Model B: Sizing a Storage System for a Wind Farm, A Pricing Approach
Eric Scott, Feb. 19, 2016

Problem

"A wind developer is selling its production directly into the ERCOT day-ahead energy market. Generation deviations greater than 2% from the forecast will be billed based on the real-time energy market price.
Using the forecast and generation data attached, propose the most optimal size of system and describe your approach to model the corresponding dispatch strategy for the battery."

This analysis continues from Model A, addressing the same problem but under a different method (read Model A first as it explains key information about the problem, the ERCOT market and the wind data). In the initial approach I assumed fixed prices for the day-ahead market price ($20/MWh) and real-time market price ($200/MWh for 'peak' hours, $20/MWh for 'off-peak' hours). I sized the battery system based on the statistical median of peak-time energy deficits. The result was a 16 MWh system (I did not look at power capacity). The model forecasted the wind farm developer could increase revenue by over 600% using energy storage.

Model B improves on Model A by bringing in a more robust financial analysis (with actual pricing data and an NPV analysis), and considering battery technical specifications in more detail.

Step 1: Bringing in the Pricing Data

In Model A I assumed the DAM and RTM pricing were fixed to simplify the approach. I started this revision by finding pricing data on the ERCOT website (http://www.ercot.com). The website is not the easiest to navigate, but I found the .csv files of interest:

1) 1-year historical day-ahead market pricing for 2014 (DAM)
2) 1-year historical real-time market prices for 2014 (RMT)
3) 1-year historical ancillary service market prices for 2014 (AS)

DAM Pricing

Found here:
http://mis.ercot.com/misapp/GetReports.do?reportTypeId=13060&reportTitle=Historical%20DAM%20Load%20Zone%20and%20Hub%20Prices&showHTMLView=&mimicKey

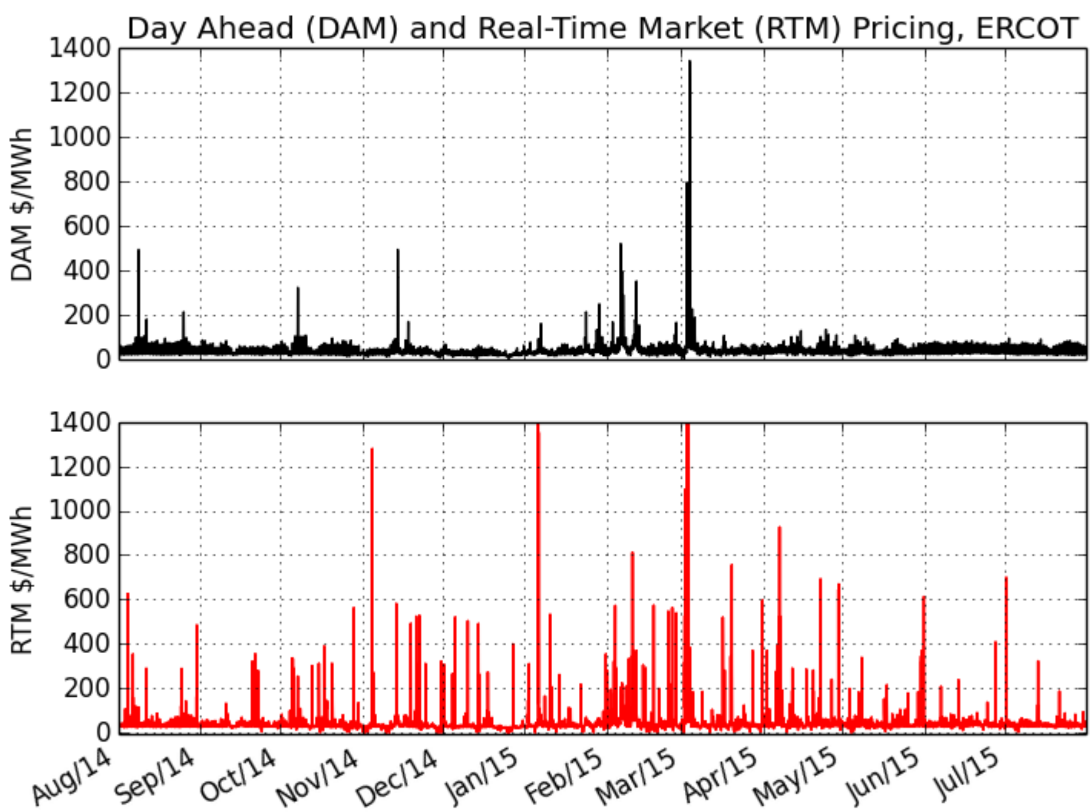
The day-ahead market pricing was taken hourly for different nodes on the ERCOT network. Because my wind data was every 15 minutes, I broke the hourly price into 15 minute intervals to match them. Also the DAM pricing data was for the year 2014, whereas my wind data was for August-2014 to July-2015. I rearranged the pricing data to match up with the wind data assuming the dates were the same (ex. May 2015 wind data matches with May 2014 pricing data). I had to manually combine several sheets of Excel data before I could read it into a pandas dataframe.

RTM Pricing

Found here:
http://mis.ercot.com/misapp/GetReports.do?reportTypeId=13061&reportTitle=Historical%20RTM%20Load%20Zone%20and%20Hub%20Prices&showHTMLView=&mimicKey

I used a similar technique to the DAM pricing data here. There were almost 1 million total values for real-time market pricing and I rearranged and averaged values to align the csv file with the wind data.

The following plow shows the DAM and RTM pricing over the period of interest after cleaning and rearranging:



AS Pricing

Found here:
http://mis.ercot.com/misapp/GetReports.do?reportTypeId=13091&reportTitle=Historical%20DAM%20Clearing%20Prices%20for%20Capacity&showHTMLView=&mimicKey

This ancillary service pricing data had information for 4 services:

1) Frequency up regulation
2) Frequency down regulation
3) Rapid responsive service
4) Non-spinning reserve

Again I re-arranged the values to align with the wind data. The following table shows a statistical summary of the pricing data for 2014 in ERCOT:

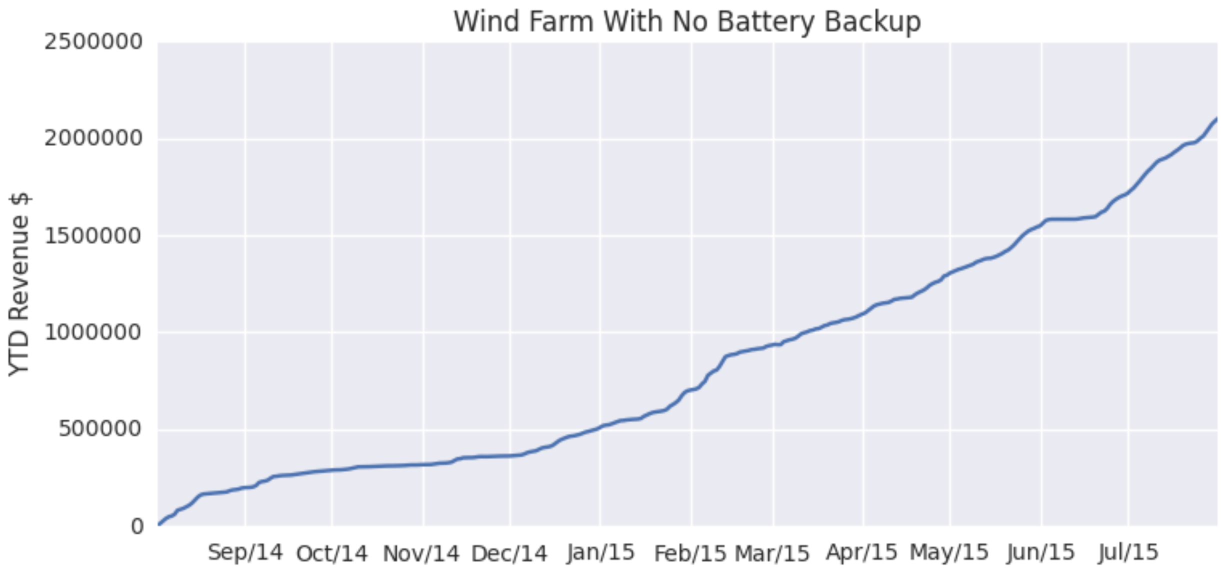
SERVICE:	DAM ($/MWh)	RTM ($/MWh)	REG DN ($/MW)	REG UP ($/MW)	RRS ($/MW)	NSPIN ($/MW)
Mean	39.06	36.49	9.77	12.48	14.15	5.47
Std:	34.58	76.64	13.23	61.94	31.82	14.02
Min:	5.02	-1.29	0.50	1.00	2.00	0.77
Max:	1342.00	4947.72	310	4999.00	1285.73	435.70

Step 2: Modeling Scenario I [No Battery]

After cleaning and combining the pricing data with the wind data, I revised the first algorithm I built in Model A (no battery backup). I used the same principle rule (sell/buy all deviations greater than +/-2% in the real-time market), but this time I had actual pricing data. Before showing the results, notice in the pricing table above the average prices for DAM and RTM (I was able to split the RTM price into peak and off-peak to find the averages listed in the table below). Comparing those averages with my assumed fixed prices in the original model it is clear that the estimated revenue of the wind farm is going to be a lot different with actual pricing data:

	ASSUMED ($/MWh)	ACTUAL ($/MWh)
DAM	20.00	39.06
RTM (peak, 7am-10pm)	200.00	41.61
RTM (off-peak, all other times)	20.00	27.56

In Model A Scenario I with the assumed prices, the wind farm generated $392,144 in revenue. By bringing in the actual pricing, over the entire year the wind farm actually generates $2,102,091 in revenue:



Of the $2.1 million in revenue, the wind farm developer ends up paying over $480,000 in charges due to energy deficits (actual generation less than forecasted). In other words, with a perfect forecast (assuming price deficits are eliminated) the developer would have made *at least* $2.58 million in revenue. Therefore they currently make at best 81% (2.1 million out of at least 2.58 million) of the wind farm's revenue potential due to poor forecasting.

Step 3: Modeling Scenario II [Battery for Energy Shifting]

Adding a battery to the algorithm, I'm interested in finding the return on investment. The energy shiftzs model assumes the wind farm developer will use a battery to store over-produced electricity during 'off-peak' hours, and use that stored energy to make up for under-generation during 'peak' time (7am-10pm). The battery allows energy generated to be 'shifted' from times of over-generation to under-generation and helps reduce RTM market pricing from deviations greater than 2%.

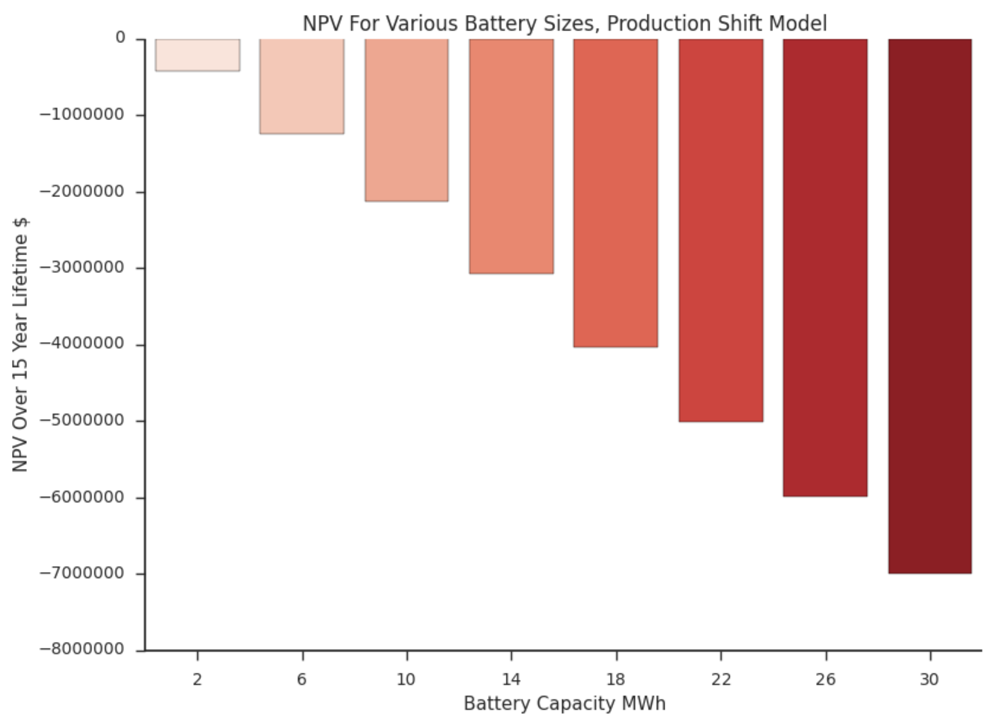
First though, I made a few technical assumptions about the battery:

- Lithium-ion Tesla Powerpack
- Round-trip efficiency of 92% (from Tesla Powerwall website)
    - The RT efficiency is applied once to all incoming energy
    - The RT efficiency is constant over the lifetime of the battery
- Bi-directional inverter efficiency of 95%
    - Applied once to all incoming energy
    - Is constant over the lifetime of the inverter
- Maximum charge of 100%
- Minimum depth of discharge of 80%
    - Corresponds to a minimum 20% state of charge
- Battery will be sized to meet the highest power transfer rate requirement

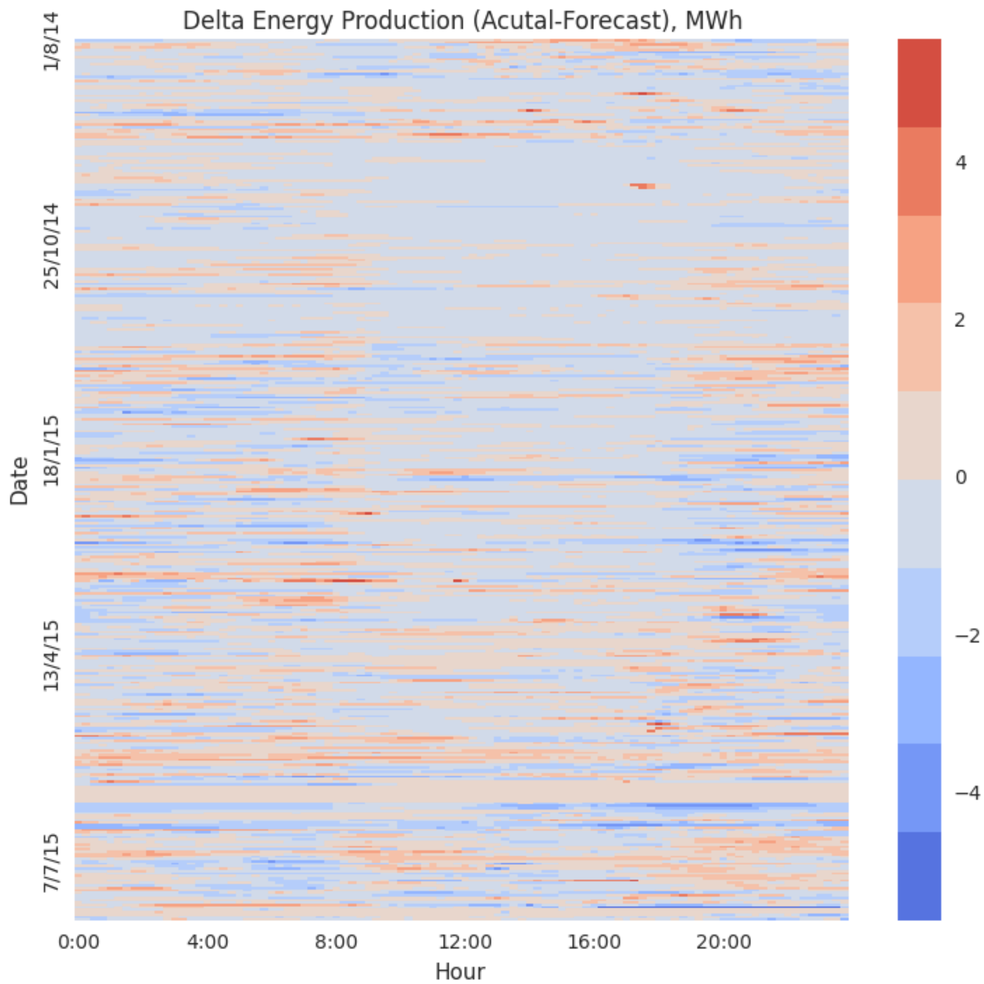
The algorithm for Scenario II calculates the annual revenue generated from the wind farm / battery system. I took this value and used it in a NPV analysis with the following assumptions:

- 10% discount rate
- One cycle per day
- No O&M costs
- No tax, no rebates, no depreciation, no salvage value
- $250/kWh of energy capacity (a very optimistic cost assumption)
- No price escalations or battery degradation (constant revenue over the lifetime)

I performed this analysis for a variety of battery energy capacities. The result below shows that there is no positive NPV scenario:



Essentially the cost of the battery is too high – even under an over-optimistic cost of $250/kWh and $0 installation / O&M costs – compared to the potential revenue increased from shifting energy production. A heatmap of the energy delta (forecast generation – actual generation) helps explain why:



The energy shift model relies on the *assumption* that there are certain *patterns* in our generation profile that are limiting the wind farm's revenue. One of those patterns I assumed is that we might tend to have a positive delta (over generation) in off-peak hours, and negative delta (under generation) during peak hours. The heatmap above shows no dominant pattern in the generation profile. Therefore the set 'control system' of charging with excess generation during off-peak and discharging with stored energy to meet under-generation during peak does not generate significant revenue on top of Scenario I.

Step 4: Modeling Scenario III [Batteries for Ancillary Services]

The final scenario uses a battery to bid power capacity into the ancillary service market as an additional revenue stream. We cannot bid into the market for all AS categories (there are four available) due to the technical constraints on the battery. To find the ideal AS categories, we are looking for two key features in the market:

1. Predictable
2. Financially attractive

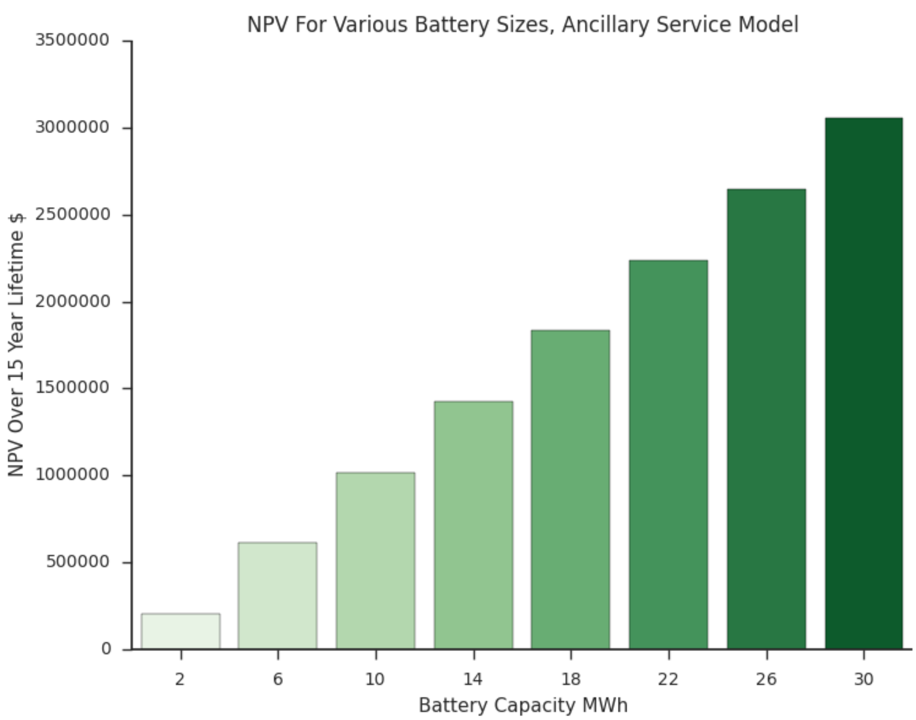
A heatmap does a good job at showing these features. The frequency up regulation market has consistency in the evening (16:00 to 20:00) of high prices (around $30/MWh) for the entire year:

The frequency down regulation shows some consistency in the morning for moderate prices:

The key here is that we can combine activity in the up and down regulation market to cycle the battery. We can bid into the down regulation market in the morning hours between 5:00am-7:00am, and bid into the up regulation market in the evening hours between 5:00pm-7:00pm. The two hours of down regulation ensure battery charging, whereas the two hours of up regulation ensure battery discharging.

In the final scenario we bid the battery capacity into the ancillary service market and combine the revenue streams with normal transactions from our wind farm. Although the battery and wind farm could share a common point of interconnection, in the algorithm I created they operate independently of one another; the wind farm sells electricity and the battery bids in power capacity. In other words, the wind farm's production does not impact the behavior of the battery system.

I updated the algorithm built in Scenario II to capture AS market revenue. I also updated the technical assumptions of the battery to set a C-rate of 0.5 (battery charges and discharges always at 50% of the rated capacity – two hours to full depletion). Keeping all the other technical and financial assumptions from before, I tested various sizes of energy storage capacity and output the revenue to the NPV analysis:



The NPV for this scenario is always positive and continues to grow as our system size increases. In other words, under the given assumptions of the model, we would max out the system size to capture as much additional revenue as possible – assuming we have access to financing for the upfront costs.

It is really important to note that the NPV analysis is very sensitive to the assumed cost per kWh of battery storage. I've assumed $250 which is a optimistic and reflects future prices and not the current situation. For any prices higher than about $350/kWh, the NPV is negative for all sizes in my model. On the other hand, some analysts predict that Tesla's Gigafactory will bring the price of battery storage to about $100/kWh.

Results of the Wind Farm Analysis

The key finding in Model B is that a battery used solely for energy shifting / arbitrage does not provide a positive financial return. In order to see a positive return on investment the developer must stack several services together to provide additional revenue streams.

Concluding, Model A used a purely statistical approach to size a battery. Model B incorporated market pricing, battery technical specifications and financial assumptions. Model B is a much better approach, and I would be more confident building off of Model B for a project proposal.

There are still many areas for improvement, particularly in the control system specifications and the ERCOT market rules. Market rules are extremely important for potential battery project developers. For example, the positive NPV shown in Scenario III relies on the assumption that ERCOT allows the type of ancillary service market participation I've modeled. Most likely there are rules for operation that need to be considered. I've also assumed that the battery can operate with the wholesale electricity market independently of the wind farm, this may not be the case.

As it stands the groundwork is all laid out in Model B, Scenario III to take this analysis to the next level. I've brought in, cleaned, and rearranged several datasets that feed into a rudimentary battery dispatch strategy. There are *three* clear next steps:

1. Research ERCOT market rules that might apply to this project and build them into the model
2. Research battery financial costs in greater detail (ex. installation, rebates, depreciation) and include them in the payback model
3. Build a cost function using the inputs in the algorithm and find an optimal battery size