

EPRI's 'HotSpotter' Tool: Identifying Potential Utility System Overloads in a Growing EV Market

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Summary

The current wave of Plug-In Electric Vehicles (PEVs) entered the market in late 2010. As of February 2016 there were 24 models of PEVs on the market and cumulative sales in the U.S. reached over 400,000 vehicles. Between the rapid pace of PEV technology development and concerns about global warming, the market for EVs is expected to continue expanding and diversifying, even though current low gasoline prices may affect growth rates.

Typical residential charge rates vary from as low as 1.4 kW for Level 1 (120V) to as high as 19.2 kW for Level 2 (240V). Battery capacities vary from a low of 5 kWh to a high of 90 kWh with a range upwards of 270 miles. Battery prices fell 35 percent last year and are on a trajectory to make unsubsidized electric vehicles as affordable as their gasoline counterparts in the next six years, according to a new analysis of the electric-vehicle market by Bloomberg New Energy Finance (BNEF). That will be the start of a real mass-market liftoff for electric cars. By 2040, long-range electric cars will cost less than \$22,000 (in today's dollars), according to the projections.

EPRI anticipated this market growth and launched a Phase 1 study of EV impacts on electric utility distribution systems in 2012. A Phase 2 study was launched in 2014 to develop a screening tool utilities could use to gauge system impacts and mitigation strategies. Functionalities include:

- The ability to assess load risks to service transformers for multiple potential PEV scenarios;
- Account for geographic clustering and variations in PEV characteristics across the utility system
- Quantify the overall risk to system assets using the utilities' existing transformer database
- Incorporate planning and business practices necessary to estimate cost impacts and potential mitigation strategies.

This paper details this screening tool developed by EPRI and provides a case study developed in collaboration with the Sacramento Municipal Utility District using actual distribution system data.

Keywords: charging, infrastructure, simulation, modeling, utility

1. Introduction

With growing customer adoption of electric vehicles (EVs), there is an increased potential for adverse consequences to distribution system operations and assets. These concerns are amplified by the fact that the PEVs are often clustered in neighborhoods or socioeconomic regions. Therefore, while adoption rates may be small, there are regions where there is higher adoption potentially causing future overloading on portions of the distribution system. There are many new large battery vehicles projected to enter the market in the next couple of years with higher associated charging levels. These large battery vehicles further emphasize the need to understand the impact of vehicle charging on electric distribution systems.

To evaluate the impacts that increased PEV penetration has on distribution system assets as well as customer TOU charging incentives, the Electric Power Research Institute (EPRI) developed a tool that assesses the effects of electric vehicle loads on transformers in a specified region or zone. The results of these simulations can be used to estimate future utility costs associated with different EV adoption scenarios. Furthermore, comparisons of different case studies can evaluate the effectiveness of different Time of Use (TOU) rates to smooth peak loads and can help quantify the money saved by delaying utility system upgrades. Other attributes discussed as part of the case study in this paper include clustering in market adoption of EVs, distribution infrastructure configuration, and vehicle types.

2. Modeling Tool Overview

The EPRI ‘HotSpotter’ tool performs a statistical simulation of transformer load impact. Using transformer asset data, expected overloads are estimated using a series of probability assumptions and inputs. This tool uses the joint probability of miles driven, charge start time, EV charging rate (kW), EV adoption probability of the chosen region and transformer peak load to estimate the statistically expected overload of transformers. With this analysis, assets can be categorized into regions of zero or non-zero risk under different PEV use conditions. This tool aids asset managers and system planners by linking the electric vehicle portfolio, customer behavior projections, utility data bases and business cost specifications. The tool runs quickly, allowing managers to perform fast reassessments as system conditions or PEV projections change over time. The EV HotSpotter is the implementation of a modeling tool concept proposed in [1].

3. Modeling Tool Methodology

The EV HotSpotter (EVHS) tool uses a probabilistic model that was developed by EPRI to compute the probability that a given asset (transformer) will be overloaded in an hour, based on its current loading, the PEV adoption probability in its zone, the type of PEVs and their charging characteristics, as well as the joint-probability matrix data of miles driven and charge start hour. The uncertainty in all these parameters that go into the model makes it impossible to predict exactly which transformer will see overloading in the future (due to PEVs); but a probabilistic model applied over the entire zone allows us to compute the expected number of transformers that would face overloading in the coming years (by hour, also by Asset Rating if desired) in each of the PEV adoption scenarios (low, med, high scenarios).

Therefore, the EVHS tool provides a statistical approach to each utility, to obtain/compute a distribution of the Cost (in cap-ex dollars) of such Transformer overloading expected over the entire service territory and thus helps the utility in planning/pre-emptive strategies to addressing/analyzing these issues that will be seen on their distribution systems in the very near future (10 to 20 years out).

4. Validation and Improvements to Prior SMUD Analysis

Prior to the EV HotSpotter tool, the Sacramento Municipal Utility District (SMUD) developed a Monte Carlo simulation of its network of residential service transformers reported in [2]. This analysis used a time sequential power flow analysis (sequential by hour and year) to assess transformer overloads on the peak load day under various EV adoption scenarios. Given the sequential nature of this simulation, an overload in one hour would not be counted as an overload in a future hour. Furthermore, a transformer overloaded in one year was removed from the simulation of future years assuming that the transformer was upgraded to a sufficiently high capacity. The same simulations run with SMUD's tool were repeated with the HotSpotter for validation. The HotSpotter simulations showed very similar results to SMUD's tool. Running different simulation scenarios required modifying software and the run time for a single simulation of SMUD's network that could take more than a day to run. Conversely, the EPRI EV HotSpotter has a graphical user interface and parameter script input file that makes scenario modification relatively simple. The HotSpotter tool required about one hour to run a single simulation of SMUD's network whereas SMUD's Monte Carlo simulation took more than a day to run.

5. Case Study with SMUD – Simulation Assumptions

5.1. Simulation Goals

The prior SMUD analysis in [2] was focused around the impact of charging start time and Time of Use (TOU) rates in delaying distribution system infrastructure upgrades. Charging start time was noted to have an important effect on distribution system infrastructure impact. One of the conclusions was that an after mid-night off-peak TOU rate was able to defer about 50% of the upgrade costs over a flat/tiered rate in over the next 10 years. The goal of the case study and simulation presented in this paper was to identify sensitivities to the geographic location of EVs (clustering and dispersion), distribution system robustness in different geographical areas, and EV charge rate (associated with vehicle type). Since the SMUD analysis in [2], major changes in assumptions include a more conservative market adoption forecast, higher charging loads associated with EVs and a transformer replacement criterion that allows for a higher overload level over short periods of time. The simulation assumptions are detailed as follows.

5.2. EV Market Adoption

SMUD provides electric power to Sacramento County as well as a small portion of Placer County in Northern California. In total, SMUD's service region covers approximately 900 square miles and serves around 550,000 residential and 50,000 commercial customer accounts. At the beginning of 2016, there were over 3,000 registered electric vehicles in SMUD's service area according to data from RL Polk compiled by EPRI. About 93,000 EVs are forecasted in SMUD's service area by 2030. This forecast is based on projected ZEV mandate numbers from [3] adjusted in proportion to SMUD compared to statewide population density, which represents about 9% of the light duty car market in 2030. This EV market adoption size is assumed for the simulation.

5.3. Clustering of EVs

Electric vehicle adoption has clustered in certain neighborhoods or socioeconomic regions. Some household indicators that have a high correlation to EV adoption are: age of EV driver, household income, and installed rooftop solar [4], [5]. Historical geographic distribution of electric vehicles from rebates issued through the California Clean Vehicle Rebate Program was used to forecast future dispersion of EVs [6]. Statistics for vehicles per household shown in Table 1 were used to adjust for the total vehicle population and clustering [7].

Table 1: Vehicles per Household in Sacramento County [7]

Vehicles/Household	% Households
0	3.8
1	28.8
2	45.4
3+	22.0

5.4. Service Transformer Attributes

Service transformers are the low voltage transformers that directly serve individual metered accounts. SMUD maintains distribution infrastructure attributes and their connection relationships in a Geographic Information System (GIS) database. Historical load data is maintained in a database. The relevant attributes used in simulation are locational information, service transformer nameplate ratings, connected accounts, and associated 24-hour peak day load data all taken from 2014. Transformer replacement criteria for distribution operations is assumed to be 130% of nameplate rating for 1 hour for pad mounted transformers and 150% of nameplate rating for 1 hour for pole mounted transformers. Transformer overload that is moderate and insufficient to blow the fuse (typically around 200% of nameplate rating) is not indicative of an immediate transformer failure, but rather an accelerated transformer loss of life [8]. The assumed overload criterion is more indicative of a voltage excursion that deviates from the service obligation to customers which is relevant in the present.

5.5. Vehicle Mix and Usage

With Chevrolet and Tesla having announced longer range BEVs (200+ miles) aimed for a more mainstream market, it is expected that range may continue to increase and also spread across other brands. With larger battery sizes, a higher Level 2 charge rate (kW) is anticipated. Table 2 shows the vehicle mix assumed.

Table 2: Long Term Electric Vehicle Mix

Charging rate (kW)	Battery Size (kWh)	% Vehicles
1.4	15	15%
1.4	30	10%
3.3	15	15%
7.2	60	15%

9.6	60	15%
12.0	80	15%
19.2	100	15%

EV electricity usage is inferred from commute statistics from the Sacramento Area Council of Governments [9] at an average vehicle efficiency of 350 Wh/mi [10]. Figure 1 shows the Average Vehicle Miles Traveled (VMT) Probability Mass Function (PMF) for Sacramento County.

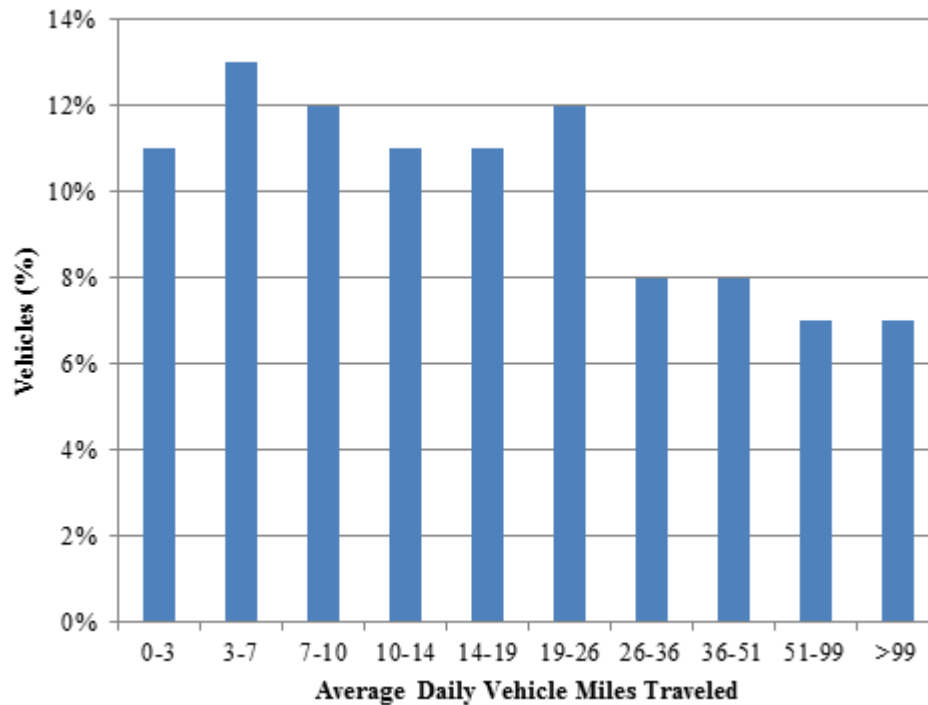


Figure 1: Sacramento County VMT PMF [9]

5.6. Vehicle and Customer Charging Behavior

Rate pilots at SMUD have shown that rates can have a significant effect on electric vehicle load shapes. Three rate options are assumed for customers with electric vehicles: Flat/Tiered rate (flat price per kWh for all kWh consumed), Residential Time Of Use (TOU) rate known as RT01, and the RT01 Residential TOU rate with an EV discount of 1.5 cents from midnight to 6:00 a.m. The 2016 RT01 pilot rate structure is shown in Figure 2. The forecasted load shapes under these three rates are shown in Figure 3. The energy consumption for each of

these load shapes is forecasted at an average 8.8 kWh/day.

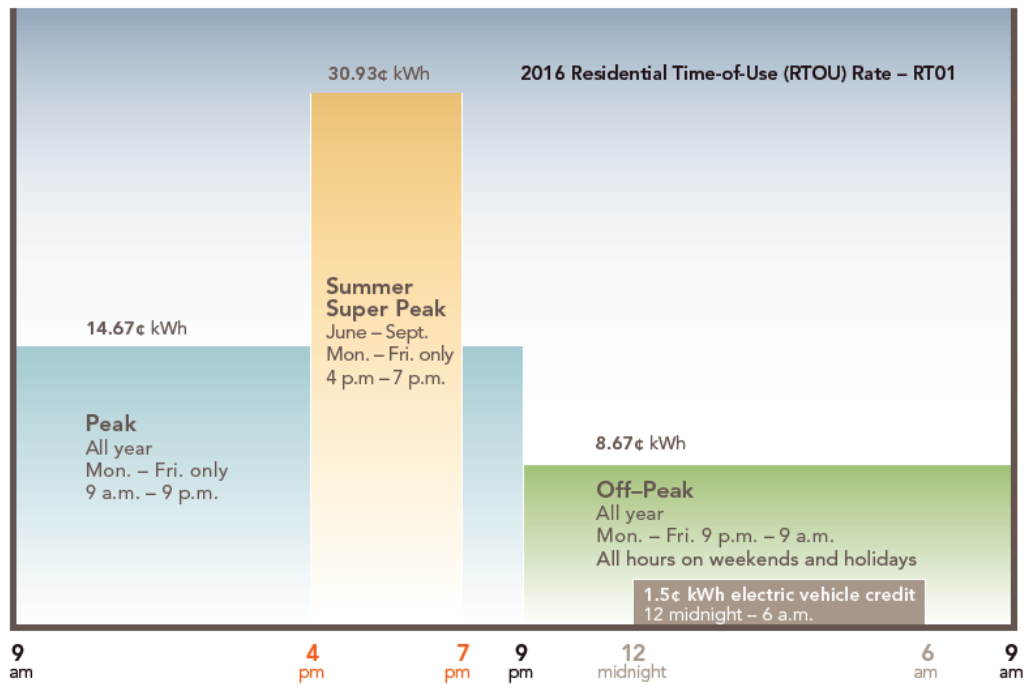


Figure 2: 2016 Residential RT01 Pilot Rate and EV Discount

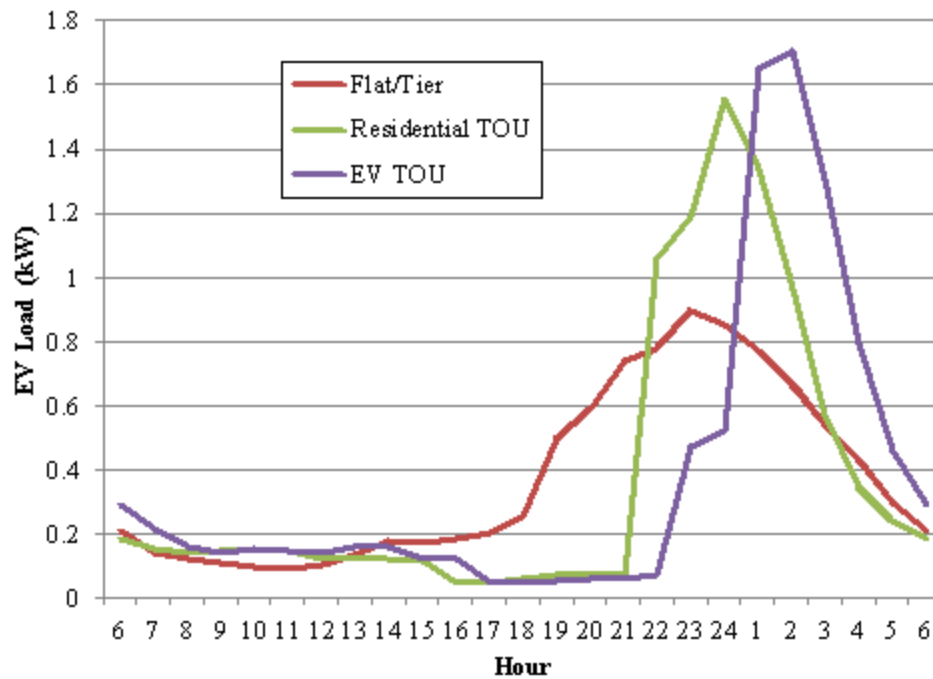


Figure 3: Forecasted Electric Vehicle Load Shapes

Currently about one-third of SMUD EV customers are on a TOU rate. As the RT01 rate is rolled out to all residential customers along with increased marketing and incentive programs, the fraction of customers on a TOU rate is likely to increase substantially. This case study used the mix indicated in Table 3 for the entire forecast period through 2030.

Table 3: Forecasted Mix of Rates among EV Customers

Rate	% Customers	Off-peak time
Flat/Tier	25%	Not applicable
Residential TOU	25%	9 PM
EV TOU	50%	12 AM

5.7. Zone Definitions for Reporting

Although the HotSpotter simulation accounts for individual transformers by associated load and emergency (overload) rating, the reporting is aggregated at the zone level. Sixteen zones were defined by grouping feeders by their associated average transformer nameplate rating and EV market adoption levels.

6. Case Study with SMUD – Simulation Results

6.1. Overall Results

By 2030, the simulation showed about 1,020 incremental transformer overloads resulting from the 2030 population of 93,000 electric vehicles. These overload estimations together with service transformer replacement costs provide a meaningful cost increase to serve the EV customer segment. In 2015, the replacement costs were approximately:

- \$4,700 for a pole mount transformer,
- \$6,000 for a pad mount transformer,
- \$19,500 for a secondary and service conductor upgrade.

These incremental cost should be taken into consideration for EV rates development and program development. Service transformers associated with about 10% of the substations accounted for about 50% of the transformer overloads indicating a notable ‘hotspot’ phenomenon. Some of these ‘hotspot’ areas are identified in Figure 4.

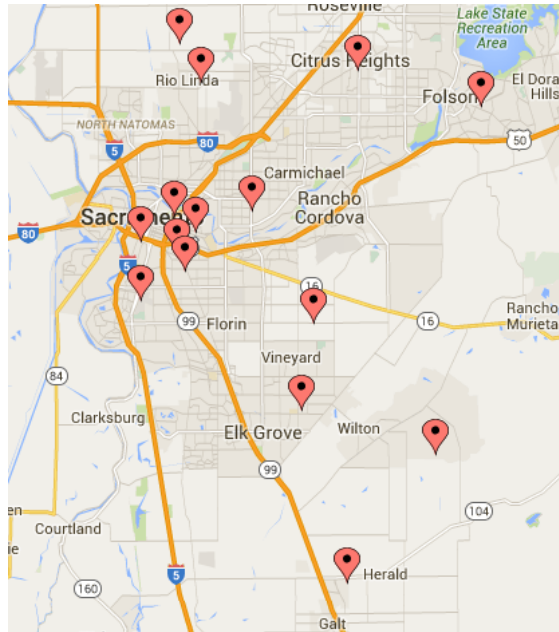


Figure 4: ‘Hotspot’ areas in SMUD service area

The following sections examine the sensitivity of transformer overloads to: 1) transformer attributes and EV adoption seen through variability within SMUD’s service area and 2) EV charging rate (power level) relative to a base scenario.

6.2. Sensitivity to Transformer Attributes and EV Adoption

It is expected that areas with higher adoption and smaller service transformers will require more transformer replacements. Figure 5 is a contour plot that shows the ratio of service transformer upgrades to number of EVs across zones (grouping of similar feeders). The x-axis indicates the percentage of EV market adoption relative to total vehicles and the y-axis indicates the transformer nameplate rating. For higher nameplate rating transformers, the overloads appear to be roughly proportional to the number of EVs. However, for lower nameplate rating transformers, the overloads increase progressively more with the number of EVs. Lower nameplate rating transformers tend to be from older neighborhoods where each transformer has fewer customers associated with it and also a lower capacity allocation per home. Older neighborhoods may have 3 - 5 kVA allocated per home while more recent neighborhoods often have 5 – 7 kVA allocated per home depending on the size of the home. In addition to larger transformers having higher capacity allocation per home, the fact that more homes are on a transformer allows for more net headroom due to natural load diversity.

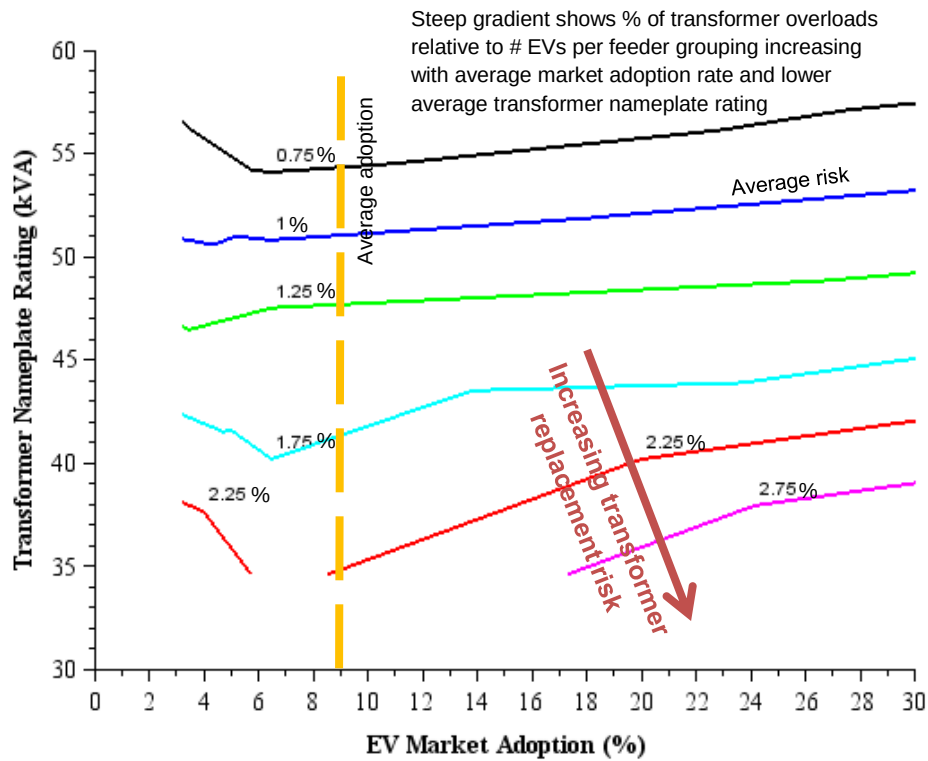


Figure 5: Contour Plot Showing Ratio of Transformer Upgrades to EVs with respect to Nameplate Rating and Market Adoption above 1.5%

Figure 6 is a similar plot as Figure 5, however, the y-axis indicates the average transformer capacity allocation per customer rather than the transformer nameplate rating. It is important to note that the sixteen zone groupings of feeders for Figure 6 were based on average transformer capacity allocation per customer rather than transformer nameplate rating as in Figure 5. This plot shows a risk that is closer to the average population risk and had a less pronounced trend than Figure 5.

Figure 5: Contour Plot Showing Ratio of Transformer Upgrades to EVs with respect to Nameplate Rating and Market Adoption above 1.5%

Some transformers with higher capacity allocation per customer are at higher risk of needing replacement, just as those transformers with lower capacity allocation per customer. This suggests that for the relatively narrow range of 3-7 kVA capacity allocation per customer, transformer size (and associated headroom due to load diversification) plays a more pronounced role in transformer overload than capacity allocation per customer. However, favoring capacity allocation per customer on the higher side rather than the lower side is still an important requirement and consideration for distribution system planning and design.

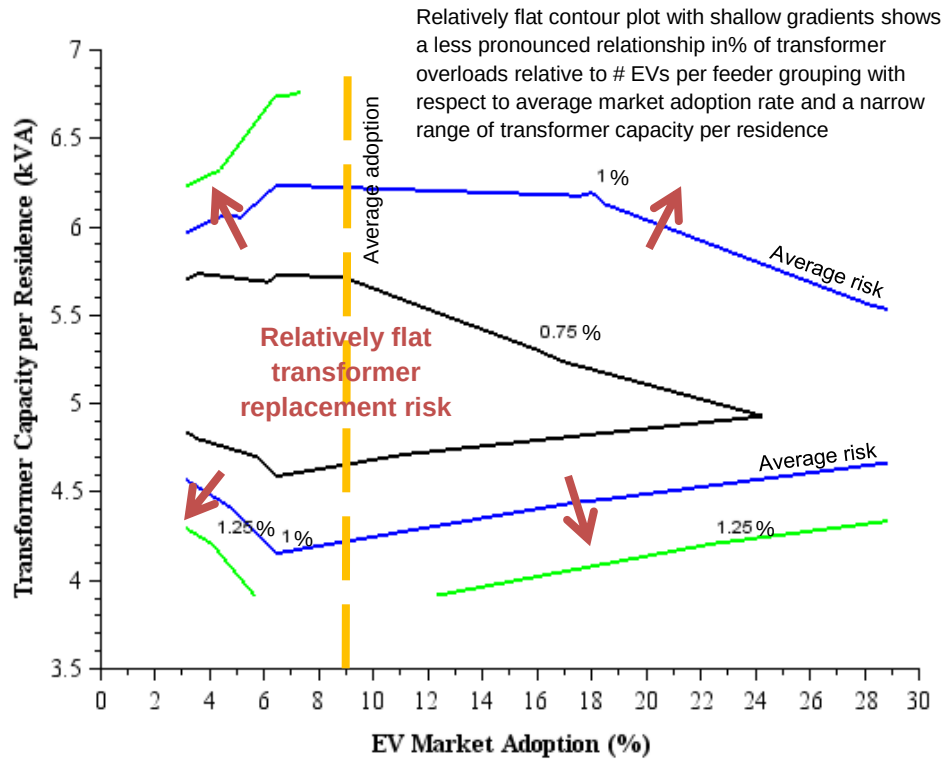


Figure 6: Contour Plot Showing Ratio of Transformer Upgrades to EVs with respect to Capacity Allocation and Market Adoption above 1.5%

6.3. Sensitivity to Vehicle Charging Rate

Sensitivity to vehicle charging rate was estimated at the margin of adoption relative to the overall vehicle mix assumed in Table 2. This marginal EV risk was calculated by adding 5% more EVs for each charging rate type and calculated as follows:

$$\text{Marginal EV risk} = \frac{\text{Overloads with } \Delta \text{ EVs added} - \text{Overloads in base scenario}}{\Delta \text{ EVs added}}$$

Figure 7 shows that the marginal risk of transformer overload increases more than linearly with vehicle charging rate. For example, for 200 additional vehicles charging at 3.3 kW (beyond the base scenario), about one additional transformer overload results (0.5%) while for 200 additional vehicles charging at 19.2 kW (beyond the base scenario), about ten additional transformer overloads result (5%).

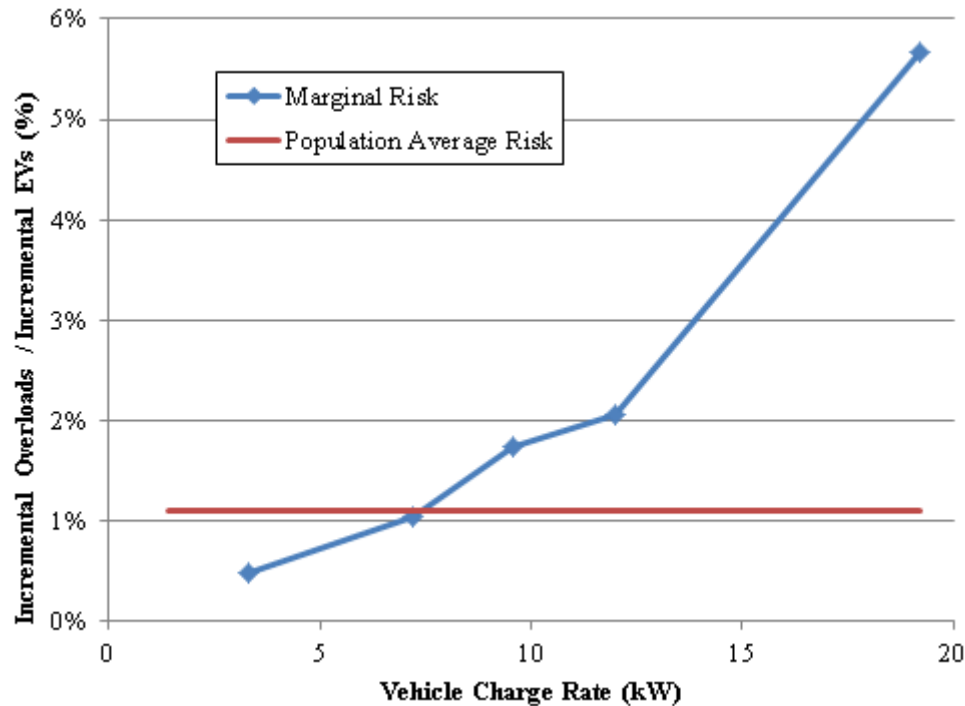


Figure 7: Service Transformer Overload Sensitivity to Vehicle Charging Rate

7. Conclusion

The EV Hotspotter is a way to estimate the transformer upgrades (and costs) associated with increasing EV adoption. While there are a large amount of inputs possible, due to Hotspotter's short running time, many scenarios can be run to test model sensitivity to input ranges and to find an ideal utility scenario. Through Hotspotter analysis, utilities can test different TOU rates to find which ones will help save money in the long run by delaying infrastructure upgrades allowing a smoother transition to higher EV loads on the grid.

References

- [1] J. Taylor, A. Maitra, M. Alexander, D. Brooks and M. Duvall, "Evaluations of plug-in electric vehicle distribution system impacts," *IEEE Power and Energy Society General Meeting*, no. 25-29 July 2010, pp. 1-6, 2010.
- [2] J. Berkheimer, J. Tang, B. Boyce and D. Aswani, "Electric Grid Integration Costs for Plug-In Electric Vehicles," *SAE Int. J. Alt. Power*, vol. 3, no. 1, pp. 1-11, May 2014.
- [3] ICF International, "California Transportation Electrification Assessment - Phase 1: Final Report," September 2014. [Online]. Available: http://www.caletc.com/wp-content/uploads/2014/09/CalETC_TEA_Phase_1-FINAL_Updated_092014.pdf.

- [4] J. Gorzelany, "Electric-Car Buyers Younger And Richer Than Hybrid Owners," *Forbes*, 22 April 2014. [Online]. Available: <http://www.forbes.com/sites/jimgorzelany/2014/04/22/electric-car-buyers-younger-and-richer-than-hybrid-owners/#248dbf72ad32>.
- [5] G. Tal, M. Nicholas, J. Woodjack and D. Scrivano, "Who Is Buying Electric Cars in California? Report UCD-ITS-RR-13-02," UC Davis Institute of Transportation Studies, Davis, 2013.
- [6] Center for Sustainable Energy, "Clean Vehicle Rebate Project, Rebate Statistics," California Air Resources Board, 1 February 2016. [Online]. Available: <https://cleanvehiclerebate.org/rebate-statistics>. [Accessed 16 February 2016].
- [7] Advameg, Inc., "Cars and other vehicles available in Sacramento County, California in houses/condos/apartment," [Online]. Available: http://www.city-data.com/county/Sacramento_County-CA.html. [Accessed 10 December 2015].
- [8] M. Kuss, T. Markel and W. Kramer, "Application of Distribution Transformer Thermal Life Models to Electrified Vehicle Charging Loads Using Monte-Carlo Method," in *25th World Battery, Hybrid and Fuel Cell Electric Vehicle Symposium & Exhibition*, Shenzhen, China, November 5 - 9, 2010.
- [9] SACOG, "Metropolitan Transportation Plan / Sustainable Communities Strategy 2035," Sacramento Area Council of Governments, Sacramento, CA, 2012.
- [10] US DOE, "Benefits and Consideration of Electricity as a Vehicle Fuel," U.S. Department of Energy, 15 November 2012. [Online]. Available: http://www.afdc.energy.gov/fuels/electricity_benefits.html. [Accessed 2 January 2013].

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