Behind-the-Meter (BTM) Solar PV Forecast Allocation: Insights and Lessons Learned

May 2, 2018

BTM PV Lessons Learned: Overview

- Last year's forecast allocation employed regression analysis to fit a Bass S-curve to cumulative adoption data, using a closed-form formula-based approach
- An Electric Program Investment Charge (EPIC)-funded demonstration project administered by SDG&E explored advanced modeling & analytic approaches to solar PV forecast allocation[1,2]
  - Bass diffusion[3] in System Dynamics (SD)[4] construct
  - Machine learning for correlating customer attributes with PV adoption
- Relative to prior forecast allocation efforts, the demonstration project yielded a number of insights & lessons learned which are described in this presentation.

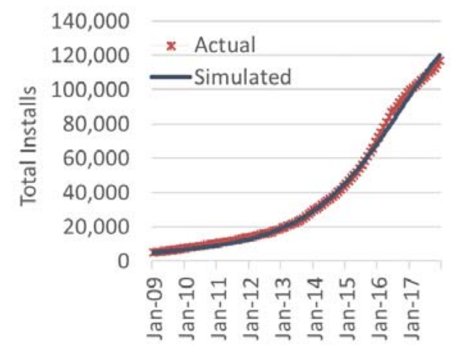
1. Demonstration of Methodology and Tools for Estimating Propensity for Customer Adoption of Photovoltaics. December 31, 2017. EPIC-2, Project 6.
2. See SDG&E presentation in the April 18, 2018 Distribution Forecasting Working Group meeting for additional detail regarding the modeling methodology.
3. Bass, F. (1969). A New Product Growth for Model Consumer Durables. Management Science, 15(5), 215-227. Retrieved from http://www.jstor.org/stable/2628128
4. Sterman. J (2000). "Business Dynamics: Systems Thinking and Modeling for a Complex World." McGraw-Hill. New York, NY.

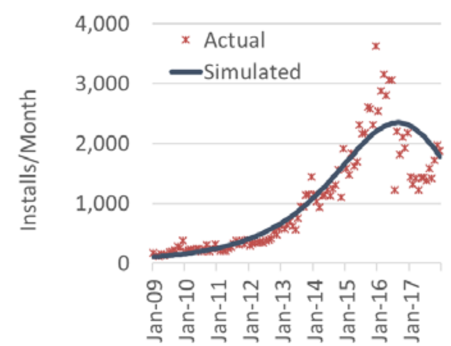
BTM PV: Lessons Learned

Lessons Learned

- Bass diffusion SD modeling approach seems to fit historical data reasonably well
  - Allowing “q” parameter to grow over time gives a better fit than using static parameter
  - Incorporating both incremental and cumulative adoption into the parameter optimization improves the fit
  - Monthly data can provide more information than annual data when change is rapid
- Incremental monthly adoption has trended downward since December 2015 peak
  - Though external forces are at play (e.g., NEM 2.0, weather, etc.), the dynamics of S-curve adoption posited by the Bass model may also be a key driver of this downturn.
  - Dynamic modeling techniques are well-suited to helping understand this phenomenon, though uncertainty still exists

Residential Installs (SDG&E – through 2017)



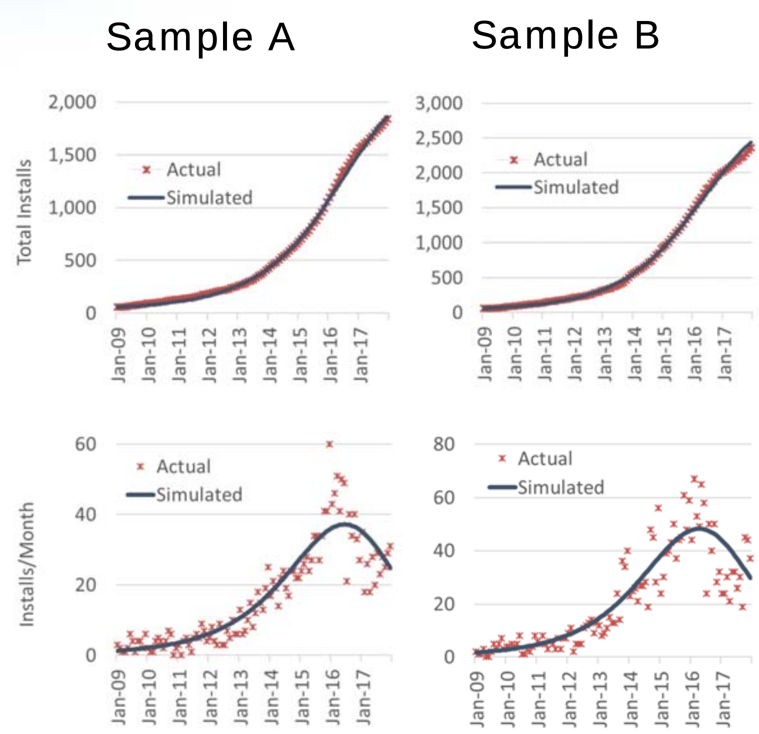


BTM PV: Lessons Learned

Lessons Learned

- Parameter fitting at the ZIP code level appears to be reasonable in many cases
  - System-wide “p” and “q” Bass coefficients tended to work well in conjunction with ZIP-code-level long-run market share parameters
  - Incremental adoption data tend to be noisier at lower adoption levels for any given ZIP code
  - Since there are ~10 times as many circuits as ZIP codes, circuit-level data are far noisier and typically inappropriate for parameter-level estimation (allocation approaches required)
  - For ZIP Codes with very low adoption, aggregation schemes (e.g., multiple ZIP codes) or use of “default” parameters may be more appropriate
- Uncertainty for DERs early on the adoption curve (e.g., EVs) is likely greater than for DERs that are further along (e.g., solar PV)

Residential Solar PV Installs for Illustrative ZIP Codes



Source: Lumidyne

BTM PV: Lessons Learned

Lessons Learned

- Retrofit and new construction markets have very different dynamics
  - Retrofit market is slowing, new construction market is growing (e.g., <1% of new homes in 2007 vs ~ 20% in 2017 – statewide)
  - CA DG Stats database does not distinguish between the two in its reporting, so …
  - A robust model should be able to aggregate both markets for purposes of parameter estimation, while segmenting them in the model to permit modeling changes to each market independently (e.g., due to SB 350, ZNE initiatives)

Lessons Learned

- Top attributes (at ZIP code level) that correlate* with PV adoption (from machine learning analysis)[1]
  - Average credit inquiries last 12 months
  - NWS Climate zone
  - % of households that are married families
  - Average balance on an open auto loan and lease trades reported in the last 6 months
  - Average household size
  - Percentage of owner-occupied housing units

* Correlation and causation are not differentiated in this analysis. Credit inquiries, for instance, are correlated, but not likely a driver of PV adoption, since PV owners are likely to have had a credit inquiry in the recent past to qualify.

1. Source: Demonstration of Methodology and Tools for Estimating Propensity for Customer Adoption of Photovoltaics. December 31, 2017. EPIC-2, Project 6.

PG&E Photovoltaics

Key Uncertainties

1. Heterogeneous zip codes not well represented by census averages
2. Customer characteristics not represented in non-res technical potential estimate
3. Propensity/regression models may have bias to early adopters

Lessons Learned

1. Model customers individually if possible, watch for lumpy adopt.
2. Continued need for insight into PV generation profiles

Proposed Improvements

1. Test using customer-level propensity modeling for Allocation
   - Develop propensity-to-adopt ML models by customer class
   - Test aggregation methods to minimize "lumpiness"
     - E.g. "expected value" approach
2. Use parallel development process
   - Run both old and new models in parallel for upcoming planning cycle
   - Compare both modeling results to understand drivers of differences and whether there are lessons learned
   - Understand impact of both approaches from planning perspective
3. Long term:
   - Work with CEC to share lessons learned and improve system level allocation
   - Work with PV providers to get more insight into PV generation profiles
   - Leverage EPIC research funding to improve forecast allocations statewide

SCE: Solar Photovoltaics

Key Uncertainties

1. Rapidly changing policy/economic landscape (NEM, Trump Tariff, etc.)
2. Customer Behavior
3. Data availability and quality

Lessons Learned

- Model performance may vary by climate zone
- "Lumpy" adoption at circuit level

Proposed Improvements

1. Rapidly changing policy/economic landscape
   - Continue to reflect latest economic and demographic changes via annual model refresh
   - Develop AAPV allocation method to account for ZNE impact

2. Customer Behavior
   - Explore improvements to clustering methods
     - Test climate zones as natural clusters (vs. k-means clustering)
     - Test improvements by weighting clustering factors

3. Model Input Data
   - Refine market potential analysis at each zip code