Maximizing the Value of Storage in Real-time Operations

Physical

- Weather
- Load
- Renewables
- Spot Prices

Financial

- Retail Contracts
- Forwards
- Options
- Hedge Evaluation

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Outline of Presentation

Modeling Methods

- Logic Flow of Decision Analytic for Real-time operations
- DA Spike Probability Forecasting
- RT SOC and Dispatch Modeling

Modeling Results

- DA Forecaster Scoring
- RT Dispatch Bidding Rules
- Annual Revenue Estimates
- Monthly Revenue Estimates

Modeling Methods

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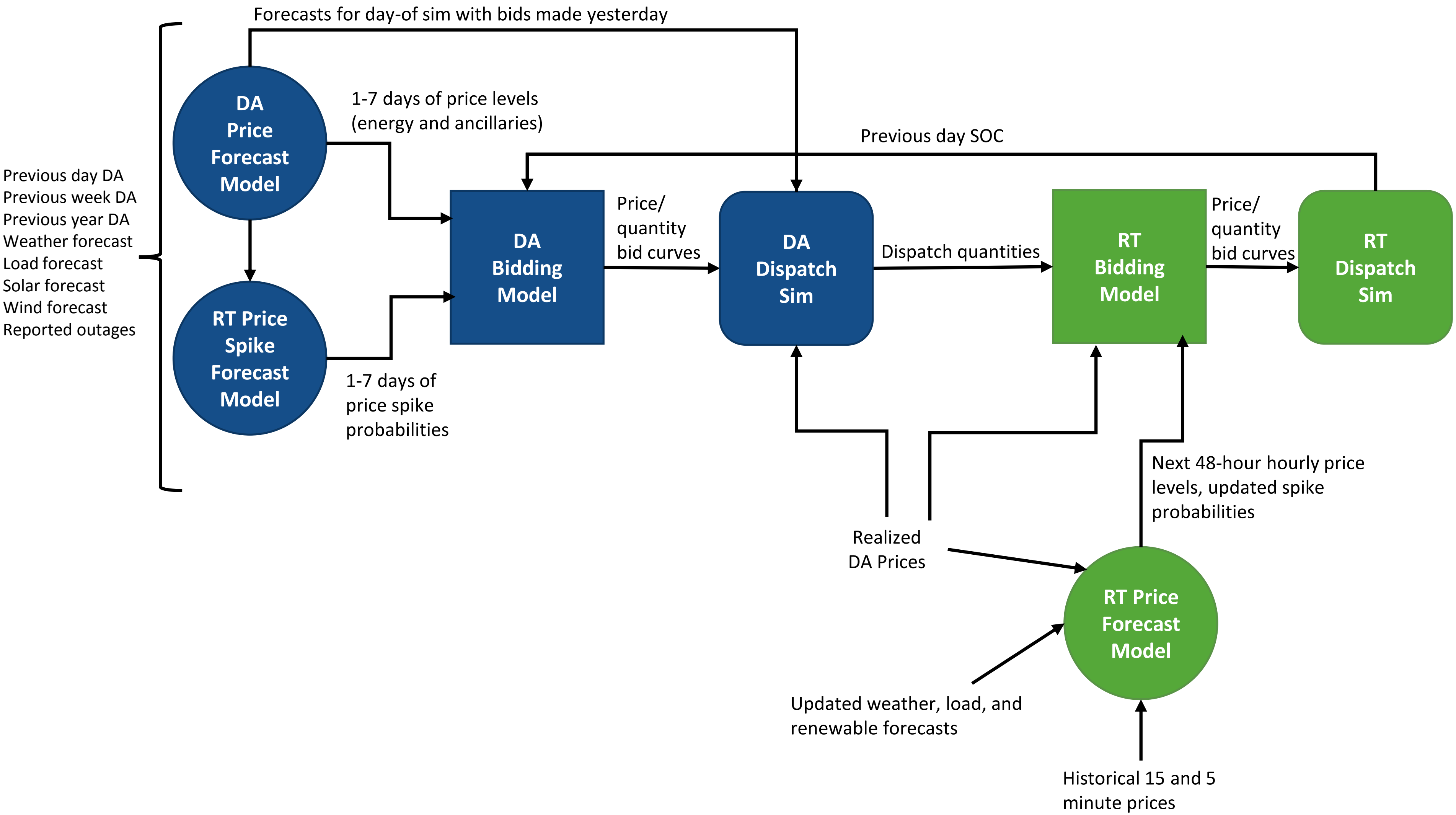
BatterySimm Ops
Backcast Evaluation Modeling Construct



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DA Forecasting

Objective

- Improve upon month hour based rules to provide spike probability forecasts unique to each day and each hour

Month	HE01	HE02	HE03	HE04	HE05	HE06	HE07	HE08	HE09	HE10	HE11	HE12	HE13	HE14	HE15	HE16	HE17	HE18	HE19	HE20	HE21	HE22	HE23	HE24
Jan	A	A	A	A	A	A	A	A	E	A	E	E	E	E	E	E	E	E	A	E	E	A	A	A
Feb	A	A	A	A	A	A	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	A
Mar	A	A	A	A	A	A	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	A	A
Apr	A	A	A	A	E	A	A	A	A	A	A	A	A	A	A	A	E	E	E	E	E	E	A	E
May	A	A	A	A	A	A	A	A	A	A	A	A	A	E	E	E	E	E	E	E	A	A	A	A
Jun	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	E	E	E	A	A	A	A
Jul	E	A	A	A	E	E	E	A	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E
Aug	A	A	A	A	A	E	A	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E	E
Sep	A	A	A	A	A	A	A	A	E	E	E	E	E	E	E	E	E	E	E	A	A	A	A	A
Oct	A	A	A	A	A	A	A	E	A	A	A	E	A	E	A	A	E	E	E	A	A	A	A	A
Nov	A	A	A	A	A	A	E	E	E	A	A	E	A	E	E	E	E	E	E	E	E	E	A	A
Dec	A	A	A	A	A	A	A	E	E	E	A	A	A	E	A	A	E	E	E	E	E	E	E	A

Methods

- Machine Learning Model that is trained on the following features:
  - Weather Forecasts
  - Recent Historical Pricing Trends
  - Market Forecasts (Load, Generation and Outage)
  - Proprietary Pre-Processed Features

Bidding

Day-ahead

- Develop a bidding algorithm that balances the need to maintain SOC with the desire to spend the maximum amount of time selling energy/ancillary services, while also minimizing the costs to purchase energy and maximize the revenues from energy sales.

$$\max \sum_{t \in dau} \mathrm{E}\left[spikeLevel_t\right] * spikeProbability_t * \mathrm{X}_t^{EnergyBidQ} + \mathrm{X}_t^{RegulationBidQ} * \mathrm{E}\left[regPrice_t\right] + E[purchasedEnergyCost]$$

S.T.

$$\mathrm{X}_t^{EnergyBidQ} + \mathrm{X}_t^{RegulationBidQ} \leq MaxPower$$

$$MinSOC \leq \mathrm{X}_t^{SOC} \leq MaxSOC$$

Real-time

- Based on historical data we train models to optimize their performance in the RT Market
  - When offering into the RT Energy Market, Bid Levels are defined as a function of SOC going into the operating hour, the hour of day and the day of year.
  - Buy and sell offer curves share the same relationship with hour of day and day of year, however, to maintain the buy bid being always lower than the sell bid, we optimize separate functions for the SOC dependency.

$$Buy\ Bid = f_1^{buy}(SOC) + f_2(hour\ of\ day) + f_3\ (day\ of\ year)$$

$$Sell\ Bid = f_1^{sell}(SOC) + f_2(hour\ of\ day) + f_3\ (day\ of\ year)$$

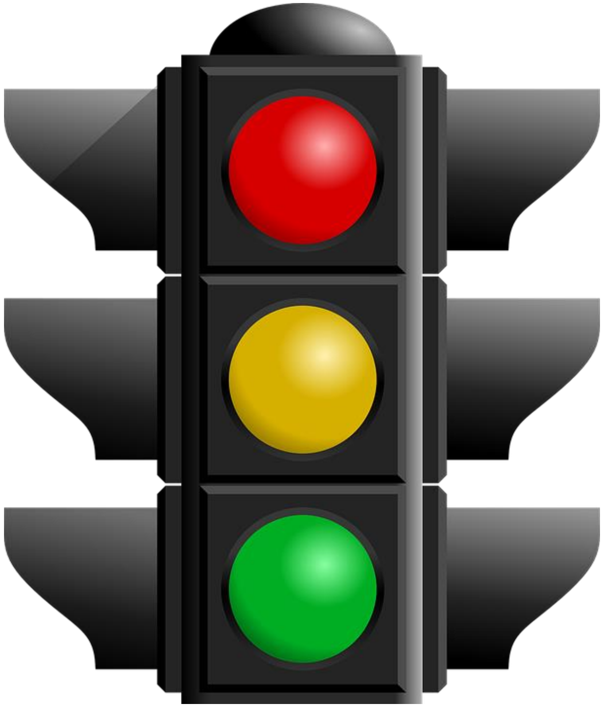
Decisions from Spike Probability

$P_i(spike \geq 100) = \ .05$

$P_i(spike \geq 500) = \ .001$

$P_i(spike \geq 100) = \ .24$

$P_i(spike \geq 500) = \ .04$



Stick with ancillaries

Go for RT energy!

Forecasting Price Spikes

Objective

- Determine profit maximizing offer of day-ahead offer for energy or ancillaries
  - Day-ahead regulation can be a firm commitment depending on ISO
  - Day ahead commitment precludes realization of real-time price spikes
- Squeeze data to best predict potential for price spikes

Absolute Value vs Probabilistic Value

- Forecasting absolute prices on five-minute intervals in both day-ahead and hour-ahead markets:
  - Mis-specifies the model to the decision analytic. Decision is to maximize expected returns
  - Absolute price forecast leave has significantly less predictive power than probabilistic forecasting. Loss of predictive information.
  - Forecast the probability of spikes best addresses binary offer decision: a) regulation or b) reserve for real-time market

Price Spike Process

- $y_i = \widehat{P}_i = \frac{r_i}{n_i} = X_i'\beta + e$, where "r" is price spikes, and "n" = time periods
  - Price spikes are a function of regressors "X" and error term "e"
- $P\{Price\ Spike\} = X_i'\beta$ (linear regression)
  - Using a Linear probability model: $E[y_i] = P_i$
- $Var[e_i] = \frac{P_i(1-P_i)}{n}$
  - The variance of the error term is a function of the probability of price spikes and the number of time periods

Estimating Price Spikes

- Logistic function:

$$f(\theta) = \frac{e^{\theta}}{1+e^{\theta}}, \text{ where } -\infty < \theta < \infty, \text{ and } 0 < f(\theta) < 1$$

- Logistic function is easy to use due to having a closed form

$$P_i = \frac{1}{1+e^{-I_i}} \text{ for } I_i = X_i'\beta \qquad \frac{P_i}{1-P_i} = e^{I_i} \text{ where } -\infty < I_i < \infty$$

$$\boldsymbol{y_i = ln\left[\frac{P_i}{1-P_i}\right] = X'\beta + e_i^*} \qquad \ln\left[\frac{P_i}{1-P_i}\right] = I_i = X_i'\beta$$

$$\boldsymbol{y_i = X_i'\beta + \frac{e_i}{P_i(1 - P_{i)}}}$$

- Price spikes are estimated through the following three step procedure, using the above equations for step 1

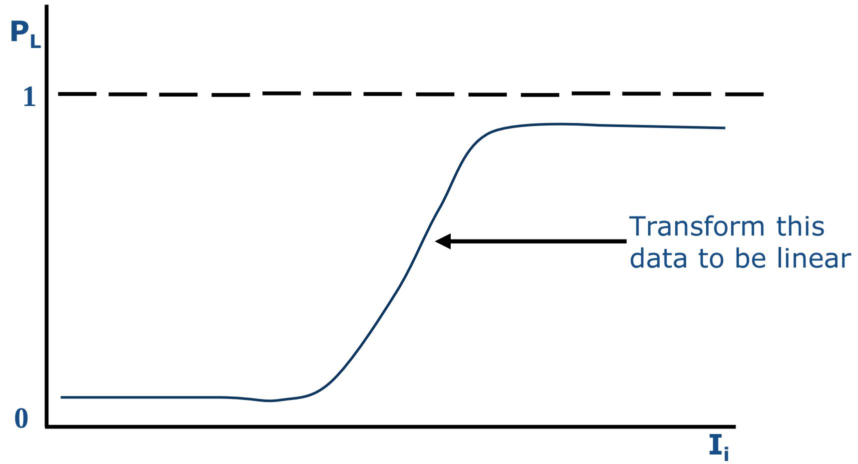
Three step process

1. Run OLS, despite heteroskedasticity, to obtain $\widehat{P_i}$ estimates
2. Predict $\widehat{P_i} \rightarrow \widehat{\widehat{P_i}}$
3. Plug $\widehat{\widehat{P_i}}$ into Var$[e_i]$ to preform Feasible Generalized Least Squares Estimation

Log Likelihood Function

$$L = \prod_{i=1} \frac{e^{X_i\beta}}{1+e^{X_i\beta}} \prod_{j=1} \frac{1}{1+e^{X_i\beta}},$$

Where 'i' = spike & 'j' = no spike



- Likelihood function describes the probability of a price spike as a function of I_i

Modeling Results

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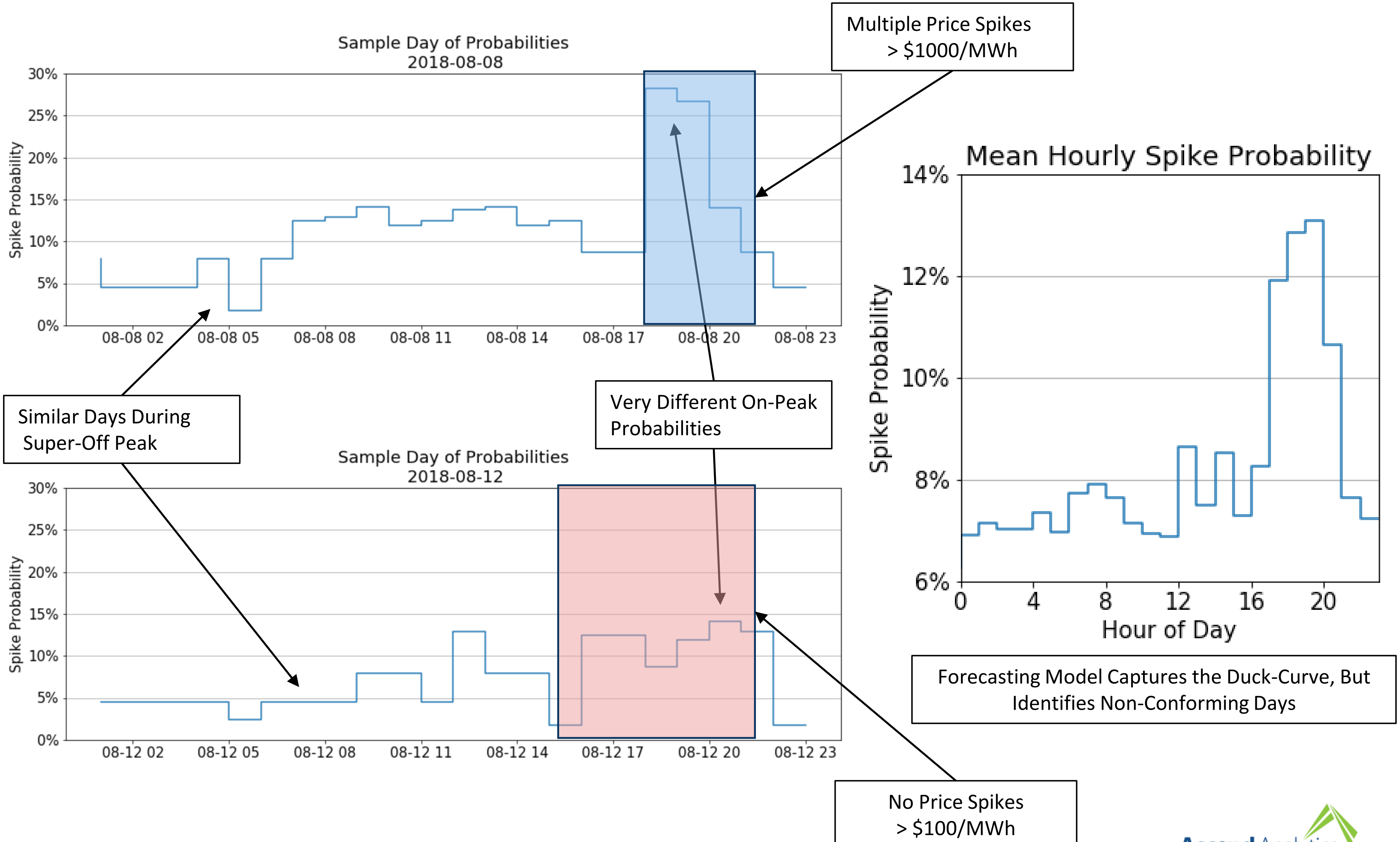
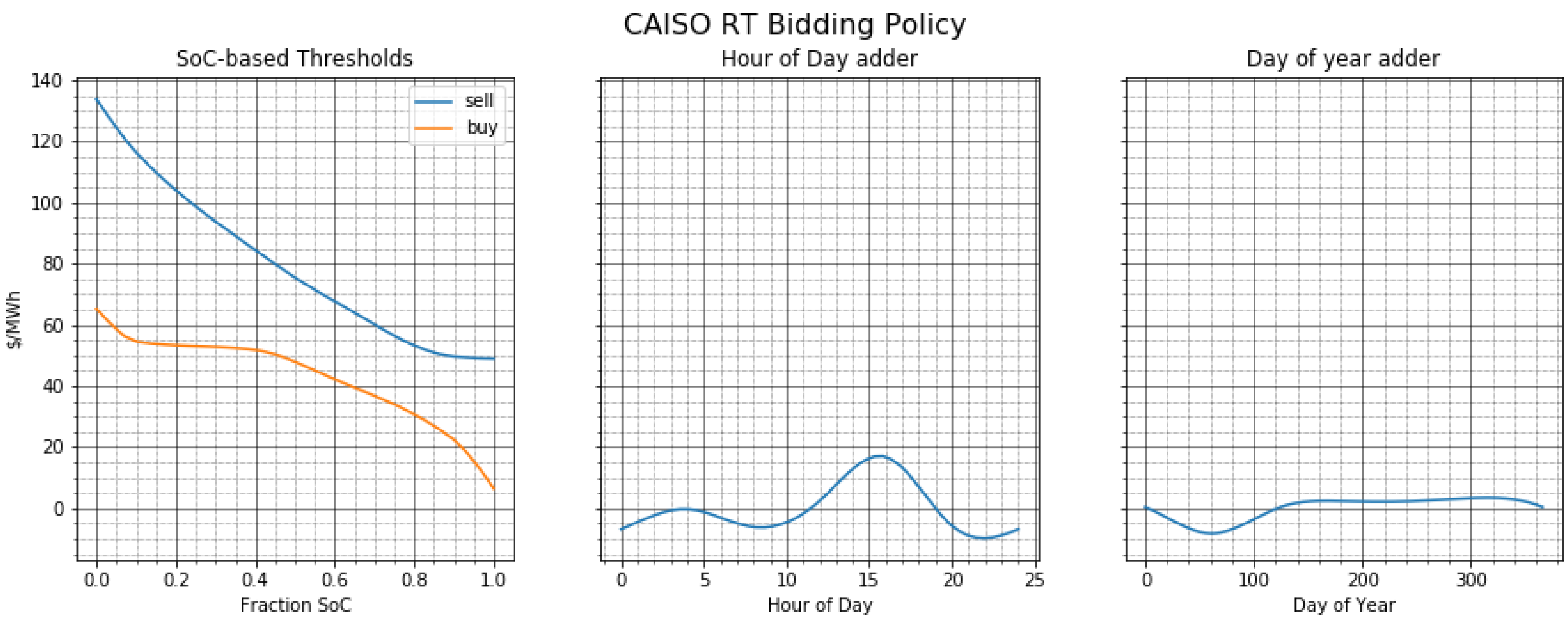


Bidding Level Optimization

Observations

- Bidding levels for buy and sell are a strong function of the SOC of the battery system
- The optimal hour of day adder follows the “Duck Curve” shape that we would expected
- Day of year is only a significant adder during late Winter/early Spring



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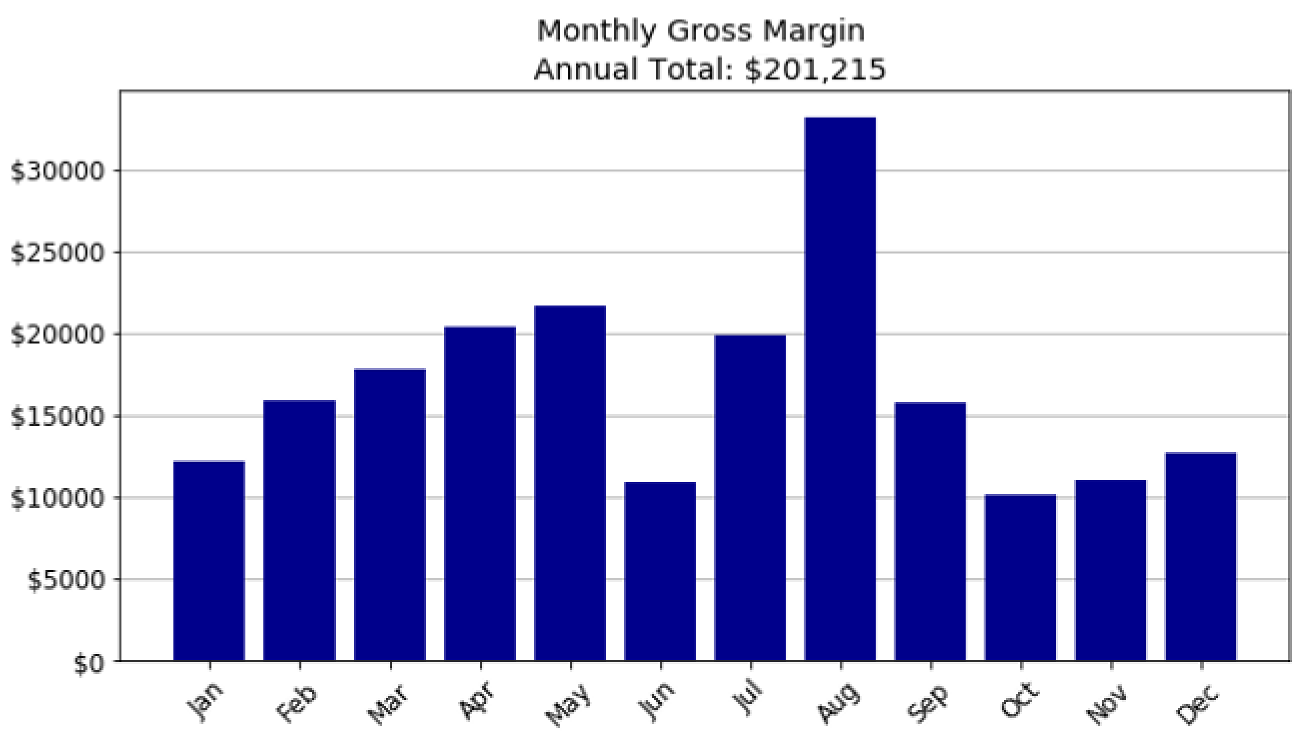
Revenue Results

4 Hour Battery Revenue per KW - 2018				
Model	BatterySimm Valuation w/ Rules	BatterySimm Ops w/ Live Bidding	BatterySimm Ops w/ Live Bidding & Reg Overrides	BatterySimm Valuation w/ Perfect Foresight
Annual Gross Margin	$196 per KW	$201 per KW	$208 per KW	$279 per KW



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