connect each region with its nearest neighbor at equivalent cost, transmission would have to cost $500,000/mi (BPA) or $1.5M/mi (ERCOT), which are unrealistically low. First-order analysis indicates that a local gas turbine would be more cost-effective than interconnection for mitigating low-probability step changes.

Conclusions

- Low-frequency fluctuations of wind are strongest, so wind can largely be balanced by slow-ramping generators
- Interconnection of wind plants within a region reduces the ratio of high- to low-frequency variability, but interconnection across longer distances provides no further reduction
- Interconnecting regional wind power output nevertheless reduces variability uniformly across all frequencies examined, reduces the magnitude of low-probability step changes, and doubles firm wind capacity (the fraction available 92% of the time)
- Benefits of interconnection are unlikely to cover transmission cable costs; mitigating wind's step changes is cheaper with a gas turbine

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Wind Power Forecasts for Operating Reserves Procurement

Brandon Mauch, Jay Apt, Paulina Jaramillo

Department of Engineering and Public Policy, Carnegie Mellon University

Motivation

Wind power experienced substantial growth over the past decade in the U.S. and Europe. Installed capacity in the U.S. increased tenfold from 4,200 MW in 2001 to 47,000 MW in 2011. The growth of wind power has created reliability challenges for grid operators. In order to cope with the uncertainty and variability of wind power, operating reserves must increase. The Electric Reliability Council of Texas (ERCOT) recently increased its requirements for operational reserves due to wind. Texas currently has more wind than any state in the U.S. Operational reserves ensure grid reliability by providing needed generation during unforeseen events. This includes unexpected load increases, unexpected wind power drops and generator outages

Load and wind power are forecasted each day in the development of generator schedules. Uncertainty of these forecasts determine the amount of operational reserves required for a reliable grid.

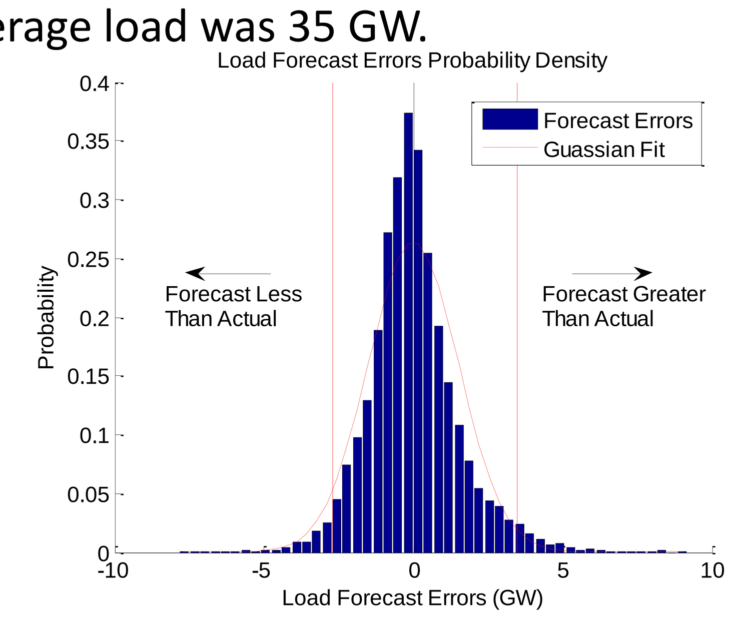
Data

Our analysis is based on forecasted hourly values of wind power and load as well as actual values from the Electric Reliability Council of Texas (ERCOT). Due to wind curtailments in ERCOT, we used estimated values of uncurtailed wind power as the actual values. Uncurtailed wind power estimates were determined by a wind forecast provider from meteorological measurements and curtailment instructions issued by ERCOT.

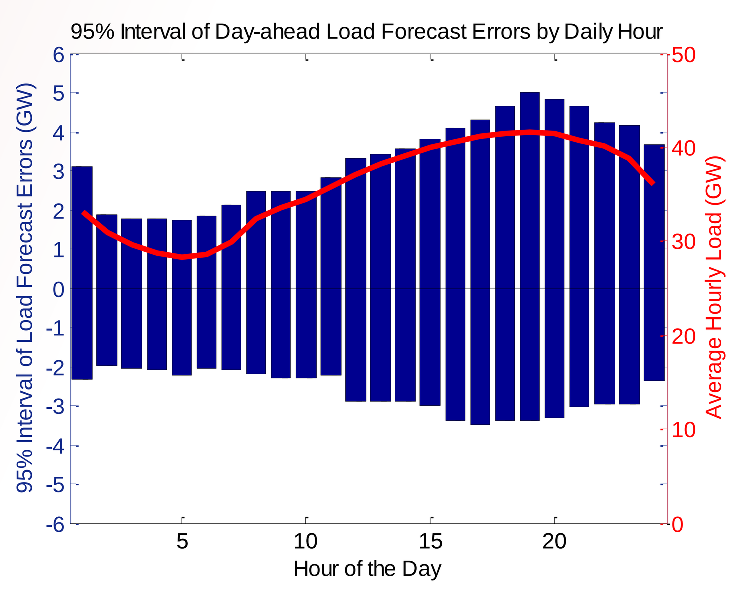
Load Uncertainty

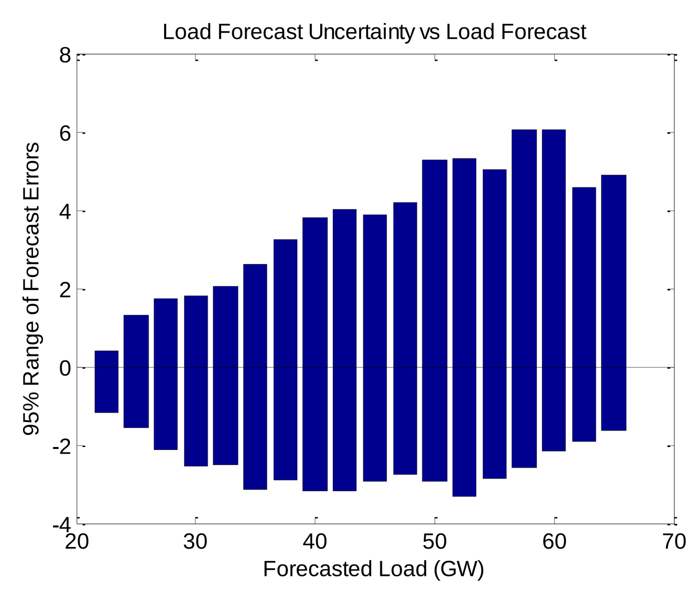
Load forecasts for ERCOT are taken roughly 20 hours before the start of the operating day. The probability density function of forecast errors shown contains data for forecasts taken in 2009 and 2010. Peak load during this time was 65 GW and average load was 35 GW.

Forecast errors are defined as the actual load minus the forecasted load. Positive errors occur when load is over forecasted. The vertical lines show the range containing 95% of the errors, -2.7 GW to 3.5 GW.



Load uncertainty depends strongly on the amount of load in the system. High loads are more difficult to predict. The left plot below shows the 95% forecast error range for each hour of the day. The red line is the average load daily load profile. The right plot shows the uncertainty of load for different levels of load forecasts.

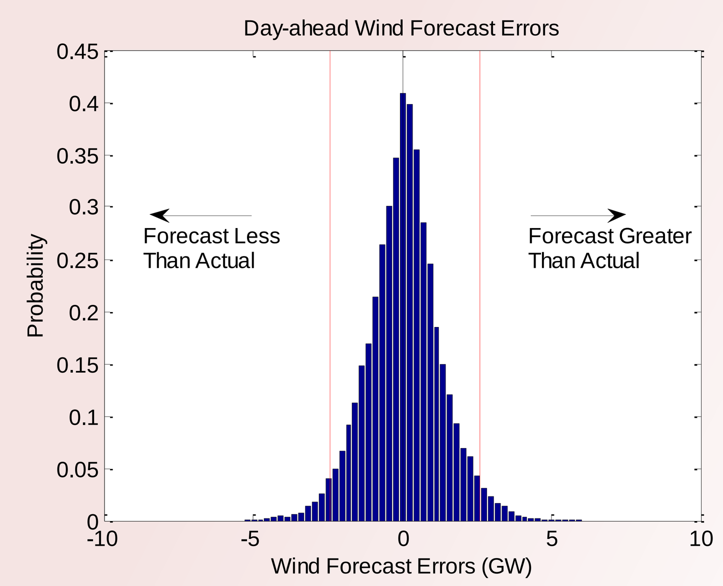


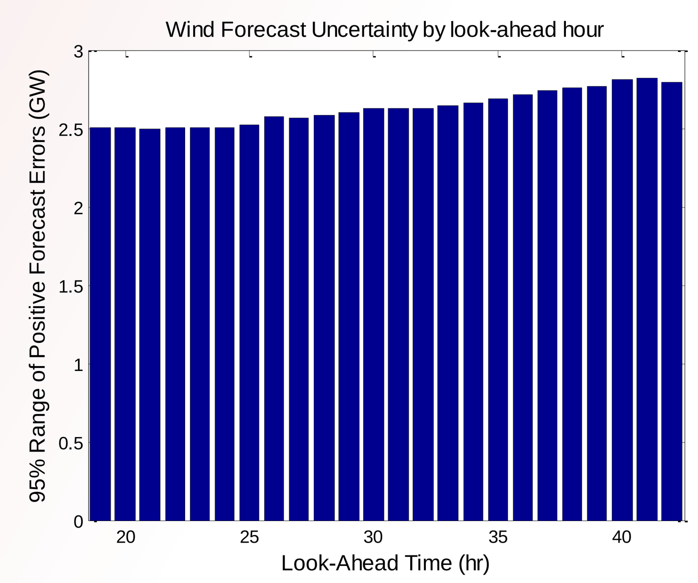


Wind Uncertainty

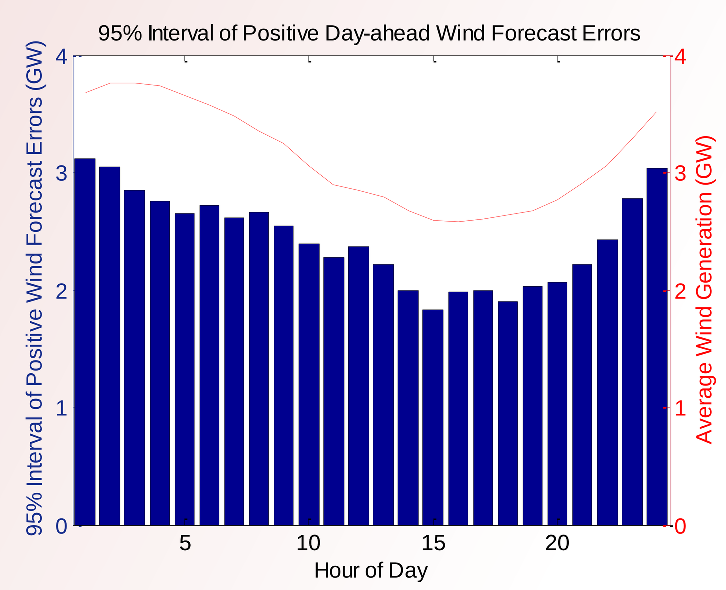
Wind power is more difficult to predict than load. Wind forecast accuracy depends on the look-ahead time and also the level of wind power predicted. Wind power forecast errors are shown in the left plot below. Ninety-five percent of the wind errors are between -2.4 and 2.6 GW. ERCOT had 8300 MW of wind power capacity at the end of 2008 which increased to 9300 MW at the end of 2010. Once again, positive forecast errors indicate that wind was over forecasted.

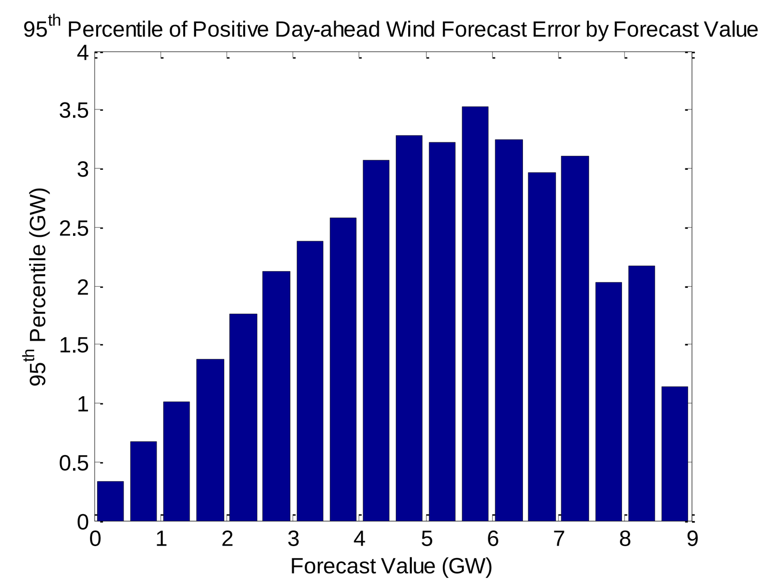
ERCOT must determine the amount of reserves required for an operating day by 6:00a.m. the previous day. Wind forecasts taken at 6:00a.m. use look-ahead times from 19 to 42 hours to cover each hour of the operating day. Over this range, the increase in uncertainty for positive forecast values is shown below to in the plot on the right. Only positive errors are displayed. The increase in uncertainty is modest in the range of look-ahead times used for day-ahead forecasts.





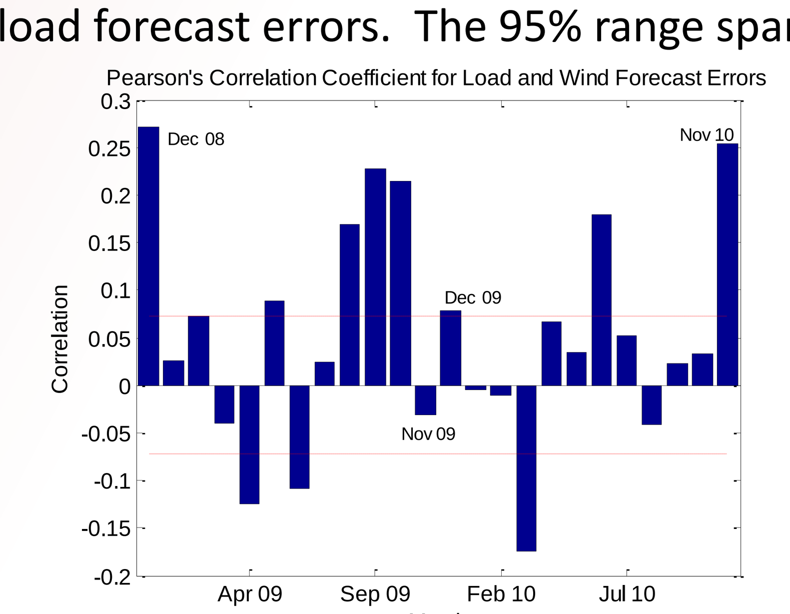
The lower left figure shows the 95th percentile of positive errors for each hour of the day with the average daily wind power profile. It clear that wind uncertainty is more strongly dependent on the level of forecasted wind. The figure on the right displays the 95th percentile of positive forecast errors for a range of forecast values.

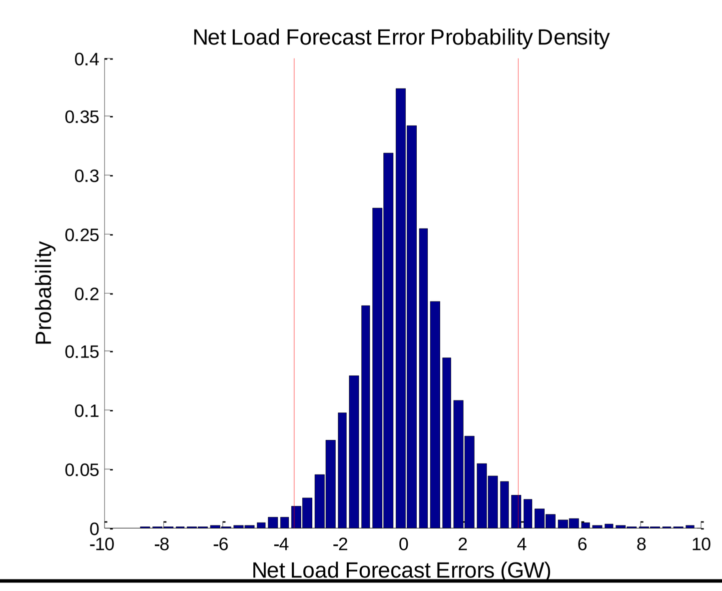




Net Load

Net load is defined as the wind power subtracted from the load. Uncertainty of net load forecasts depends on the uncertainty of wind and load as well as the correlation of wind and load forecast errors. The plot on the left below shows the Pearson's correlation coefficient for wind and load forecast errors for each month over two years. The dotted lines indicate the levels of correlation that are statistically insignificant from zero. Also shown is the probability density of the net load forecast errors. The 95% range spans from -3.6 to 3.9 GW.





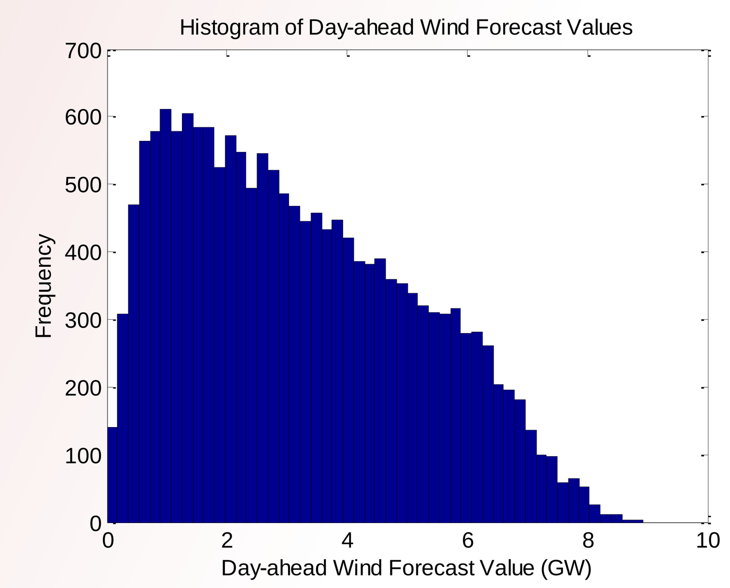
Operating Reserve Procurements

ERCOT uses historical data on net load forecast errors to make operating reserves procurement decisions. They ensure that the level of operating reserves is sufficient to cover 95% of past forecast errors. However, there is no direct use of forecasts to determine operating reserve amounts. Reserve calculations are made at the beginning of the month . Each day the same level of reserves are procured throughout the month.

Analysis

We use historical wind and load forecast uncertainty to determine the 95th percentile of positive net load errors for each hour of the day. The uncertainty is conditioned on the forecasted amounts of wind and load. This allows direct use of the forecasts to determine reserve requirements for each day. An algorithm based on this approach would calculate different reserve amounts each day .

By taking advantage of the fact that wind and load forecast uncertainty is much lower for low forecast values, it may be more cost effective to adjust reserve procurement each day based on forecasted levels of wind and load. This is especially true since the majority of wind forecasts in ERCOT from 2009 to 2010 were below 4 GW as shown in the histogram below.



Next Steps

Once hourly reserves are calculated for an entire year, we plan to compare the cost of procuring reserves with forecast to the current method in ERCOT using prices from the ancillary markets. We also plan to compare reserve procurements with each method to deployments in 2010 to compare exhaustion rates of reserves. Finally, we will extend this analysis to estimate the reserve generation costs with high levels of wind power by scaling up our analysis.

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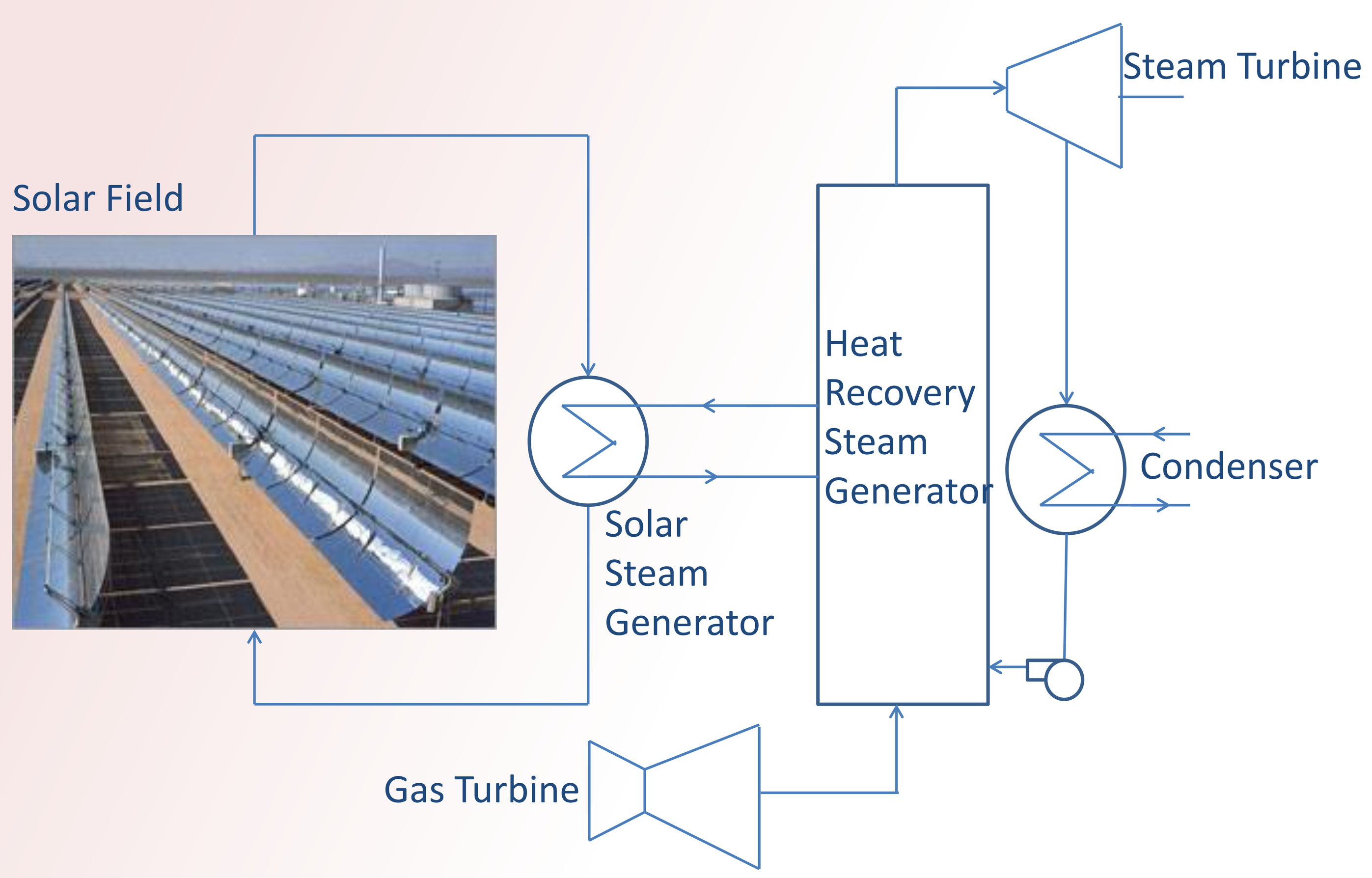
The Cost Effectiveness of Hybridized Solar and Fossil Power Plants Compared to Stand-Alone PV or CSP Plants

Jared Moore, Advisor: Jay Apt

Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, PA 15213

Integrated Solar Combined Cycle: Integrated Solar Combined Cycles (ISCC) are natural gas combined cycle (NGCC) power plants hybridized with solar thermal energy to boost the output of the heat recovery steam generator. The principal advantage to hybridization for solar power is the ability to directly off-set fossil fuel energy without having to pay for a power block or transmission lines dedicated to solar energy. The power block of a stand-alone CSP plant is appreciable, accounting for approximately 40% to 50% of the capital costs. Assuming that the capacity factor of stand-alone CSP plants are around 25%, sharing a power block with a fossil fuel power plant greatly increases its utilization. Additionally, since maintenance personnel are already on hand to monitor and maintain the power block, maintenance costs assigned to the solar portion are reduced.

Diagram of an Integrated Solar Combined Cycle



Solar thermal energy in integrated into the HRSG. Heat transfer fluid (HTF) is heated in the solar field by parabolic trough shaped mirrors. Hot HTF is then used to make steam in a heat exchanger before the steam returns to the HRSG. The added steam from the solar field is intended to off-set less efficient duct firing.

Efficiency with Duct Firing and with Solar Energy

	Base Load		Duct Firing		Solar and Duct Firing	
	Efficiency	MW	Efficiency	MW	Efficiency	MW
CEC Application for Certification	55.2%	463	52.6%	563	58.8%	563
My Model	54.9%	463	52.9%	567	59.2%	564

Solar energy boosts the efficiency of the power plant. If duct firing is used to reach full capacity, efficiency of the power plant decreases. With solar energy, the efficiency of the power plant increases at full load.

Economic Model

Hourly Solar Thermal Output to Power Block Extracted from NREL's Solar Advisor Model

Hourly Grid Price Data from CAISO Grid

→ Thermodynamic Model runs plant to maximize hourly marginal profits. Plant either does not run, runs at base load, or runs with duct firing with whatever solar energy is available.

→ Hourly (8760) Profit and Performance Data is aggregated

→ Annual Operation Statistics used to calculate Net Present Value, Levelized Cost of Mitigation, and Cost of Mitigation

Capacity Factor of the ISCC Power Plant / Capacity Factor of Solar Portion of ISCC Power Plant (Location: Phoenix)

		Average Wholesale Price of Electricity [$/MWh]					
		$ 35	$ 45	$ 55	$ 65	$ 75	$ 85
Price Of Gas [$/MCF]	2	88 / 22 %	89 / 22 %	90 / 22 %	90 / 22 %	91 / 22 %	91 / 22%
	4	71 / 21 %	83 / 21 %	86 / 22 %	88 / 22 %	89 / 22 %	89 / 22%
	6	27 / 10 %	55 / 18 %	74 / 21 %	82 / 21 %	85 / 22 %	87 / 22%
	8	8 / 2 %	23 / 9 %	44 / 15 %	63 / 20 %	76 / 21 %	82 / 21%
	10	4 / 1 %	9 / 3 %	21 / 8 %	38 / 14 %	55 / 18 %	68 / 20%
	12	4 / 1 %	5 / 1 %	9 / 3 %	20 / 8 %	34 / 12 %	47 / 16%

The capacity factor is defined as the number of MWh produce divided by the number of MWh that could have been produced if the plant ran at capacity for all 8760 hours of the year. The capacity factor for the solar portion of the power plant is close to the observed ~25% capacity factor for CSP generators. Since the solar side of the plant can run only while the power block is available, the capacity factor is slightly lower due to a forced outage rate of 5% on the fossil side of the ISCC plant.

Cost Assumptions

	NGCC	Solar Thermal (Trough, No Storage)	Solar PV	Solar Part of ISCC
Capital Costs $/kW	1000 ± 100	5800 ± 500	4400 ± 500	3900 ± 600
Fixed Maintenance Costs $/kW-year	5.8 ± 1	65 ± 15	25 ± 10	30 ± 10
Lifetime of Plant (Years)	25	25	20	25

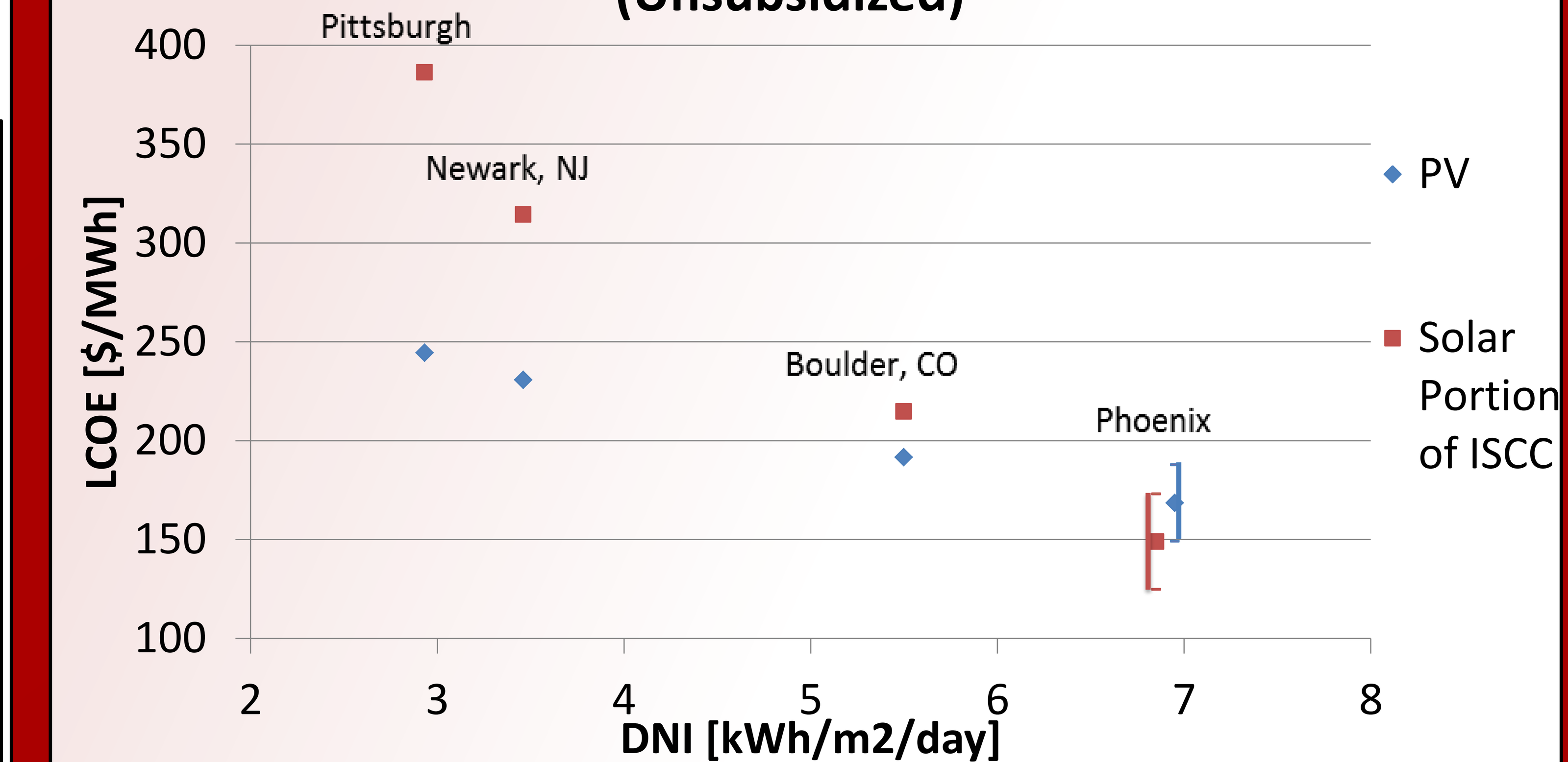
The cost estimate for PV is based on the cost per AC watt. Cost estimates for PV are frequently quoted in $\$/\mathrm{Watt}_{DC}$. To arrive at the cost per watt AC, we multiply the DC cost estimates by 1.15 for the AC to DC capacity difference. Therefore, the mid-value for capital costs for PV we garnered from studies was $\$3.8/W_{DC}$.

Levelized Cost of Electricity of Solar Portion of ISCC Power Plant (Location: Phoenix)

		Average Price of Electricity [$/MWh]					
		$ 35	$ 45	$ 55	$ 65	$ 75	$ 85
Price Of Gas [$/MCF]	2	**$150**	**$150**	**$150**	**$150**	**$150**	**$150**
	4	**$160**	**$150**	**$150**	**$150**	**$150**	**$150**
	6	$330	$180	**$160**	**$150**	**$150**	**$150**
	8	$1,500	$370	$220	$170	**$160**	**$150**
	10	$2,800	$1,300	$400	$240	$180	**$160**
	12	$3,300	$2,400	$1,100	$430	$270	$200

LCOE for PV from model is $170 / MWh, for CSP from model is $190 / MWh. Bold signifies ISCC solar portion LCOE is lower than PV or CSP

LCOE of Solar Electricity at Different Locations (Unsubsidized)



CSP power plants can only utilize direct beam radiation (aka DNI). Therefore, the solar portion of ISCC power plants would likely only be more competitive than PV power plants if located in areas with strong DNI—Southwest U.S.

Cost of Mitigation for Solar Portion of ISCC Plant in Phoenix, AZ (If coal is off set / If NGCC if off set) [$/tonne CO_2 avoided]

		Average Wholesale Price of Electricity [$/MWh]					
		$ 35	$ 45	$ 55	$ 65	$ 75	$ 85
Price Of Gas [$/MCF]	2	**$110 / 310**	**$110 / 310**	**$110 / 310**	**$110 / 310**	**$100 / 310**	**$100 / 310**
	4	**$120 / 340**	**$110 / 320**	**$110 / 320**	**$110 / 310**	**$110 / 310**	**$110 / 310**
	6	$310 / 810	**$140 / 400**	**$110 / 330**	**$110 / 320**	**$110 / 320**	**$110 / 310**
	8	$1,700 +	$360 / 940	$180 / 500	**$130 / 360**	**$110 / 330**	**$110 / 320**
	10	$3,200 +	$1,400 +	$400 / 1000	$210 / 570	**$140 / 400**	**$120 / 340**
	12	$3,800 +	$2,800 +	$1,200 +	$430 / 1,100	$240 / 640	$160 / 460

Bold font signifies a lower COM for the solar portion of the ISCC plant compared to PV and CSP. The COM for PV and CSP if coal was offset $140 and $160/tonne of CO_2. The COM for PV and CSP if natural gas was offset is $410 and $440/tonne of CO_2.

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The Environmental Impacts of Variability

David Luke Oates, Paulina Jaramillo

Department of Engineering and Public Policy, Carnegie Mellon University, Pittsburgh, PA 15213

Carnegie Mellon University

Introduction

In 2009, approximately 38% of the 103 quadrillion BTUs of primary energy consumed in the U.S. was used to produce electricity (EIA 2011). The electric power sector produced more than 2.4 billion tons of CO_2 (40% of national total), 2.2 million tons of NO_X (18%) and 6 million tons of SO_2 (63%) (EPA 2012a; EPA 2012b). These large values make the electric power sector a focus of many Life Cycle Assessments (LCAs).

A common approach taken in LCA is to use a fleet-wide average emissions factor, or a marginal emissions factor for a particular unit type, to calculate changes in emissions resulting from a process. In this work, we determine use-phase reductions in CO_2, NO_X, and SO_2 emissions associated with the introduction of wind power into a model of the PJM Interconnection in 2006. The aim of the work is to compare an emissions factor approach to one that accounts for power system economics, unit and system operating constraints, and the variability of wind. We find that an emissions factor approach can lead to substantial (up to 40% in the case of SO_2) error in emissions calculations.

PJM Interconnection

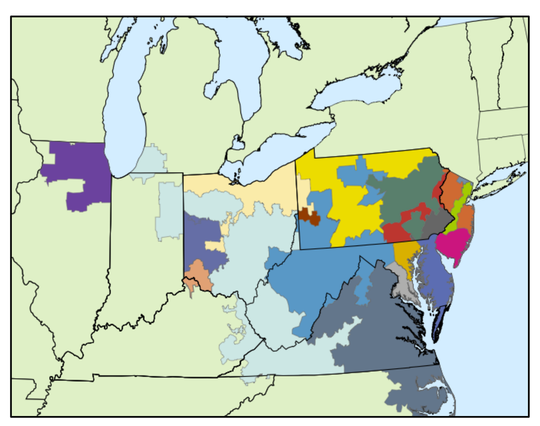
The PJM Interconnection is a Regional Transmission Organization serving all or part of 14 states in the North East and Midwest U.S., including the District of Columbia. The system is one of the largest competitive wholesale markets in the world and in 2006 had the capacity breakdown and emissions factors shown below.

Type	Number of Units	Net Winter Capacity [GW]	Net Summer Capacity [GW]
Nuclear	31	30.8	30.8
Coal	208	64.7	65.0
Hydro	87	2.6	2.6
Gas Steam	9	1.3	1.3
Oil Steam	22	7.6	7.6
Gas Combined Cycle	111	22.4	21.4
Gas Turbine	245	20.6	20.1
Oil Turbine	183	6.3	5.6
Other	91	1.2	1.2
Total	987	157.5	155.6

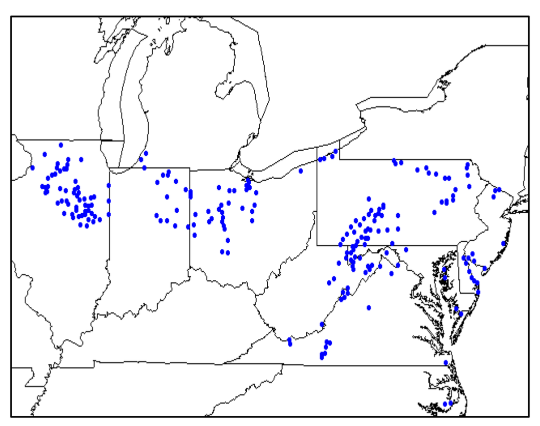
Emissions Factors	CO_2 [lb/MWh]	NO_X [lb/MWh]	SO_2 [lb/MWh]
Observed Average 2006	1251.6	2.2	8.0
Coal	2085.3	2.0	21.7
Gas Combined Cycle	955.8	0.3	0.2

Wind Input Data

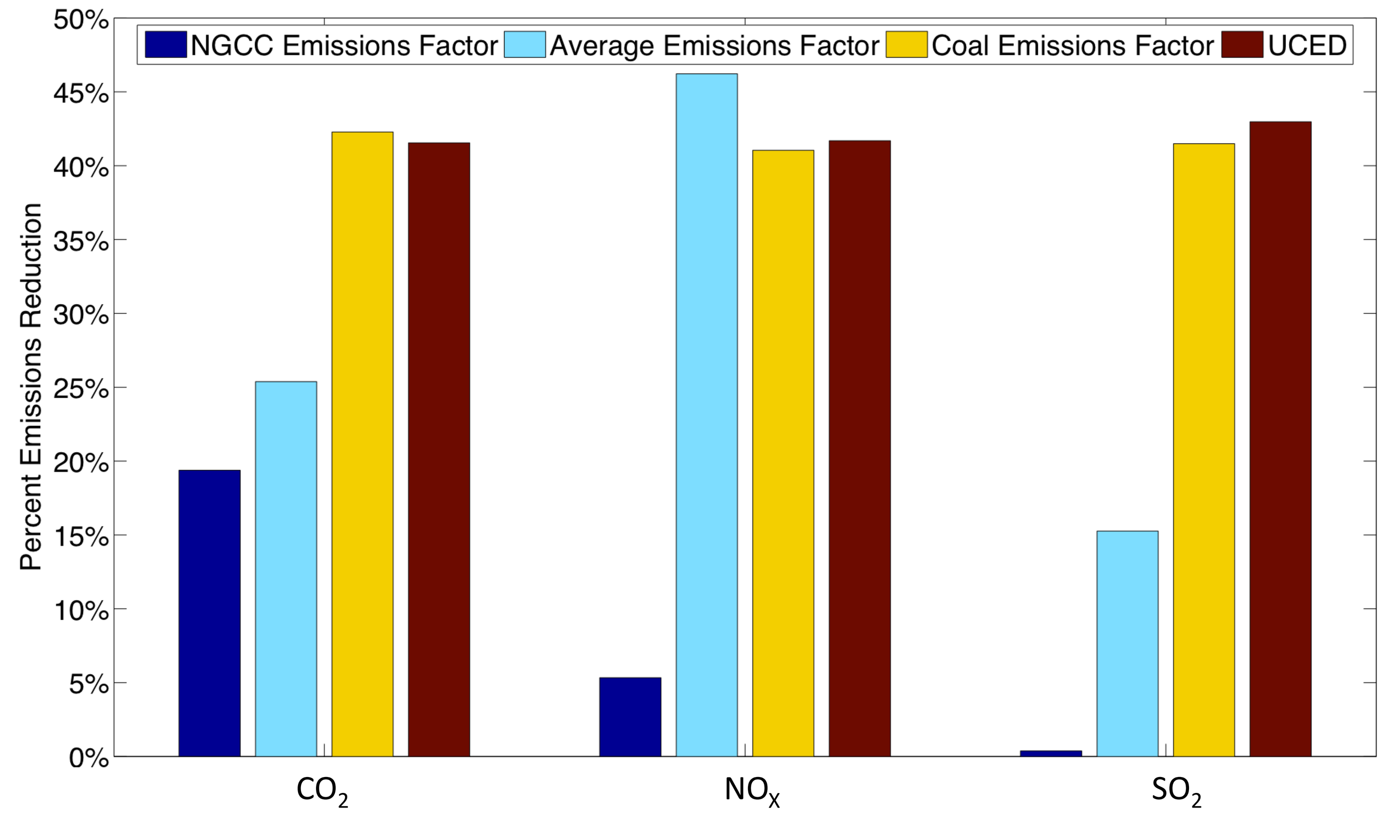
The location and timing of wind energy production has significant impact on the emissions reductions achieved (Katzenstein & Apt 2009). To account for these effects, the UCED uses simulated wind output from NREL's Eastern Wind Interconnection and Transmission Study (EWITS). Wind sites were selected in order of decreasing capacity factor until the cumulative capacity reached the target level. The maps below show the PJM region and the EWITS sites used in the model.



PJM Region



EWITS Sites



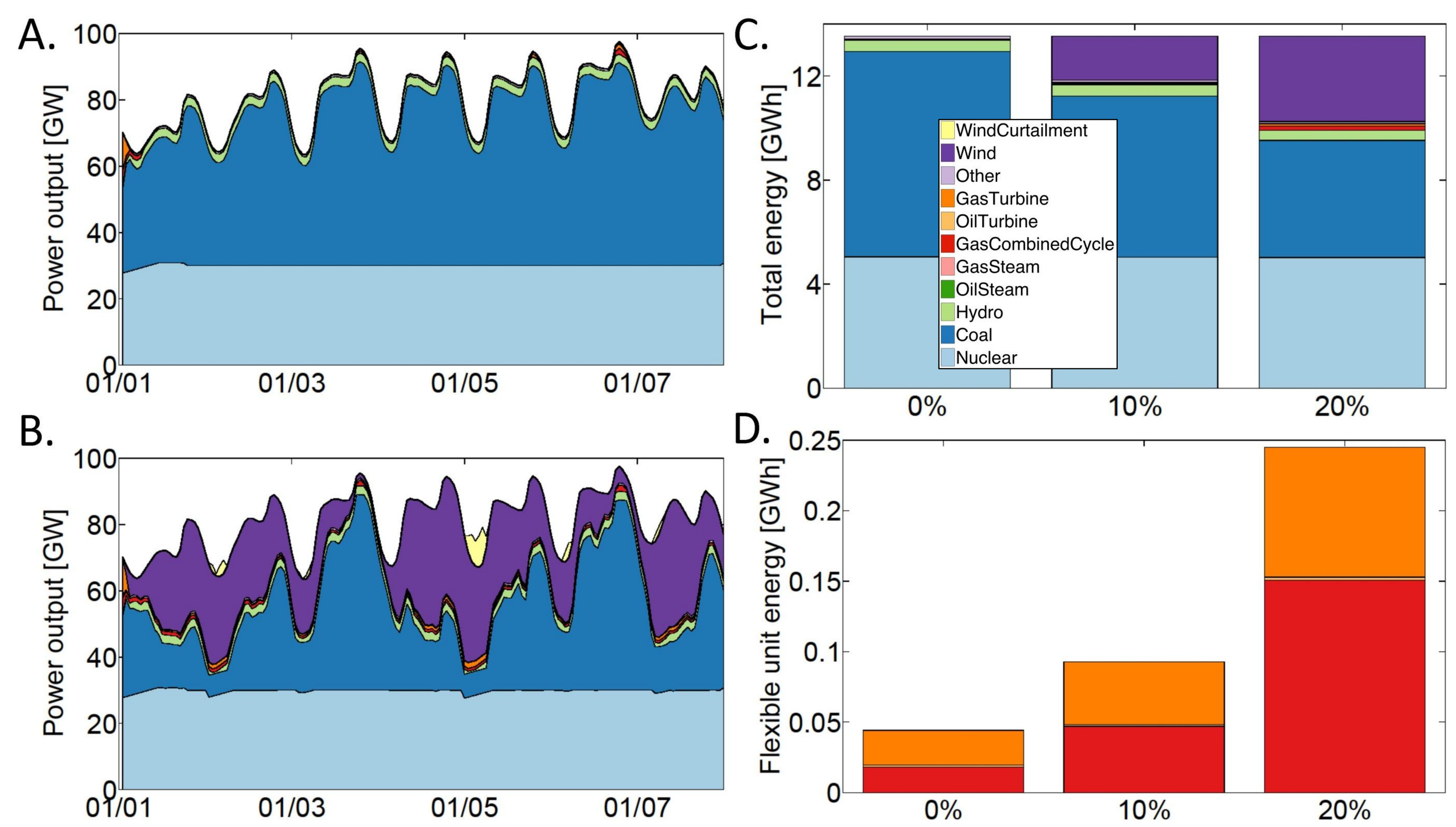
Emissions reductions at 20% wind penetration. Use of natural gas combined-cycle and fleet-average emissions factors generate misleading results, while use of the coal emissions factor approaches the UCED result. Total weekly emissions at 0% wind were 8×10^6 ton CO_2, 8×10^3 ton NO_X, and 9×10^4 ton SO_2.

Results

- Constant emissions factor calculations diverged substantially from UCED results
- Most of the wind power generated during the study period displaced coal, due to high utilization of coal in the no-wind case, disproportionate wind generation at night, and security constraints requiring gas units to remain online
- Output of gas turbine and combined cycle units *increased* 500% at 20% wind

Conclusions

LCA practitioners should consider the merits of using average emissions factors, marginal emissions factors, or a more sophisticated approach such as the one employed here depending on the physical parameters of the problem and level of accuracy required.



A) Hourly resource use at 0% wind. B) Hourly resource use at 20% wind. Note wind curtailment during off-peak hours. C) Total resource use. Note wind is mostly displacing coal. D) Total resource use, flexible units only. Note the increased use of flexible units with wind penetration to satisfy reserve requirements. The type of offset unit has significant implications on emissions calculations. Note that the average price of natural gas delivered to U.S. utilities in 2006 was \$7.11/tcf, compared to \$4.87/tcf in 2011 (EIA 2012).

Unit Commitment and Economic Dispatch Model

The unit commitment and economic dispatch (UCED) model constructed for this work is a unit-level representation of the PJM system. The model is structured as a mixed-integer optimization problem whose objective function is to **minimize production costs** subject to the **supply-demand balance**, **unit operating constraints**, and **system security constraints** (such as the spinning-reserve requirement). Production costs include fuel, variable operations and maintenance, and unit startup. The result produced by the model is a schedule of the energy produced by each unit in each period, from which emissions can be calculated using unit-by-unit emissions factors.

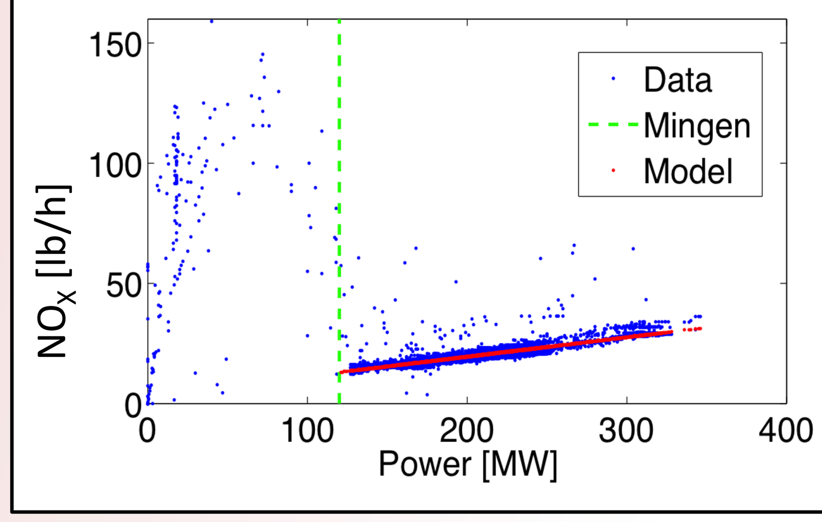
$E_{i,t}$ Energy produced by unit i during hour t [MWh]
L_t Total system load in period t [MWh]
W_t Total wind energy available in period t [MWh]
W_t^C Wind energy curtailed in period t [MWh]
R_t^S Spinning reserve requirement in period t [MWh]

Supply-Demand Balance: $$L_t = \sum_i E_{i,t} + W_t - W_t^C$$

Spinning-Reserves: $$R_t^S = 0.03L_t + 0.05W_t$$

Future Work

The variability introduced into the power system by high levels of wind can substantially affect emissions from fossil fueled units by causing them to perform emissions-intensive cycling (Katzenstein & Apt 2009). Future work will assess the implications of this affect at high wind penetrations. The unit shown in the figure below would produce much more NO_X if it were required to startup and shut down frequently.



Hourly NO_X emissions data from a PJM gas combined cycle unit (EPA 2006). Note the high emissions rates below the minimum generation level (mingen). Emissions from this unit can be modeled separately above and below mingen.

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This project was conducted as part of the National Energy Technology Laboratory's Regional University Alliance (NETL-RUA), a collaborative initiative of the NETL under the RES contract DE-FE0004000, and with the support of CMU's RenewElec Project.

Effects of Government Incentives on U.S. Wind Innovation and Capacity

Nathaniel Horner[*]

Advisors: David Hounshell,[†] Inês Azevado,[*] Francisco Veloso[*]

[*]Department of Engineering and Public Policy, Carnegie Mellon University

[†]Department of Social and Decision Science, Affiliate of Department of Engineering and Public Policy, Carnegie Mellon Univerisity

Research Questions

History has shown that government policy has a profound effect on wind generation capacity. In addition to policy and market drivers, the viability of the wind industry also depends on the state of the technology. This project will examine the interplay between policy and innovation.

Innovation Impacts:

What are the effects of government renewable energy policies in the United States on innovations, and on the value of such innovations, for the wind industry?

Industry Impacts:

What are the effects of government renewable energy policies on installed wind capacity, wind electricity generation, and job creation in the United States?

Theories of Policy Dynamics

How do policy mechanisms incentivize innovation?

"Demand-Pull"

- Market characteristics drive innovation
- Innovation relies on evolution and iteration to meet needs defined by market
- Demand-side policies increase private payoffs for innovation
- Policy Examples: DoD procurement, PURPA (1978)

"Technology-Push"

- Advances in S&T drive innovation
- Linear model of research described by Vannevar Bush in post-WWII years
- Supply-side policies reduce private costs of innovation
- Policy Examples: Manhattan project, DOE/NASA MOD program in 1970s-1980s

Historical Examples

(Based on information in Righter, 1996)

Demand-Pull:

The California Wind Rush, 1978-1986

- State and Federal tax credits totaled 50% on wind system installation costs
- Loan guarantees also available
- Led to boom in 1983: wind farms as tax shelters
- 12K turbines totaling 911 MW installed 1981-1986

Bust, 1986

- Tax credits expired
- Huge reliability problems
- Many operators and manufacturers went bankrupt
- *Incentives did not lead to development of reliable technology—everyone was too busy building!*

Technology-Push:

The DOE/NASA MOD Program, 1973-1988

- R&D program funded by DOE Solar Energy Research Institute and led by NASA; Boeing and Hamilton Standard were industry partners
- Focus was megawatt-class turbines for eventual commercial production
- >$285 mil. From 1973-1988
- Experimental units failed: were not reliable enough and never went commercial
- Meanwhile, promise in small and intermediate turbines, but little federal interest
- *Technology-driven policy fought the market.*

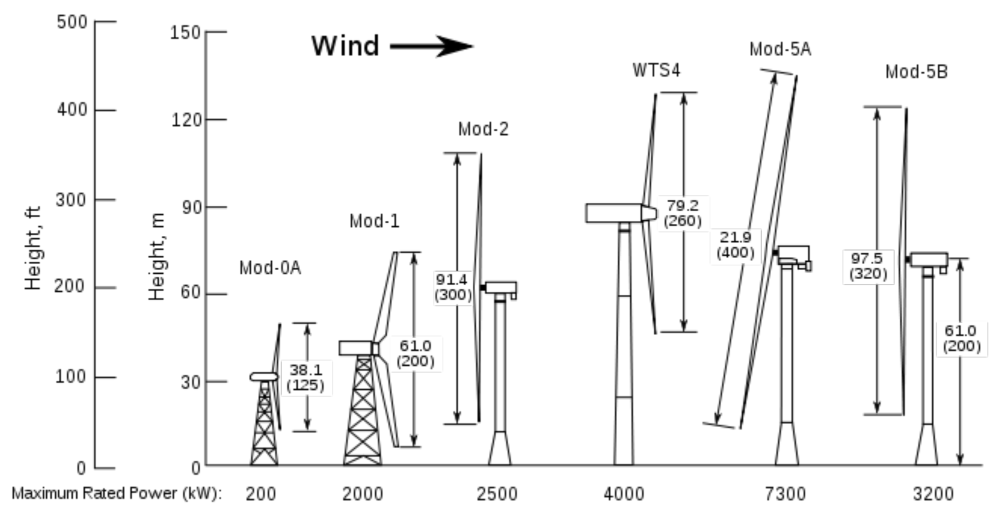

Photo source: http://en.wikipedia.org/wiki/File:Wind_generator_comparison.svg

Methodology

We will build an econometric model relating wind capacity and innovation to a time-series of policy variables and controls. Innovation will be measured by patent counts, an approach widely used in studies of technology development.

Previous work in this area (Johnstone, Haščič, & Popp, 2009) using similar methods suggests that different policy types have markedly diverse effects on innovation for different technologies. However, many of these studies suffer from lack of precision in defining the relevant technology areas (as noted by Braun, Hooper, Wand, & Zloczysti, 2011) or from not considering the implementation details of the policies believed to have affected innovation (as noted by Johnstone, Kalamova, & Haščič, 2010). In addition, much of the work occurred prior to recent developments in the industry; for instance, the conclusions regarding induced innovation in Nemet (2009) rely on data from the California wind-boom of the 1980s.

This project will use a class- and keyword-based patent search to identify relevant patents and an updated policy timeline that includes variables such as policy stringency, where possible, to address these concerns.

Expected Results

Previous work in the renewable energy and related domains have found that effectiveness varies across policy type and renewable technology (Johnstone, et al., 2009), that demand-pull policies have little effect (Nemet, 2009), and that technology-push policies do affect innovation (Margolis & Kammen, 1999; Lee, Veloso, & Hounshell, 2011).

We expect to find a positive effect of policy stringency on innovation and that technology-based policy has a stronger effect than market-based policy.

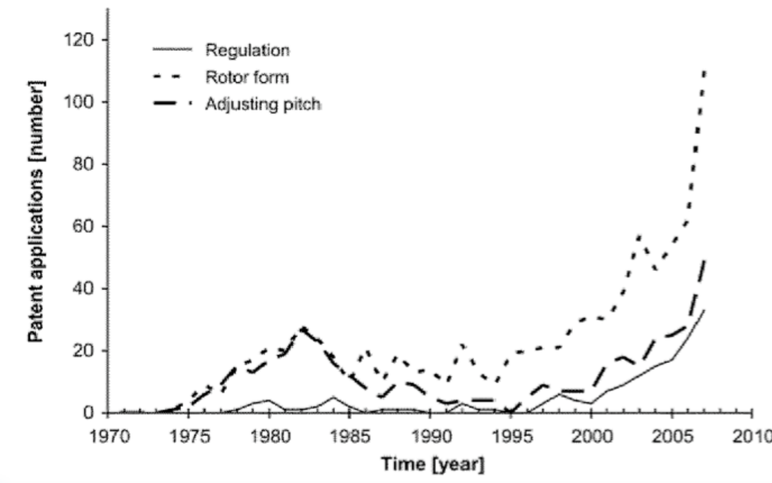

Chart of patent trends in wind generator technology from EPO database (Dubaric, Giannoccaro, Bengtsson, & Ackermann, 2011).

Note increased patenting activity during periods of increasing policy interest.

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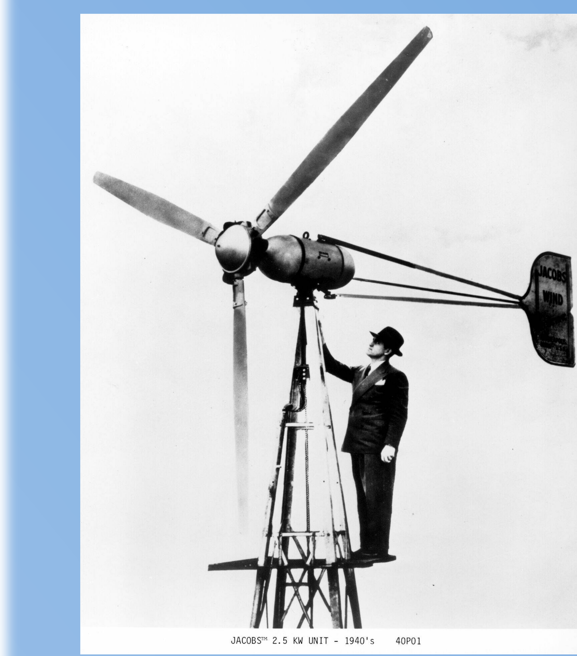

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Funding from the National Science Foundation is gratefully acknowledged.

Photos (top to bottom):

(1) Wind dynamo installed by inventor Charles F. Brush in his Cleveland backyard, operational from 1888-1908. 12 kW, 56' diameter rotor. [http://wiki.windpower.org/index.php/Charles_F._Brush]

(2) Smith-Putnam wind turbine at Grandpa's Knob, VT. Private venture produced first megawatt-class turbine in 1941. [http://www.wind-works.org/photos/Smith-PutnamPhotos.html]

(3) Jacobs wind motors exemplified the small wind plants installed throughout the American plains from the 1930s through the 1950s. [http://www.wincharger.com/jacobs/jacobsphoto.jpg]

(4) One of three DOE/NASA MOD-2 2.5 MW Boeing turbines erected at Goodnoe Hills, WA in 1980. [http://en.wikipedia.org/wiki/File:Mod-2_Wind_Turbine_Cluster3.jpg]

(5) Wind farm at Altamont Pass, CA, using "low technology," rugged Danish design. [http://www.theepochtimes.com/n2/science/wine-turbines-bats-4075.html]

(6) Modern Vestas V90 3 MW wind turbine [http://www.rechargenews.com/business_area/finance/article197073.ece]

Regional allocation of biomass to competing U.S. energy demands under a portfolio of policy scenarios

Kimberley A. Mullins* [1,2], Aranya Venkatesh* [2], Amy L. Nagengast [2], Matt Kocoloski [3]

[1] Department of Engineering & Public Policy, [2] Department of Civil & Environmental Engineering, [3] Tepper School of Business at Carnegie Mellon University, Pittsburgh PA

1. Motivation

Policy efforts are in place to increase the use of cellulosic biomass in the transportation and electricity sectors in order to reduce greenhouse gas emissions and increase domestic resource use. The competing feedstock demands encouraged by these parallel, but independent, efforts can result in sub-optimal bio-resource allocation. Previous studies have explored this space, but they tend to focus on single or multiple feedstocks allocated to individual or a limited subset of end uses.

This work answers two questions:

1. What feedstock is used for which end use, and where, to minimize system costs?

2. What greenhouse gas emissions reductions can be obtained by different policy mechanisms?

2. Optimization Model Construction

•Three feedstocks: switchgrass, corn stover, and forest thinnings. Each varies in geographic availability, processing costs, GHGs.

•Three fossil energy demands to potentially be displaced by biomass: residential heating, electricity (coal), transportation (gasoline).

•Geographic aggregation level: agricultural statistical district (ASD).

•**Model objective**: Minimize total system costs

$$\begin{aligned}\text{system cost} = \sum_{ASD} \{ & \text{biomass feedstock, shipping, conversion costs} \\ & + \text{bioenergy product shipping, end use costs} \\ & + \text{fossil fuel use costs} \\ & + \text{fossil fuel, bioenergy emisisons costs} \}\end{aligned}$$

•**Decision variables**: For each ASD, the quantity of each available feedstock (biomass or fossil) allocated to each end use. The choices are illustrated in Figure 1 below.

•Four policy scenarios modeled: no additional, carbon price, carbon emissions cap, and increased ethanol volume mandate.

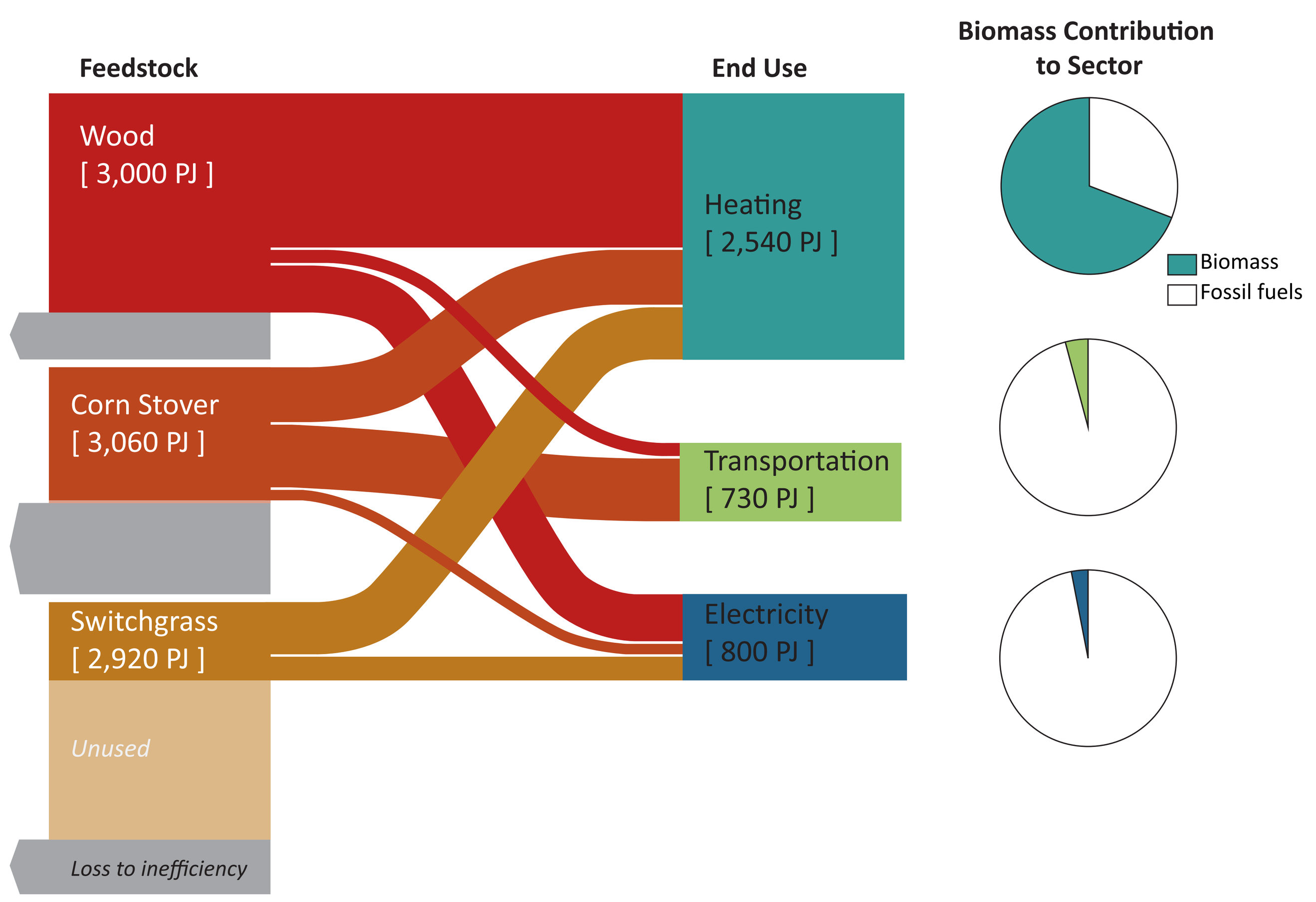
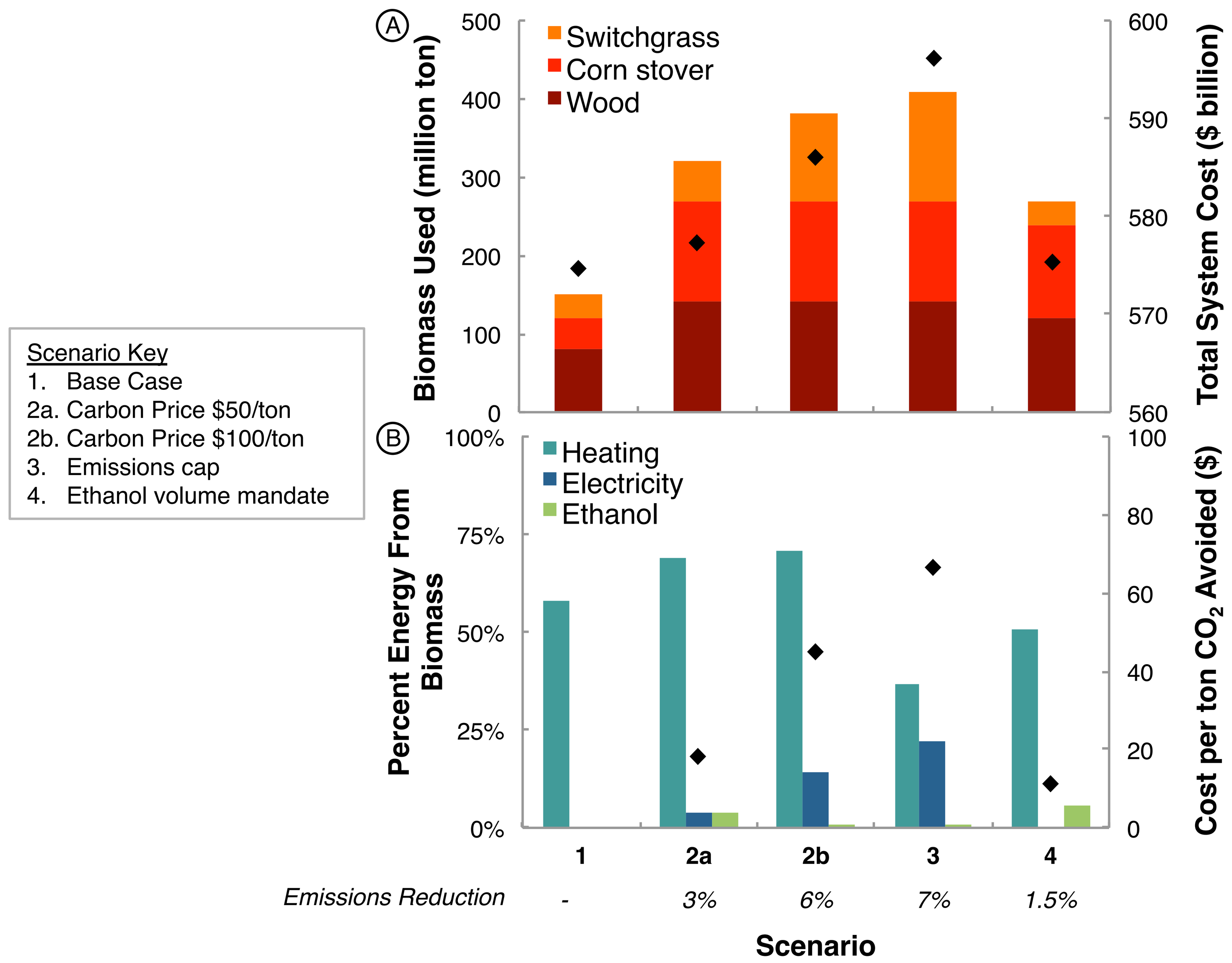


Figure 1. Sankey diagram ($50/ton carbon scenario) illustrating flows of energy from feedstock to end use, with percent of end use energy from biomass.

3. Preliminary Results

Results show modest biomass usage for home heating without biomass policy incentives. Woody biomass is the preferred feedstock due to relatively high energy density, and widespread availability. Increasing biomass use results from climate policies, and are associated with higher total system costs. Results are sensitive to fossil fuel prices, though some biomass for heating persists under all examined prices (see Figure 4).



Figures 2.A. System costs and biomass utilization; 2.B. \$/ton CO_2e avoided, percentage of energy demand met by biomass and percentage reductions in CO_2e emissions. Percent emissions reduction are from Base Case. Bars are measured by the primary (left) y-axis while the markers are measured by the secondary (right) y-axis.

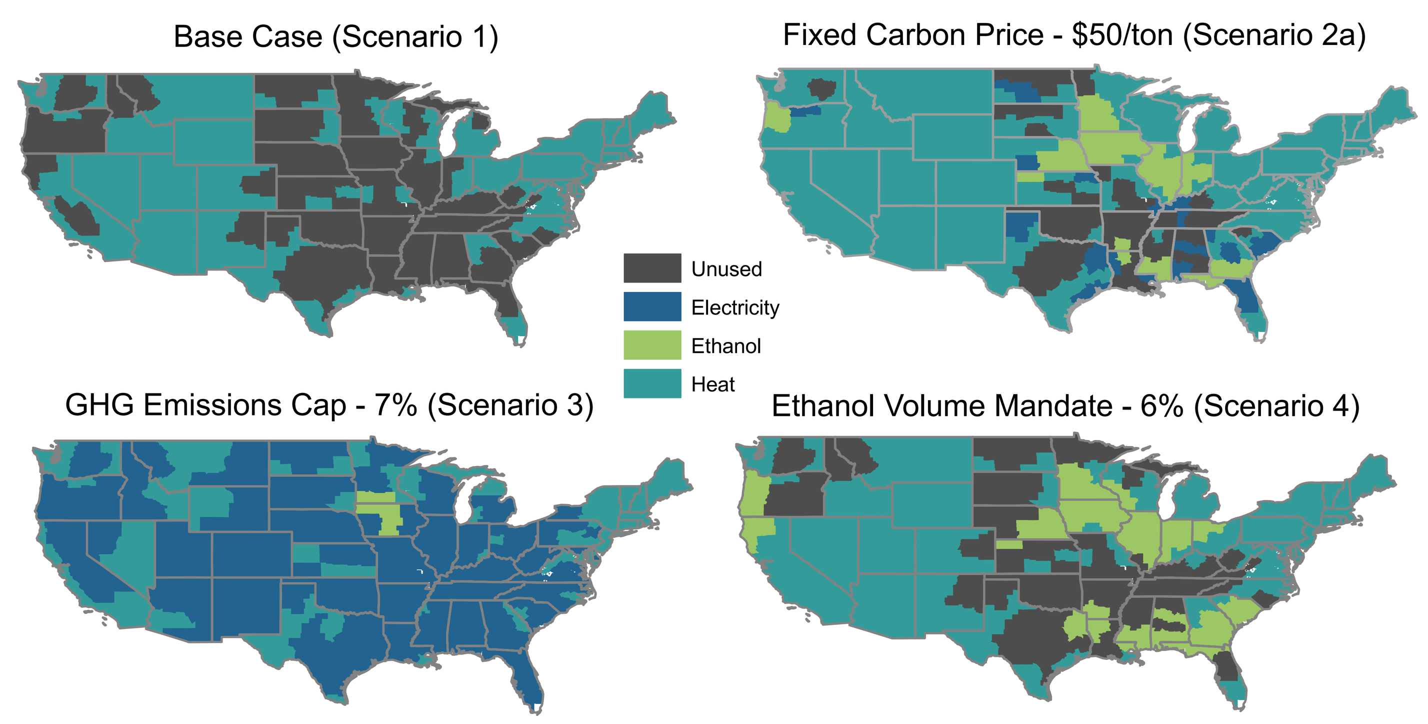


Figure 3. Primary end use for biomass for each ASD. Regional trends for feedstock usage are apparent: heating preferred in the Northeast and the West, ethanol produced only in close proximity to feedstock availability, and biomass electricity more common in regions with higher emissions.

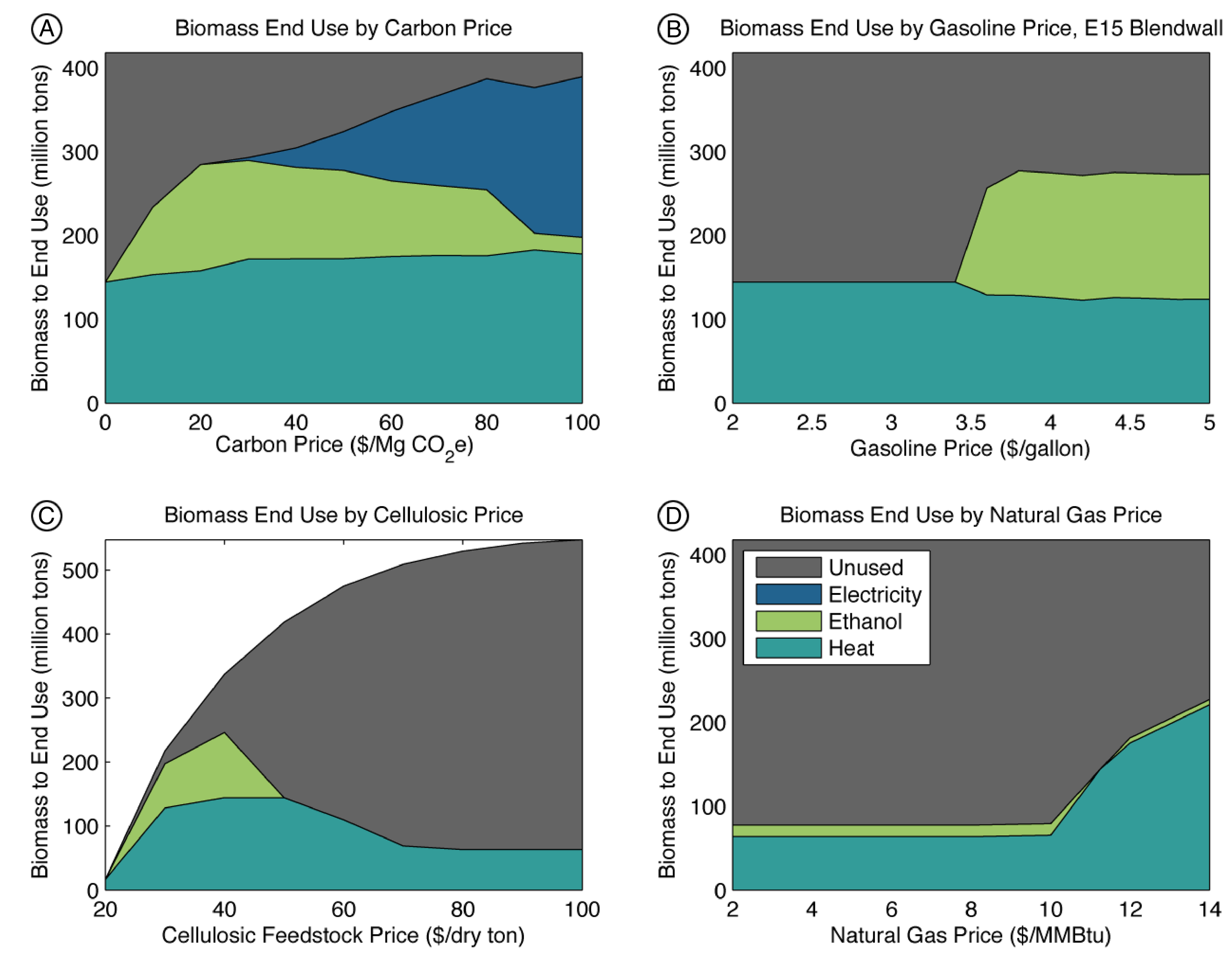


Figure 4. Sensitivity of quantity biomass used to various input parameters. With increasing carbon prices, biomass electricity is preferred to ethanol production. Ethanol is cost competitive only at higher gasoline prices. Higher feedstock prices decrease utilization, though some use for heating remains. Increasing natural gas prices also make biomass residential heating more attractive.

4. Policy Implications

•There are widespread opportunities to reduce greenhouse gas emissions through increased use of biomass for residential heating at a modest cost, a particularly robust conclusion in the Northeast. This could be encouraged by increasing the availability of pellet stoves in this area.

•Biomass policies need not be national, as biomass feedstocks are processed and used nearby to where they are produced. As a result, they are good candidates for state or regional climate policy initiatives.

5. Next Steps

•Add other low-carbon electricity options to model

•Examine possible market-mediated effects (e.g., rebound effect)

•Limited Monte Carlo simulation for highly uncertain parameters

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*For further information, please contact Kimberley Mullins (kmullins@cmu.edu) or Aranya Venkatesh (aranya@cmu.edu)

Information and Communication Technologies Institute
Carnegie Mellon | PORTUGAL

INSTITUTO SUPERIOR TÉCNICO
Technical University of Lisbon

Private rents coming from wind feed-in tariffs (FIT) in Portugal during 1992-2006

I. Pena*[1,2], I. Azevedo[1]

[1]Department of Engineering and Public Policy, Carnegie Mellon University, USA.

[2]IST - Technical University of Lisbon, PT.

*ipenacab@andrew.cmu.edu

Summary

The wind FIT in Portugal (in \$/MWh) is designed to provide sufficient profitability for the investment (Mendonça 2007), is supported through rate payers, and it is currently guaranteed for 15 years. Despite the tremendous positive impact of the policy reflected in average annual wind capacity additions of 220 MW over the last 20 years, and in having 17% of total electricity production coming from wind by 2010 (INEGI 2010), the total funding provided by the government was approximately \$750 million (\$2005) between 1992-2006 (ERSE 2011) and \$3.6 billions up to 2010. The purpose of this work is to determine whereas these payments have overcompensated Portuguese wind electricity producers, or if the guaranteed payments have been cost-effective. We estimate that the cumulative private profits coming from the FIT policy between 1992-2006 are between \$178 millions and \$196 millions*, which corresponds to an average net profit of \$98,000/MW-\$110,000/MW installed (20% of the investment incurred**). The same capacity additions of 1,800 MW over the period could have been achieved by spending 25% less by the portuguese government.

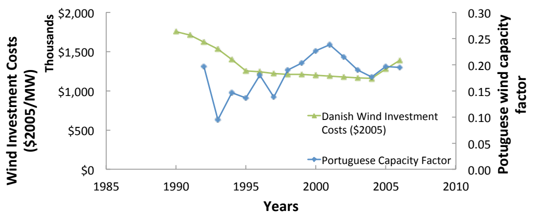
*Assuming a 10% discount rate and a 20 year life-time, ** Average investment costs over 1992-2006 were \$560,000/MW

Introduction

1. As part of the energy policy aiming to reduce energy dependence and CO_2 emission levels, Portugal has established since 1988 Portugal a feed-in tariff (FIT) system for all renewable electricity producers (Diário da República), including wind electricity, that make very attractive to engage in renewable electricity generation.
2. The average wind FIT paid over the last 10 years has been \$106.5/MWh, approximately 60 percent above electricity spot market price (by 2010), and have varied between \$87/MWh and \$113/MWh.

Data

Data on average annual wind investment cost, from DEA and Portuguese wind FIT, capacity additions and wind production from ERSE



Wind investment costs and capacity factor, 1992-2006 (DEA 2011, ERSE 2011)

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Methodology

The annual profits in year *i* of parks that connected to the grid in year *k* are:

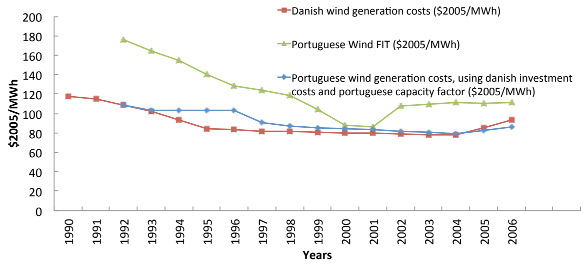
$$\pi_{k,i} = \begin{bmatrix} FIT_{k,i} & \text{if year} \leq 15 \\ price_{k,i} & \text{if year} > 15 \end{bmatrix} - LCOE_{k,i} \Big] * windgen_{k,i}$$

$FIT_{k,i}$ (\$2005/MWh): average Portuguese wind FIT paid
$price_{k,i}$ (\$2005/MWh): Portuguese wind price paid after FIT is over
$LCOE_{k,i}$ (\$2005/MWh): levelized national annual wind generation costs
$windgen_{k,i}$ (MWh): wind electricity generation

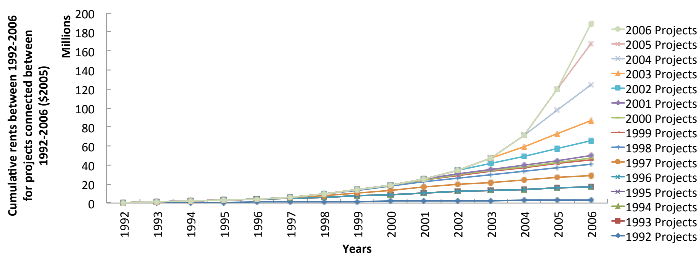
Base case scenario: 10% discount rate, 20 years lifetime of wind parks

Results

(a)



(b)



(c)

	Assumptions*	Total cumulative rents up to 2006 (any project without FIT), \$2005 millions	Total cumulative rents for FIT period, 15 years, \$2005 millions	Total cumulative rents for 20 years life-time, \$2005 millions†
Case 1	Capacity factor of year i= annual average capacity factor of year k**	\$178	\$1,017	\$600
Case 2	Capacity factor of year i= annual average capacity factor of year i	\$189	\$1,195	\$703
Case 3	Capacity factor of year i=0.2	\$196	\$1,070	\$634

* For all cases FIT and generation costs same as year k, lifetime of 20 years and FIT for 15 years. ** year k = connection year.
†Assuming spot electricity market price paid for last 5 years, after FIT is over.

(a) Portuguese wind generation costs (\$2005/MW), (b) cumulative private rents of Portuguese wind parks in 1992-2006 (\$2005) and (c) cumulative rents for all scenarios (ERSE, 2010; DGEG, 2010; DEA, 2011)

The same wind capacity additions could have been achieved with 25% less funding provided by the government (approximately \$180 millions).
Future work: comparison of wind FIT policy with other alternative policies (energy efficiency, mini-hydro and electric vehicles) that could have been established with the same funding that was provided to wind producers.

Modeling for Insight Using <u>T</u>ools for <u>E</u>nergy <u>M</u>odel <u>O</u>ptimization and <u>A</u>nalysis (Temoa)

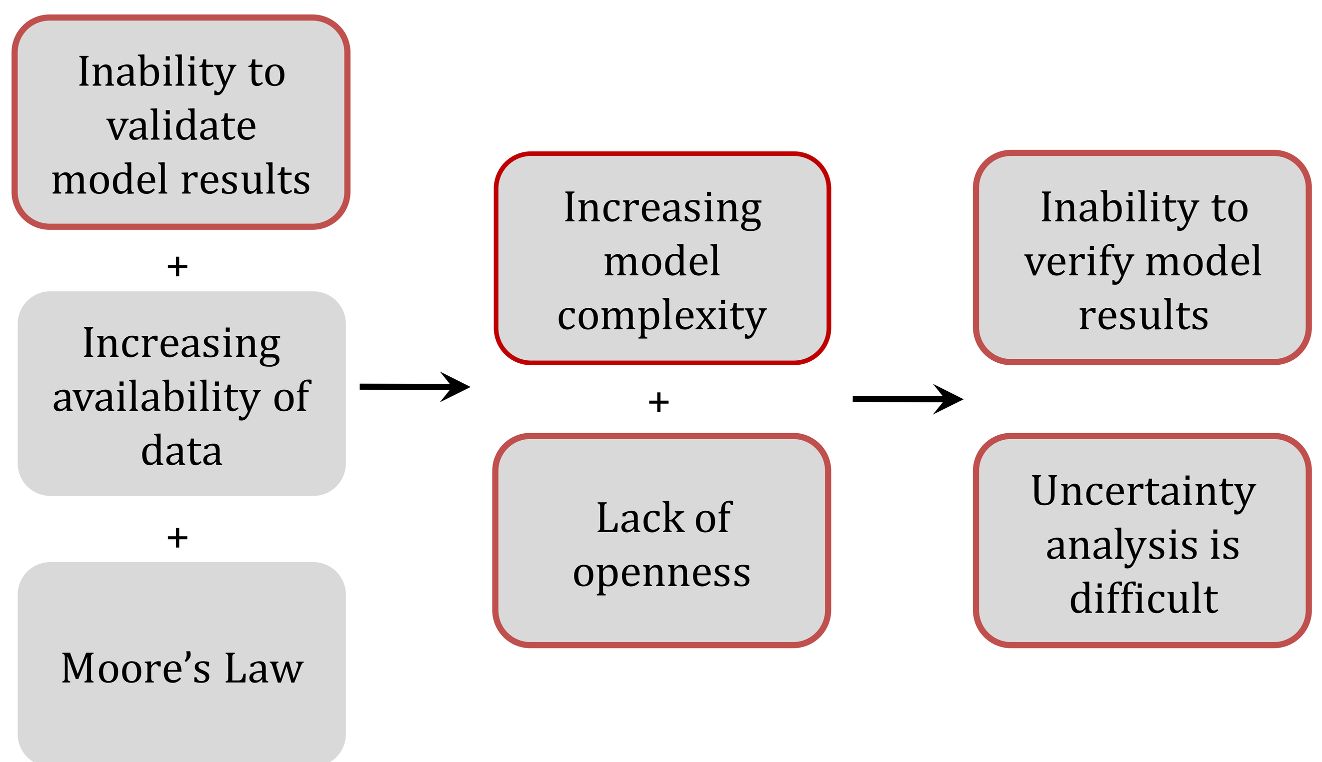
Joe DeCarolis (jdecarolis@ncsu.edu), Kevin Hunter, Sarat Sreepathi
Department of Civil, Construction, and Environmental Engineering, NC State University

Motivation

Energy economy optimization (EEO) models employ formal search techniques to explore the future decision space over several decades in order to deliver policy-relevant insights.

Such models have been used to produce **high visibility analysis** that informs energy and environmental policy at scales ranging from local to global.

However, there are **several problems** associated with the development and application of such models:



We are building **<u>T</u>ools for <u>E</u>nergy <u>M</u>odel <u>O</u>ptimization and <u>A</u>nalysis** (Temoa) to address these concerns.

Our approach involves :

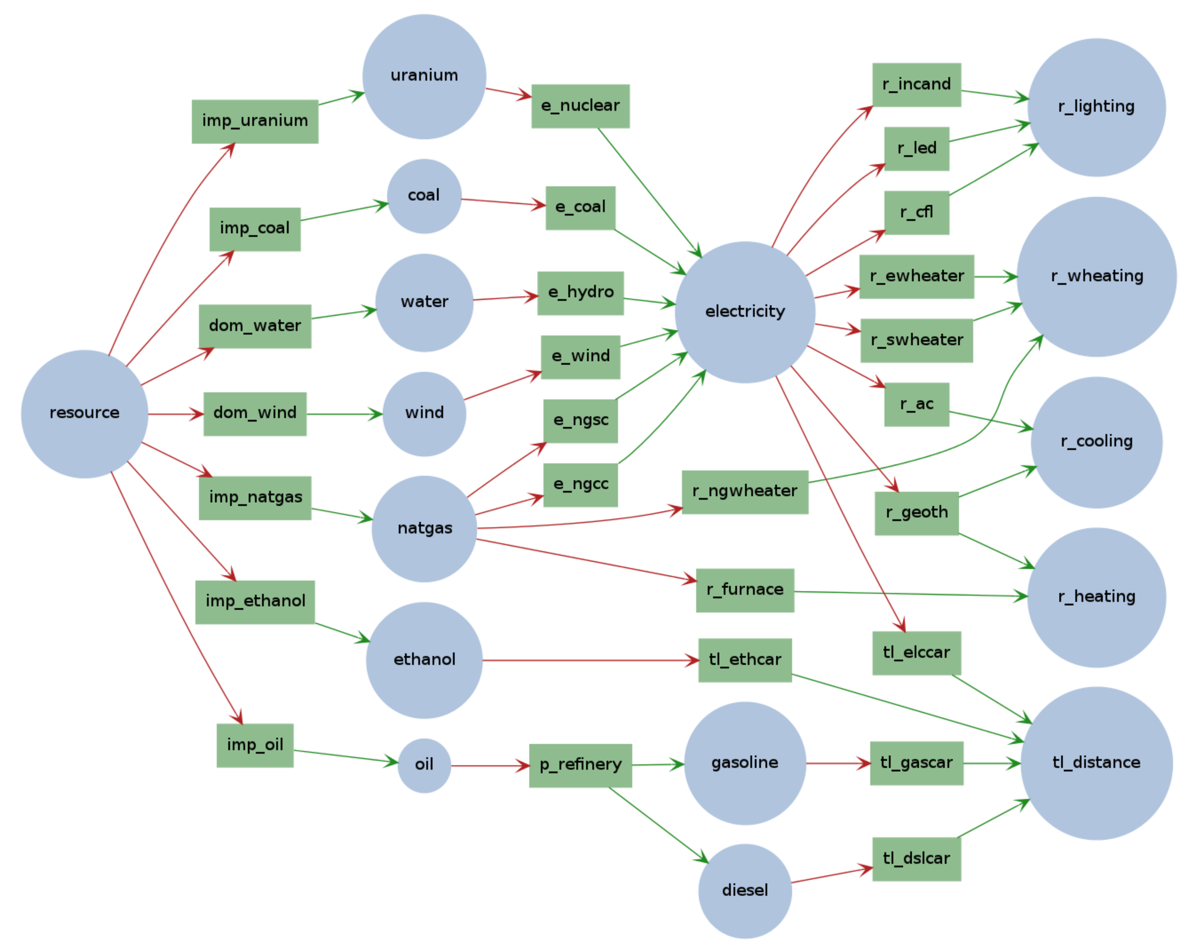
Making model-based analysis replicable with **public access to source code and data**

Building the Temoa framework to operate in a **high performance computing (HPC)** environment to enable rigorous uncertainty analysis.

Framework

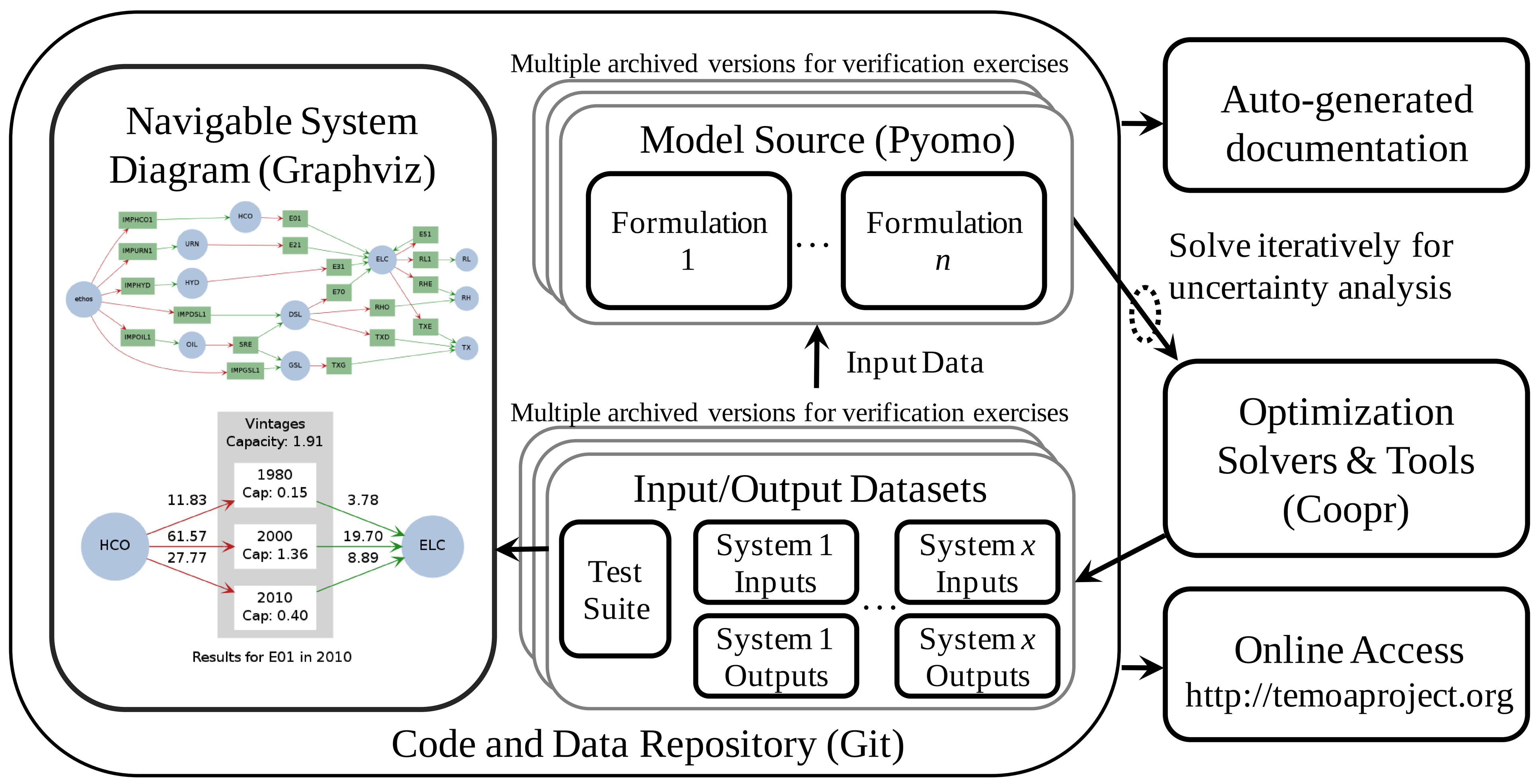
The core component of Temoa is an **open source EEO** model that:

- Utilizes **engineering / economic** parameters to represent energy technologies
- **Links energy technologies** together via commodity flows
- **Minimizes the cost** of energy supply
- Explores the decision space over a **multi-decade horizon**



The Temoa model is embedded in a larger framework, which utilizes an **open source software stack**:

- Built against Sandia's <u>Py</u>thon <u>O</u>ptimization <u>M</u>odeling <u>O</u>bjects (**Pyomo**), which enables algebraic model formulation
- Utilizes Sandia's **Coopr** package to link the model to solvers
- Employs **Git** to publicly archive source code and data
- Incorporates **Graphviz** to generate energy system network maps



Website: http://temoaproject.org

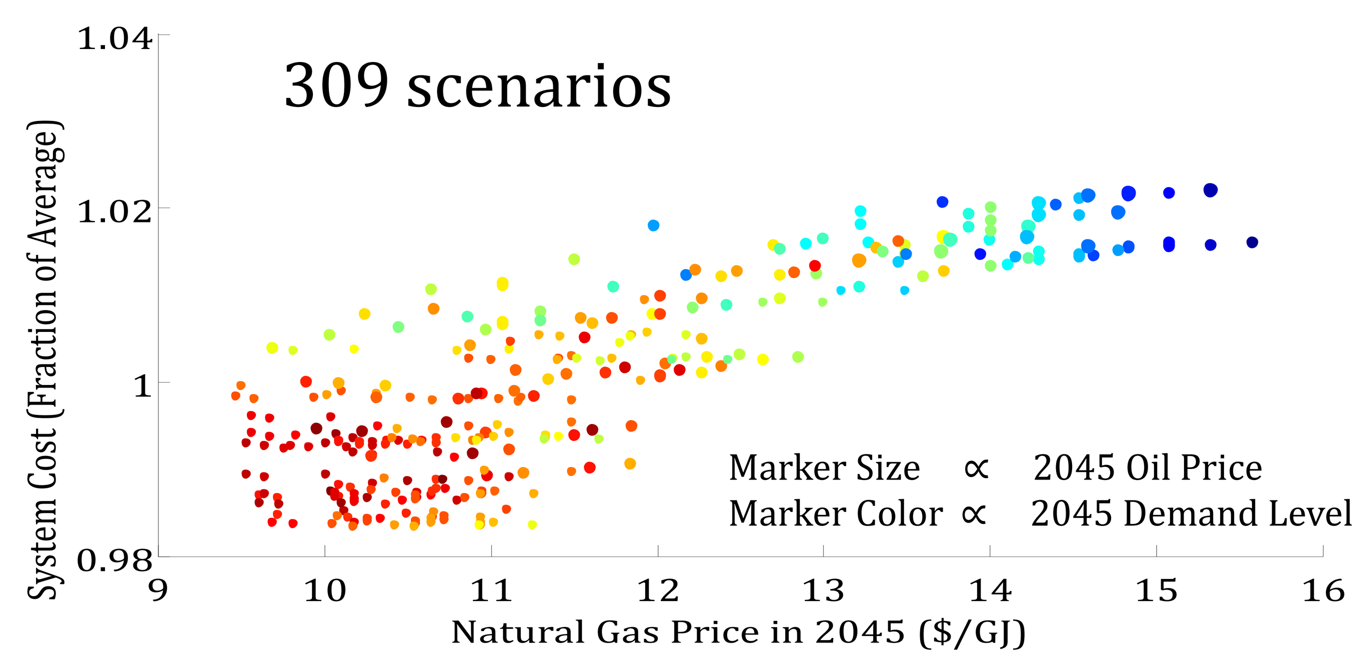
Analysis

Approaches to uncertainty analysis

- Quantify the effect of key inputs on outputs (**Monte Carlo simulation**)
- Develop hedging strategies that account for future uncertainty (**stochastic optimization**)
- Test the robustness of the hedging strategy (**modeling-to-generate alternatives**)

Sample application

- Treat crude oil, natural gas, and energy demand as stochastic parameters
- Calculate conditional probabilities based on historical 5-year moving averages, 1969-2010
- Build and run stochastic formulation using Sandia's Python-based Stochastic Programming (**PySP**)



Future Work

- Application to examine U.S. climate policy
- Relational database schema for I/O data
- Modeling-to-generate-alternatives
- Parallel implementation of PySP

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REGIONAL VARIATION IN POWER PLANT TURNOVER RESULTING FROM THE TIMING OF CLIMATE CHANGE POLICY

Catherine F. Izard,[1,2] Inês Lima Azevedo,[2] Constantine Samaras,[3] H. Scott Matthews,[1,2] and Chris T. Hendrickson[1]

[1] Dept. Civil & Environmental Engineering, Carnegie Mellon University; [2]Dept. Engineering & Public Policy, Carnegie Mellon University; [3]The RAND Corporation, Pittsburgh

MOTIVATION

Achieving significant emissions reductions of the electricity grid will require a radical change in the technology mix of the U.S. electricity sector (Johnson and Keith, 2004). The inertia in the electricity sector makes such rapid change difficult. Morgan et al. (2005) estimate that building an average of 25 GW of zero-carbon capacity a year between 2010-2050 can meet 100% of projected demand with carbon-free electricity. Given that the historical single-year maximum construction of carbon-free energy was 10GW (1986; primarily nuclear), this represents an enormous undertaking. Delaying the transition to low-carbon electricity compounds this problem: construction must proceed more rapidly in order to meet cumulative emissions targets. It has been suggested that as decarbonization is delayed the electricity sector is likely to build new carbon-intensive fossil fuel plants to meet demand, increasing the amount of capacity that must be replaced. A rapid increase in the rate of construction may lead to increased costs and/or short-term labor and material shortages. Delay also risks the forced early retirement of newly built plants (e.g. Morgan et al., 2005). If the delay in emissions reductions does cause new plants to be retired before their capital costs are recovered, it would drastically increase the cost of emissions reductions and create a significant stranded capital problem. The potential cost of either increased construction rates or the prospect of prematurely retired capital are likely to increase political opposition to climate change abatement policy. We investigate two questions: 1. How much extra capacity must be built as a result of delaying the imposition of emissions-reduction policy? and 2. Whether delay is likely to cause large numbers of newly built plants to be forced into early retirement.

METHODS

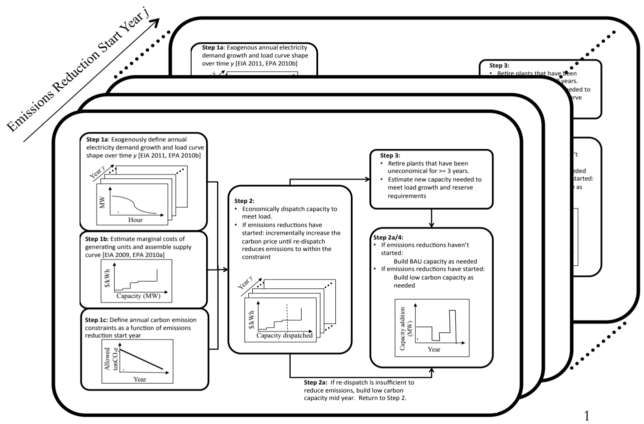


Fig. 1 shows our methodology for estimating capacity turnover resulting from climate change policy. We build a dispatch-based model of the electricity sector in each NERC region. Every year in the model period (2012-2050), the grid is constrained to meet both demand and an emissions cap (if an emissions reduction policy is in place). At the end of each year, plants that have had negative profits for two consecutive years are retired. New capacity (either low carbon or the business-as-usual (BAU), depending on whether emissions reductions have started yet) is then built to meet both projected new demand and a specified reserve margin. The emissions cap is calculated annually such that cumulative emissions over the period 2012-2050 are 20% less than BAU scenario. The model is iterated over every possible emissions reduction starting year between 2014-2050. Here we present preliminary results for emissions reduction scenarios of 20%, 30% and 40% below BAU for ERCOT (Texas) as well as nationwide results at a NERC region level for the 20% below BAU scenario. In all cases, new low carbon capacity construction is a mix of 50% wind and 50% nuclear.

RESULTS: ERCOT

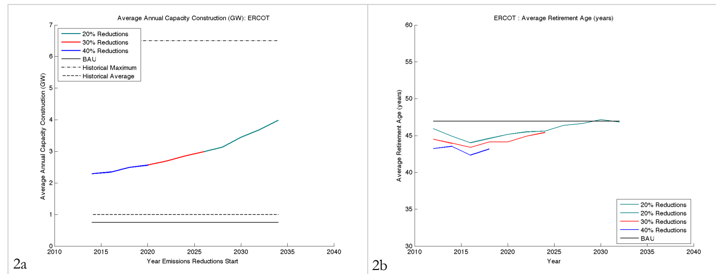
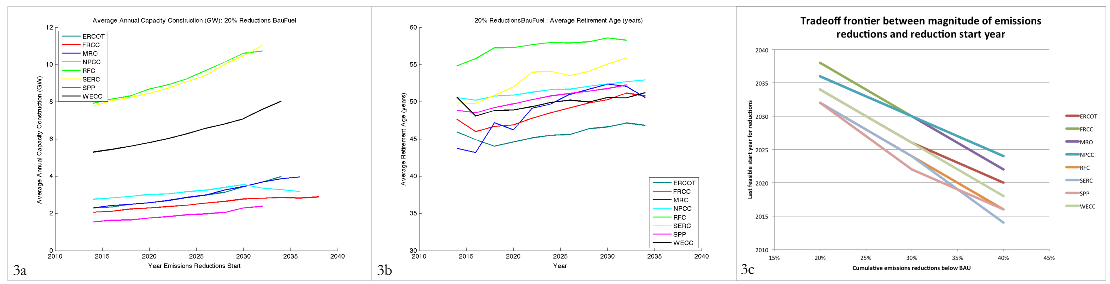


Fig. 2a shows the average annual new capacity construction in ERCOT after emissions reductions commence as a function of when emissions reductions begin, for emissions reduction scenarios of 20%, 30% and 40% below BAU. Waiting 20 years approximately doubles the rate of construction needed to meet reduction targets. All three scenarios have the same construction requirements; this is because the entire fossil fleet is replaced in all three scenarios. However, more aggressive scenarios become impossible to achieve at later starting dates.

Fig. 2b shows the average age of retired capacity after emissions reductions starts. All scenarios retire plants slightly younger than BAU, and aggressive emissions targets increase this effect. Delaying the implementation of climate change policy has little effect on the average age of retired plants

RESULTS: NATIONWIDE



Figs. 3a-3c show the effects of a 20% emissions reduction below BAU scenario for all eight NERC regions. Fig. 3a shows average annual construction rates after emissions reductions start as a function of when reductions start. The variation in the rate of new construction across regions is roughly proportional to the size of the regions. The penalty for waiting 20 years to start emissions reductions varies from 25-50%. Fig. 3b shows the average age of retired capacity in each region. The average retirement age varies by about 10 years across regions. Most regions see a slight increase—up to about 8 years (MRO)--in the age of retired capacity from waiting to begin emissions reductions. Fig. 3c shows the trade-off frontier between the aggressiveness of emissions reductions and delaying their implementation—the figure shows the point at which achieving the target becomes impossible without pulling carbon out of the air. There is about a 10 year difference across regions, with SERC needing to act the soonest and NPCC/FRCC able to delay the longest. Increasing the emissions reduction target to 40% requires starting 12-18 years earlier than a 20% reduction target.

CONCLUSIONS

Preliminary results suggest that for emissions reductions targets of 20% below BAU, waiting to implement reductions can increase the rate of capacity turnover in the electricity sector by 25-50%, depending on the region. Despite the increase in turnover, delaying the start of emissions reduction policy does not seem to cause large numbers of very young plant retirements. There is moderate regional variation in capacity turnover, mostly due to the characteristics (age and carbon intensity) of existing stock. Regional variation is the strongest when considering the last possible start date for emissions reductions, which vary by about 10 years. These results suggest that issues related to inter-regional equity should be considered when implementing a climate change mitigation policy.

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