Distribution Forecasting Working Group

Electric Vehicle Uncertainty and Proposals to Improve DER Methods

Meeting 2: May 2, 2018

Electric Vehicles
(Allocation Model Overview)

Suppliers

Inputs

- Demographic and Socio-Economic Data was obtained from the American Community Survey (ACS)
- EV historical adoption data (POLK) at ZIP Code level provided by EPRI for SCE territory
- Map of ZIP Codes to circuits within SCE provided by SCE's Geospatial Analysis team
- Clean Vehicle Rebate Project (CVRP) consumer survey results provided by Center for Sustainable Energy

Process

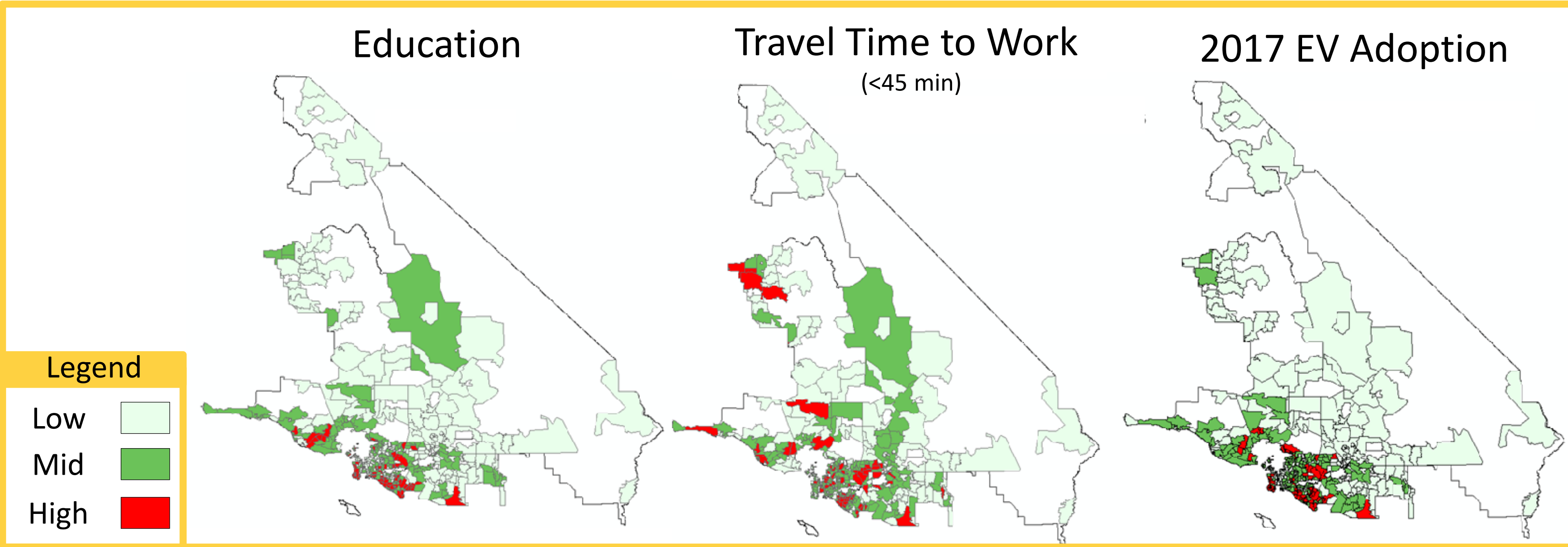
1. Identify key indicators of adoption
   - Perform Regression analysis to assess the correlation between the potential propensity indicators (ACS) and EV adoption (EPRI)
     - ➢ Education↑(Bachelor's Degree or Higher) & travel time to work↓(45 minutes to work)
     - ➢ Results compared to CVRP*
2. Score each ZIP Code
   - Utilize regression results to determine weights for each propensity indicator
   - Calculate EV potential based on Propensity Indicators and convert to % for each ZIP Code
3. Allocate IEPR forecast to ZIP Code based on relative ZIP Code propensity
4. Allocate ZIP Code forecast to circuit using electrical hierarchy and GIS

* According to CVRP survey 83 percent of EV adopters have Bachelor's Degree or Higher.

Electric Vehicles
(Key Indicator Identification)

Allocation Model Step 1: Identify key indicators of adoption via regression

- Bachelor's Degree or Higher (Education)
- 45 minutes or longer (Travel Time to Work)

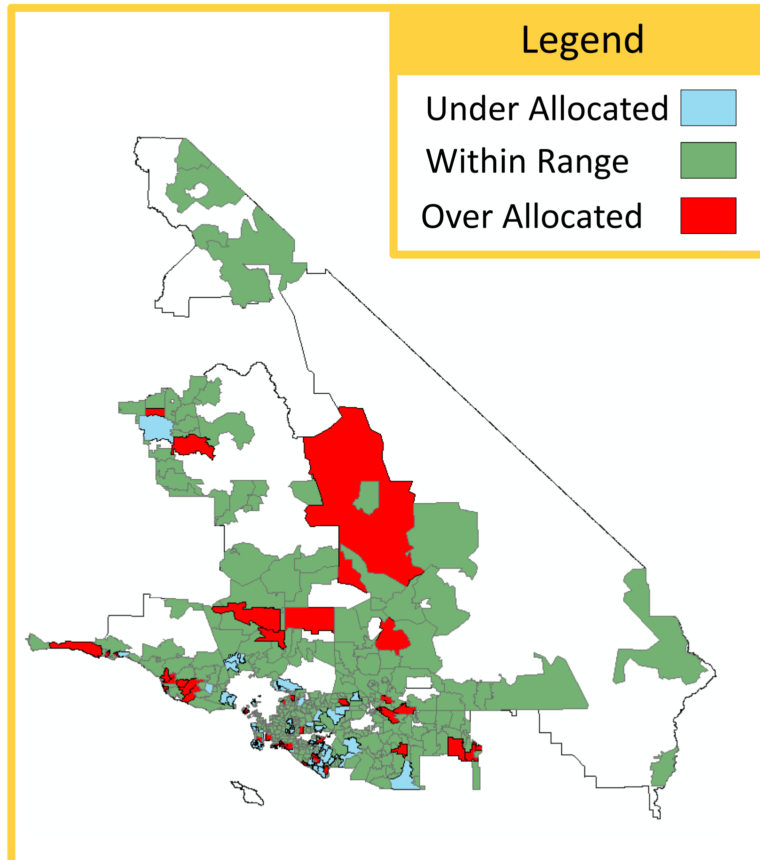


- CVRP survey results validated statistically significant indicators of adoption

Electric Vehicles
(Allocation Evaluation)

<u>Allocation Model Steps 2-4:</u> Score each ZIP Code and allocate to ZIP Code and circuit

- Map shows the error of allocation of IEPR EV forecast for each Zip Code
- Testing revealed outliers in adoption
- Results are informative but robust model evaluation requires testing over several years of adoption



Electric Vehicles

(Outliers)

- Other indicators may provide additional explanatory power for outliers.

Zip Code A: Example of Under-allocation

ZIP Code Potential:

- Household Size: 16K

Key Indicators:

- Bachelors Degree or Higher: 71%
- Travel Time to Work (> 45 min): 16%

Other Indicators:

- **Income over 100k: 50%**
- Home Ownership:61%
- Detached House: 54%

Zip Code B: Example of Over-allocation

ZIP Code Potential:

- Household Size: 13K

Key Indicators:

- Bachelors Degree or Higher: 75%
- Travel Time to Work (> 45 min): 18%

Other Indicators:

- Income over 100k: 41%
- Home Ownership:22%
- **Detached House: 9%**

SCE - Electric Vehicles
(Summary)

Key Uncertainties

1. Location of EV Customers
2. Driving and Charging Patterns

Lessons Learned

- Additional data would support addressing outliers observed in 2017 actual adoption

Proposed Improvements

1. Location of EV Customers
   - Obtain additional adoption data (DMV data with vehicle locations)
   - Perform analysis on SCE's Clean Fuel Rewards Program applications (Around 30 percent of EV Adoption)
   - Investigate indicators for the EV adoption Statewide
2. Driving and Charging Patterns
   - Perform analysis on CEC's 2016 California Vehicle Survey and 2017 National Household Travel Survey – California Add-On*
   - Reflect Changing adoption rates over the 10 year panning horizon

*Transportation Secure Data Center." (2017). National Renewable Energy Laboratory. Accessed April. 29, 2018: www.nrel.gov/tsdc.

PGE - Electric Vehicles

Key Uncertainties

1. Location of most EV customers unknown
2. Driving & charging patterns unknown
3. Propensity/regression models may have bias to early adopters

Lessons Learned

1. Critical need for insight into EV charging profiles
2. EPIC load disaggregation project showed large type I/II errors, so need to find better method for ID customers

Proposed Improvements

1. Locate more customers though better aggregation of non-AMI data to identify EV customers
   - Cross reference EV-rate customers, Clean Fuel Rebate, CVRP, EPRI, other datasets to build more complete map of EV customers
2. Improve Test using customer-level propensity modeling for Allocation
   - Test propensity-to-adopt ML models by customer class
   - Test aggregation methods to minimize "lumpiness"
3. Long term:
   - Develop better training algorithms to detect charging behavior
   - Consider developing a 'charger forecast' system-level forecast rather than an EV forecast
     - Chargers are stationary and meter could be isolated
   - Leverage EPIC research funding to improve forecast allocations statewide

Electric Vehicles

Key Uncertainties

- Lack of geospatial and time-series based data
- Commercial and workplace adoption of charging stations will be "lumpy"

Lessons Learned

- DMV registration data might become available
- Fast charging stations could significantly impact site specific loading

Proposed Improvements

- Co-ordinate with known commercial and workplace charging station projects
- Work with CEC and/or DMV to obtain more comprehensive adoption data
- Identify key adoption indicators
- Apply Bass diffusion/system dynamic model for residential home charging