A Smart Step Forward: Analytics for Equitable Electrification Program Planning

Jess Kursman, Energy Solutions
Eileen Eaton, Energy Solutions
Ari Mytelka, Energy Solutions
Hunter Johnson, Ph.D., Res-Intel
Hal T. Nelson, Ph.D., Res-Intel

ABSTRACT

There is a significant need for utilities to develop strategic plans for beneficial electrification and to ensure equitable implementation. Electrifying existing buildings has historically been limited to owner-occupied properties. Scaling up equitable electrification to include multifamily and commercial properties requires improved program design and delivery due to electrification barriers and split incentives. Furthermore, robust electrification programs need to mitigate impacts to the electrical grid.

This paper presents one utility's planning efforts to design an equitable electrification program across its service territory for existing residential and commercial buildings. This project is notable given the breadth of data used for the planning effort. Planning data modeled and visualized in this work includes building characteristics (e.g., building type, vintage, square footage, and energy use intensity), customer attributes, environmental and social justice designated areas, climate zone, and electrical distribution circuit characteristics. Outputs of the modeling consist of load impacts of energy efficiency, load management measures, and measure adoption barriers.

This paper provides readers with insights on how to leverage available data to develop equitable electrification strategies. This is outlined by documenting the data sources, data stitching methodology, and lessons learned from this project; this paper does not discuss methodology for applying measure analysis modeling to the dataset.

Readers will understand how data can directly inform power service availability strategies and planning. This paper also captures lessons learned about the availability of data, difficulties encountered, and how to best leverage scenario planning for multiple use cases to inform a variety of program strategies.

Setting Goals: Evaluating Electrification

In April 2022, Energy Solutions contracted with Southern California Edison (SCE) to evaluate barriers and identify solutions for meeting energy-efficient building electrification goals within SCE's service territory. The primary objective of this initiative was to develop and test database tools and analyses to promote a data-driven strategy for building electrification.

To help SCE identify their electrification goals, Energy Solutions worked to furnish SCE with a detailed site assessment by geography, building types, and measures that were modeled to make the most significant impact on achieving California's energy savings and greenhouse gas (GHG) reduction goals. The driving purpose behind this set of recommended measures and their associated grid impact was to allow SCE to effectively allocate resources and make informed decisions to shape their electrification strategy, including, but not limited to, program design, codes and standards, and infrastructure investments. Overall, this analysis aimed to play a crucial role in SCE's efforts to assess electrification barriers, recommend the most impactful portfolio of measures, and yield a data-driven building electrification strategy that supports an equitable transition to electrification.

The Energy Solutions and Res-Intel project team analyzed available building characteristics and energy consumption data to classify building types, vintage, size, and energy use in Los Angeles County and Orange County. By mapping these building characteristics, specific electrification barriers such as poor envelope insulation and sealing, lower-capacity electric panels, and knob-and-tube wiring could be identified. Energy Solutions also assessed electrification barriers dependent on customer attributes, with a particular focus on underserved communities and climate zones.

The team compared load implications of measure adoption at these locations against the remaining capacity of the associated circuits to indicate where flexible load technologies should also be part of the building electrification strategy. The team then compared these characteristics to the energy savings of different energy efficiency and building electrification measures to identify the best locations and measures to pursue in Los Angeles County and Orange County.

Data Sourcing and Stitching

Data Sources

The team leveraged a range of data sources to ensure a comprehensive analysis, as follows:

- Acxiom data on residential building and customer characteristics
- ATTOM building permits processed through Res-Intel's Building Permit Insights Tool
- CalEnviroScreen 4.0 data on environmental and social (ESJ) factors by census tract
- California Energy Commission (CEC) climate zone designations and maps
- CoStar property records
- Dun & Bradstreet (D&B) data on commercial building and customer characteristics
- National Renewable Energy Laboratory (NREL) ResStock and ComStock gas consumption models
- Res-Intel low-income database aggregated from the California Housing Partnership (CHP) database, the Tax Credit Allocation Committee (TCAC) database, and CoStar
- Res-Intel-aggregated tax assessor data
- SCE energy efficiency, building electrification, discounted rates, and energy audit program data
- SCE Grid Needs Assessment (GNA) data and forecasts
- SCE electric meter data, net energy meter (NEM) data, and metadata aggregated annually

Table 1 below shows how the sources were used to populate data categories and subcategories.

Table 1. Data sources

Data category	Data subcategory	Data source
Building characteristics	Building type	Acxiom, D&B, CoStar, Res-Intel tax assessor data, SCE meter metadata
	Vintage	CoStar, Res-Intel tax assessor data
	Size	CoStar, Res-Intel tax assessor data, Res-Intel low-income database
	Existing equipment	SCE program data, ATTOM permit data, Res-Intel predictions based on energy disaggregation
	Electric panel capacity	ATTOM permit data, SCE energy audit program data
Energy use	Electricity use	SCE electric meter data
	Gas use	NREL ResStock and ComStock gas consumption models
	Solar generation battery storage	SCE NEM data
Customer attributes	Renter	Acxiom
	Low income designation	SCE discounted rates program participation data, Res-Intel low-income database
Local conditions	ESJ area designation	CalEnviroScreen
	Circuit capacity	GNA data
	Climate zone	CEC

The data sources listed above were stitched together primarily using unique SCE site identifiers and the sector designation. When incorporating external information sources, the data was mapped using other geographical fields such as building addresses, latitude and longitude coordinates, and census tracts. When working at the level of individual meters, SCE's meter identifiers were also used, and when working at the circuit level, sites were grouped based on recorded circuit name.

Res-Intel compiled building attribute data with its existing data sources, including CoStar, county assessor (Lightbox), satellite imagery, geographic information (GIS), and building footprint data. Res-Intel classified and validated these data sources as part of that process and used the validated data to identify and aggregate individual tax lot information into larger residential and commercial complexes.

Res-Intel also used satellite imagery, building footprint, and light detection and ranging (LiDAR) to convert property inventory into a building inventory. Res-Intel identified and categorized every building on each property as occupied or unoccupied by differentiating homes and outbuildings, such as sheds and parking structures. Res-Intel assigned each building a unique Geo-ID number. Remote sensing was leveraged to support the building inventory by using rooftop height to predict occupancy, building volume, and occupied square footage. Res-Intel also performed artificial intelligence (AI) analysis to identify missing building attributes.

Identifying Single Family, Multifamily, and Commercial Properties

Res-Intel identified single family and multifamily properties using lists of agreed-upon use codes. Property use codes are reported by tax assessors and were assigned at the parcel level. To identify single family properties, Res-Intel assumed that each unique Assessor's Parcel Number (APN) represented one property. Any property within the SCE service territory boundary and with one of the 12 targeted single family use codes was considered a relevant single family property, and any property within the SCE service area boundary and with one of the 11 targeted multifamily use codes was considered a relevant multifamily property.

Multifamily use codes were also assessed for relevance to multifamily properties with five units or more. Large multifamily complexes were often recorded in county assessor data as separate parcels that developers purchased. These parcels sometimes had mixed-use codes including non-multifamily codes such as commercial or single family residential. Res-Intel's aggregation process identified these multi-parcel developments (MPD) by owner name and adjacency and aggregated them into complexes. MPD sites were assigned the most common use code among the aggregated parcels. Some multifamily properties had been aggregated with non-target residential or commercial properties. As a result, Res-Intel added two multifamily use codes to the list of over-five-unit multifamily use codes as relevant to part of its ongoing analyses of SCE's building stock.

Compared to residential properties, commercial properties belonged to a much larger and wider variety of use codes. Res-Intel and Energy Solutions worked with SCE to agree upon 116 use codes in the team's categorization of commercial properties. This process was again replicated for large commercial properties, which were often recorded in county assessor data as separate parcels developers purchased. These parcels often had mixed use codes including noncommercial codes (residential, industrial, or agricultural).

Res-Intel didn't analyze information for use codes that were identified as industrial or vacant. Commercial buildings classified as industrial were also removed from the property meter dataset. Because most transportation use codes were identified as industrial, many were not available in the database. Energy Solutions intends to add industrial use codes to a future iteration of a database to allow identification and assessment of transportation hubs as well as other use cases that involve industrial properties.

Circuit Integration

Energy Solutions incorporated circuit data in two ways: associating individual sites with circuits by matching to the circuit name and mapping the circuit segments' geometry in a layer of the map visualizations. Associating sites with circuits was important in determining which sites were on load-constrained circuits and to see measure intervention circuit impact on groups of sites. Mapping out the circuit segments enabled visualizations to show where circuits were, color-code them by remaining capacity or other attributes, and geographically validate the associations between sites and circuits. Combined with estimated measure impacts, the circuit data was key for determining which circuits might require upgrades to accommodate electrification and other elements of grid planning.

To associate sites with circuits, Energy Solutions cleaned the circuit names provided by SCE and then matched the sites' circuit names in the Acxiom data to the GNA circuit data. This yielded a match rate of 98.0 percent for the residential sites and 97.5 percent for the commercial sites. To map circuit geometry, Energy Solutions referenced the integration capacity analysis

(ICA) layer of SCE’s Distributed Resource Plan External Portal. This resource included start and end points for line segments indicating each circuit, provided as latitude-longitude pairs. Energy Solutions mapped these circuit segments as a separate layer and matched them to the sites and GNA data based on circuit name.

Environmental, Health, and Socioeconomic Inventory

Energy Solutions incorporated environmental data from CalEnviroScreen and climate zones with boundaries as specified by the CEC. This CalEnviroScreen data included pollution burden variables such as ozone and particulate matter levels, drinking water contaminants, children’s lead risk, and toxic releases from facilities as well as population characteristics like asthma, low birth weight, education, housing burden, poverty, and unemployment. Like the circuit data, the environmental data needed to be associated both with the individual sites and with its geographical borders.

The climate zones and environmental factors from CalEnviroScreen applied across regions with irregular boundaries. Energy Solutions incorporated these climate zone and census tract areas into the visualizations as a background layer behind the circuit segments and the individual sites. With so many layers, the maps could be complex to parse visually, so Energy Solutions simplified the CalEnviroScreen data by taking the site-weighted averages across zip codes and binning each zip code into quintiles.

Binning the CalEnviroScreen data into quintiles enabled decision-makers to digest the layers of data and more readily incorporate it into choices on which measures to pursue and where. The CalEnviroScreen data could show where measures would benefit ESJ-designated areas and enable targeting of areas with poor air quality, which could be improved through electrification or energy efficiency measures. This layer could also be combined with building characteristics to determine correlations between equity metrics and electrification barriers or provide evidence to support the need for financing measures to facilitate electrification in target areas.

Data Validation

Energy Solutions employed a bottom-up validation approach, where it was ensured that each data component was accurate enough to have confidence in the overall results. This approach was taken due to the lack of a control dataset. Verification was completed by ensuring individual data components matched with available information and benchmarks for a county.

As part of the property inventory process, Res-Intel combined building attribute data compiled by Energy Solutions with its existing data sources (including CoStar, county assessor (Lightbox), satellite imagery, GIS, and building footprint data). Res-Intel classified and validated these data sources and used validated data to identify and aggregate individual tax lot information into larger residential and commercial complexes.

While matching residential and commercial meters onto properties using utility meter metadata, Res-Intel validated the matches between SCE service addresses and property information using statistical and manual validation methods. After the data was sufficiently matched, Energy Solutions and Res-Intel were able to assess null values and take steps to fill in data gaps with data extrapolations and predictions. The accuracy of these extrapolations was directly tied to the quality of the data. As a result, analysis was completed to validate the data.

Some key steps in the validation process were energy benchmarking, identifying outliers, checking invariants, and energy disaggregation.

Energy Benchmarking

To complete the benchmarking step, Res-Intel calculated the energy use intensity (EUI) in $kBtu/ft^2$ by property, based on the property aggregation (total property ft^2) and kWh consumption for matched meters. The EUI was used in building energy benchmarking models to make like-for-like comparisons of energy use at each property, controlling for property age, the presence of a pool, local climate, and other property attributes. The benchmark score helped identify large energy-consuming properties and assess whether a property is a cost-effective candidate for building electrification.

Building energy benchmarking models adapted for California from the US Environmental Protection Agency's Portfolio Manager were used to make similar comparisons of building energy efficiency. Benchmarking requires reliable occupied building square foot estimates. As a result, in addition to commercial properties, benchmarking only single family and two-to-four-unit multifamily properties with single buildings on single parcel properties was recommended. Res-Intel stratified the single family and two-to-four-unit multifamily properties into five bins based on square footage to make valid comparisons among properties and control for all relevant property attributes such as property age, presence of a swimming pool, and climate.

Res-Intel recommended targeting five commercial property types that had both high existing natural gas use for space and water heating as well as process energy use for benchmarking. SCE identified the highest priority commercial property types for analysis as education, health, lodging, office, and restaurant. Res-Intel then identified which individual properties in each of these types were expected to have existing natural gas versus electric fuels for large end uses based on predictions from machine learning models trained on energy efficiency audit data. For example, hotels and motels that were predicted to use natural gas for communal area space heating could be targeted for heat pumps.

During the building energy benchmarking, Res-Intel validated energy data for buildings and provided building energy benchmark scores that generated like-to-like comparisons of the energy efficiency of SCE customers' properties. This benchmarking controlled for building attributes like conditioned square footage, age, and building configuration, to accurately identify EUI. Benchmarking has been found to be more useful than energy audit data in explaining actual energy use. Benchmarking was completed for the single family detached properties as well as selected commercial property types smaller than 50,000 square feet.

Measure-Level Energy Benchmarking

Energy Solutions evaluated heating, ventilation, and air conditioning (HVAC) heat pump and heat pump water heater measures using multiple methodologies to provide additional assurance of the results. Energy Solutions evaluated the measure savings using Building Energy Optimization (BEopt) models and referencing the California electronic Technical Reference Manual (eTRM). Benchmarking the savings using the BEopt methodology against savings calculated using the eTRM methodology enabled Energy Solutions to confirm that these measures had reasonable savings.

The square footage per unit and the number of units per site were two of the most important factors for determining the magnitude of savings from residential measures, so Energy Solutions flagged sites with an unusual square footage or number of units. Flagging these sites enabled SCE to decide whether to include sites that are likely to either have faulty reported data or unusual circumstances, where our measure modeling may have been less likely to apply. Energy Solutions identified residential sites as outliers based on a common statistical practice: outliers were those having square footage per unit 1.5 interquartile ranges larger than the third quartile.

To ensure that joining the data sources and deriving calculated attributes did not generate new errors, Energy Solutions checked invariants, or values that should be unchanged before and after an operation is performed, after each join and each calculation of a derived field. When joining data sources to describe features of each site, Energy Solutions checked the invariant of the number of rows for unique sites. Thus, while mapping electrification barriers, building characteristics, and measure savings to each site, the team ensured that duplicate values did not emerge in the final combined data. While calculating derived fields, Energy Solutions ensured that relevant sums, averages, and ratios remained constant before and after the transformations.

To validate the available data on existing equipment and offer more relevant energy efficiency and building electrification recommendations, Res-Intel disaggregated the hourly meter data. They leveraged their series of classification models, which were designed to detect each meter's end use based on its energy consumption pattern or load path signature. This is also referred to as load disaggregation, which involves binning energy consumption into distinct categories including heating, cooling, and baseload energy. These models also used meter metadata joined with hourly load profile data in a machine learning model to identify tenant versus communal area energy usage.

Data Extrapolations and Predictions

Building Characteristic Data

While this project has benefited from data directly from SCE in combination with a large number of external data sources, the dataset still had gaps that needed to be addressed. Energy Solutions focused on resolving the null values for the most critical variables and worked with Res-Intel to impute missing values for building vintage.

Res-Intel used a machine learning method called extreme gradient boosting (XGBoost) to impute values where not reported. This method relied on available property attributes to help make accurate predictions for other attributes such as year built, square footage, number of floors, number of buildings, and number of units. Only a minority of properties required imputation; for year built and area, only 6.2 percent and 13.1 percent, respectively, of records were imputed.

Existing Equipment Data

The primary sources of existing equipment data came from SCE customer data and building permit data through Res-Intel's building permit text mining tool. Additionally, Res-Intel filled in remaining gaps by generating equipment predictions based on disaggregating meter data. Energy efficiency program participation, building electrification program participation, and building energy audit program participation were combined with the purchased building permit data.

To better understand existing equipment conditions and electrification barriers, such as electrical panel capacity, Energy Solutions purchased building permit data for all counties in SCE's service territory. Res-Intel built a building permit text mining tool to characterize specific electrical infrastructure attributes of residential and commercial properties in SCE's service territory. The tool extracted and analyzed text descriptions of permits to predict the prevalence of electrical equipment, such as solar photovoltaic (PV) systems, battery storage systems, electric vehicle (EV) charging, electrical panel upgrades, and transformer replacements. Benchmarked against a manual sample of 50 permits, the classification accuracy of the tool was over 93 percent for all equipment categories, with some attributes correctly classified 100 percent of the time.

Existing Equipment Predictions

Res-Intel created predictions of each property's existing equipment based on customer program, building permit, and hourly meter data. Res-Intel used hourly kWh data and meter metadata to predict the energy end use at each meter and employed energy disaggregation algorithms to identify heating, cooling, and baseload energy use. The end use classification models use load signatures to assign end uses to the meter, including laundry, electricity, lighting, pool pumps, and water heaters.

Existing equipment predictions leveraged multiple data sources that varied by property type and included the following: ATTOM Building Permit Data, SCE Energy Efficiency Audit Data, SCE Energy Efficiency Program Data, and SCE Energy Savings Assistance (ESA) Install Data.

These data sources were used as ground truth in developing and validating predictive machine learning models to determine the presence of various types of equipment. The existing equipment that was predicted includes, but is not limited to: space heat fuel (gas or electric), water heat fuel (gas or electric), presence of central air conditioning, presence of in-unit laundry, presence of in-unit water heater, presence of attic insulation, cooking fuel (gas or electric), and presence of efficient lighting.

By establishing a given meter's end-use category and location served (such as common area versus tenant), Res-Intel was better able to predict the types of existing equipment at each property in the inventory. Developing existing equipment predictions was a significant step in the data process as these were used to identify appropriate energy efficiency and building electrification measures to recommend for that end use. The disaggregated load data also enabled identification of the sources of high energy consumption in a property, allowing for more targeted energy efficiency and building electrification upgrades.

Solar Generation Predictions

To generate solar predictions, Energy Solutions assumed that sites would install enough solar capacity to offset consumption provided the roof was large enough. For some sites, the meter data was missing or low. Where meter data was missing or under 10 kWh per year, Energy Solutions used BEopt models and the number of units at the site to estimate the site energy consumption for the solar prediction calculation. This was accomplished by mapping sites to BEopt models based on vintage, climate zone, square footage, and building type, and then multiplying the BEopt model's total baseline kWh per year by the number of units at the site. NEM data and equipment predictions enabled identification of sites that already had solar and disaggregation of the existing solar production.

Measure Adoption Barriers

Measure adoption barriers were determined from existing customer variables, including low income and renter versus owner, and from existing equipment, including insulation and panel capacity. Additional barriers were predicted based on building vintage and square footage. These predictions enabled analyses of where barriers occur, which barriers were likely to co-occur, and how prevalent barriers were in target areas. Understanding these factors could enable program administrators to plan strategies to overcome the most common barriers and effectively allocate budget to equity initiatives.

Data Challenges

Property Inventory Challenges

One of the most significant challenges encountered in this work was developing the property inventory, which serves as the source of truth for many of the datasets employed in analysis. Tax assessor data assigned each property to one of more than 250 property use codes, and it wasn't always clear how these use codes mapped to the more general property types. The following questions needed to be considered:

- Should condos and mobile homes be counted as single family or multifamily properties?
- Should government properties be considered?
- Should nursing homes or student dormitories be considered relevant multifamily properties?

These determinations had to be made by conferring with SCE at the start of the property inventory. All subsequent tasks in the property inventory depended on this initial identification. In addition, the first phase of the project required determining how to handle multi-parcel developments (MPDs). It is common for multifamily and commercial properties to consist of multiple adjacent parcels. Res-Intel has developed methods to aggregate these parcels into single properties if they share a common owner name or property address.

It was helpful to clarify whether multifamily and commercial properties included the full site area aggregated or were split into individual units, especially when a property had multiple meters. An example of a simple MPD would be a property consisting of two adjacent parcels with a common owner name that were both identified as apartment complexes by use code. These two parcels should be considered a single property in order to properly identify the residency type and number of units, which would impact the suitable electrification measures.

Data Cleaning

The main challenges with cleaning and preparing property data were missing and outdated data. Energy Solutions identified missing variables within the initial Acxiom dataset provided and submitted additional requests to obtain those valuable to the project. For the Dun &

Bradstreet dataset, Energy Solutions identified many null values, and only a few fields were reliable enough to be used. In some cases, Res-Intel used statistical methods to impute missing data, such as for building vintage. However, this added an additional layer of uncertainty to results so was used only when necessary.

CalEnviroScreen data was valuable for designated ESJ areas. However, it was at the census tract level, and so it did not provide information about individual addresses. Energy Solutions addressed this through geocoding using the Geocodio tool so that all sites could be connected to their corresponding census tracts.

Proper matching of utility meters to properties was also critical for accurate energy analysis. Res-Intel matched utility meters to properties using address matching where possible and geocoding as a secondary method. Using address and geocode matching methods, Res-Intel was able to match more than 95 percent of SCE's 5.1 million residential and commercial meters to properties (or parcels) in SCE territory.

A difficulty with meter matching was that it was not clear how reliable meter class codes were, making it more difficult to validate meter matching results. Figure 1. below gives an example of possible issues with meter class codes. The blue circles show the coordinates of meters classified as commercial in SCE meter metadata. The green polygons show parcels classified as commercial according to tax assessor use codes, and the gray polygons indicate non-commercial parcels. Figure 1 shows that many commercial-class meters are in areas that are apparently residential.

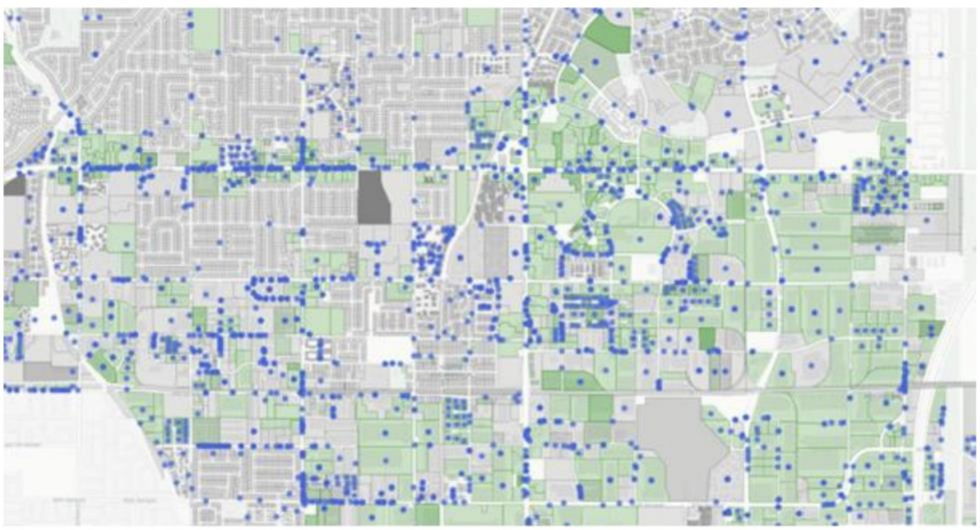

Figure 1. Commercial class meter locations

If a property was only matched to some of its meters, this would result in a lower EUI estimate for the property. This can have downstream effects on later energy analytics. If the EUI estimate is dramatically lower than for similar properties, the property may not be included in the aggregation process for developing benchmarks.

Meter Data Matching: Electric

Receiving electric meter data and processing consumption data presented several challenges. Consumption data had to be requested for each property type once the property inventory was created and meters were matched to the properties. Energy Solutions requested daily consumption data (typically spanning two years) and Res-Intel matched it to properties. This data formed the foundation of subsequent energy analysis and benchmarking. Consumption data requests can often take several weeks or more to fulfill.

Energy Analysis

Following the integration of consumption data with properties, Res-Intel performed a variety of energy analytics including calculating EUI and energy benchmarking. The primary challenge in working with SCE's data was the lack of metered gas data, given that SCE is an electric-only utility. As a result, all EUI calculations were electric-only, causing EUI benchmarks derived from these sites to be both biased downward and against properties that have electric resistance heat.

Res-Intel and Energy Solutions aimed to rectify the lack of metered gas data by using modeled gas data from ResStock and ComStock modeling as benchmarks to compare individual sites against. These models represent averages for different building types, defined by the property type, structure, number of units, and other features.

The energy analysis stage of the project also faced other difficulties, such as obtaining reliable weather data; there is often a tradeoff between finding weather data that is both mostly complete and close to the relevant property. Closer weather stations may be smaller and have less reliable data compared to more distant, larger weather stations.

Existing Equipment Analysis

Existing equipment was identified at each property so that property-specific energy efficiency recommendations could be made. This required the compilation of multiple data sources indicating existing equipment at the different property types. Available data sources were fraught with several issues:

-
- Data sources may not have been representative of all properties. In particular, some equipment types in the multifamily sector used Energy Savings Assistance (ESA) installation data, which drew from a pool of lower-income customers and may not have represented the full range of incomes. This may have impacted the overall estimates for distribution of these equipment types and obscured differences related to income. However, a benefit of using data from lower-income customers is that the results should be most accurate for lower-income customers, which could be useful for planning equity-focused measures.
- Audit data was a major source of equipment data for residential properties, which could have resulted in inaccuracies when survey respondents were not fully informed about their properties and equipment.
- Equipment data sources were sparse, so machine learning predictions were needed to fill in missing data. Although the machine learning models had high accuracy in predicting key equipment types on test data set aside from the models' training data, imputations introduced an additional layer of uncertainty.
- Building permits were often incomplete. County assessor permit data came from a free-form text field completed by each permit applicant, which varied widely and could include inconsistencies or errors. Even so, the building permits provided information not available through other sources, especially on electrical panel size and asbestos.

Selected Results

Barrier Identification

Barriers identified for SCE included low income, renting, insufficient electrical panel capacity, outdated electrical panel, knob and tube wiring, asbestos, and pre-existing measure adoption. In residential buildings, the biggest impediment to measure adoption was the renter barrier, followed by outdated electrical panel barrier. The asbestos and knob and tube wiring barriers were found not to have significant impact on measure adoption. The impact of the six residential barriers is broken out into Figure 2. and Figure 3., which look at barriers related to non-electrical adoption and electrical adoption, respectively. Almost all sites had some barriers, and many had multiple, suggesting that a successful electrification measure would need to address the more common barriers, for example, by increasing incentive amounts or providing financing to cover electrical panel upgrades.

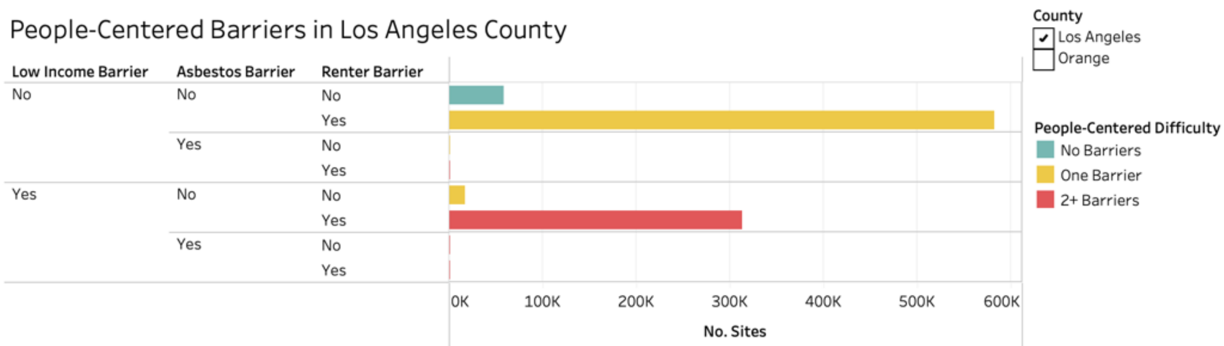

Figure 2. Number of residential buildings with non-electrical measure adoption barriers in Los Angeles County

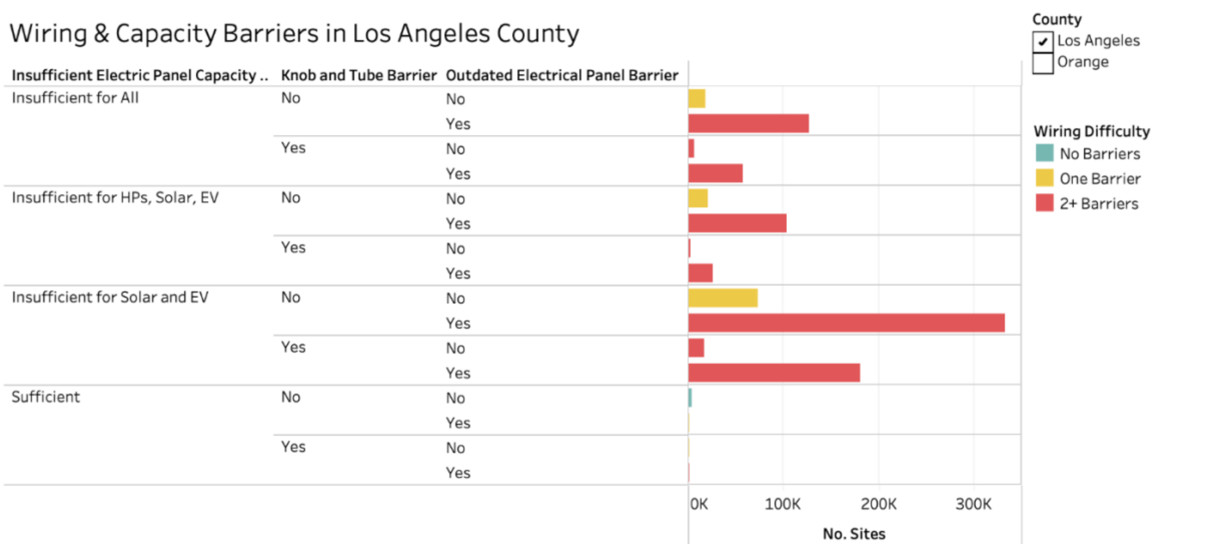

Figure 3. Number of residential buildings with electrical measure adoption barriers in Los Angeles County

Measure, Grid, and Building Stock Insights

The database allowed decision-makers to filter based on barriers and see the interactions with other attributes or forecast the impacts of adopting measures at those sites. Figure 4. shows a combination of geographical, building, and customer attributes for sites that have no barriers to implementing heat pump measures, where SCE might expect measure adoption without intervention. Figure 5. shows the maximum potential grid impact of increased EV adoption on individual circuits, providing insight into which circuits would need upgrades or load management strategies in order to handle significant EV uptake. Each of these dashboards can be configured to visualize a host of different scenarios to support utility planning.

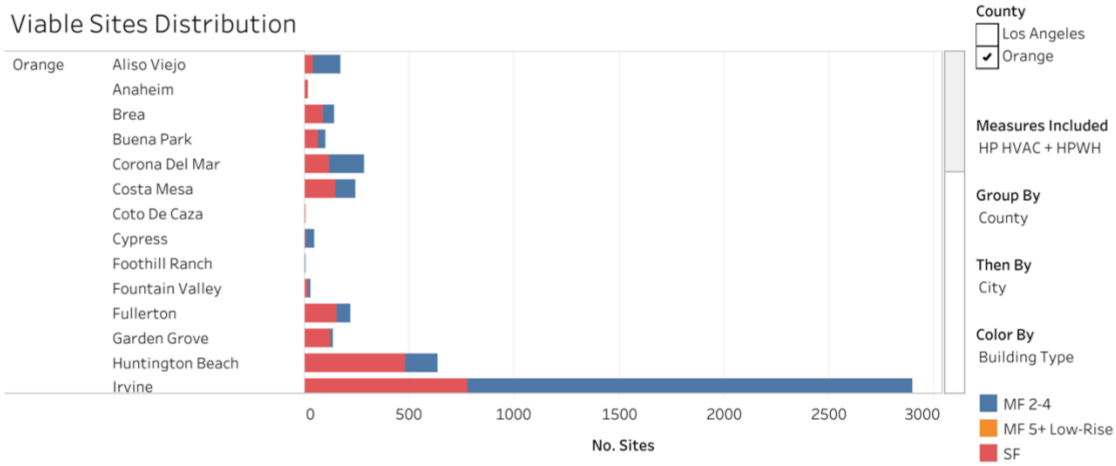

Figure 4. Building type by city of viable buildings for residential heat pump adoption in Orange County

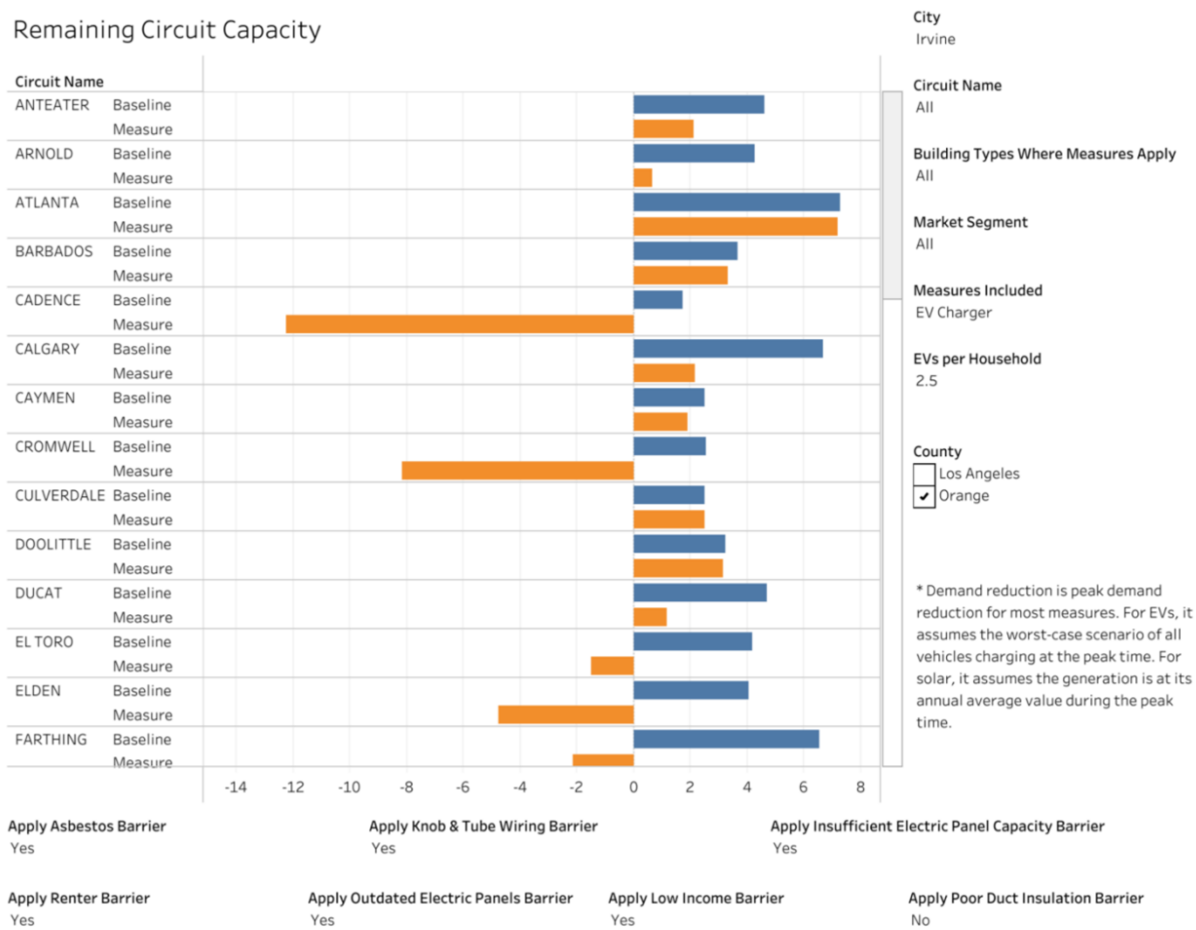

Figure 5. Circuit impacts of significant electric vehicle adoption

Additional maps and charts could support a range of other activities. A map overlaying wildfire risks from CalEnviroScreen data with circuits color coded by their remaining capacity could support plans for grid infrastructure upgrades. A list of measures by their energy savings potential in each zip code could help with selection of the most impactful measures across the building stock. Combining a view of ESJ-designated areas with the savings potential and likely barriers could assist with selecting locations for zonal electrification.

Limitations and Areas for Expanding Scope

Expansion of Building Type

The project scope was intentionally limited to residential and commercial building types and focused on specific commercial use codes only. This scope limitation prevented SCE from identifying and assessing transportation hubs as part of this effort. Energy Solutions notes that adding industrial use codes to a future iteration of the building inventory GIS (BIG) database could allow the use case of identifying and assessing transportation hubs as well as other use cases that involve industrial properties for a limited set of end uses.

Expansion of Measures

Energy Solutions indicates that the number of measures included in the BIG database could increase. Specifically, measures with interactive effects and load management measures could be added to the scope.

More sophisticated building energy modeling would allow utility partners to better see the combined impacts of residential measures. Residential measures are all tied to building envelope and are known to have interactive effects with heating and cooling measures that should be included when calculating load impacts and energy savings. For future scope, Energy Solutions could leverage the BEopt electrification models to include envelope improvements. This could capture the interactive effects between envelope improvements and electrification.

The load management measures included in the project scope were limited to electric battery storage and smart thermostats. Adding more in future scope would provide more options for modeling energy savings and peak load reduction.

Expansion of Cost Analysis

At the onset of this effort, Energy Solutions had planned to develop total cost and incremental cost assumptions for all measures to support their customization to different combinations of building characteristics. A more detailed cost-effectiveness analysis could be completed in the future by leveraging SCE's electric service upgrade pricing tools.

Additionally, it was determined that operational cost is more important to calculate than the initial purchase and installation cost, as these initial costs are frequently offset with utility and government incentives, and the operational costs directly inform whether bill savings are achieved. Energy Solutions recommends the calculation of bill savings for each building as part of future project scope. These building-level bill savings would be calculated by multiplying the measure savings against the average publicly available bill rates.

Expansion of Renter Barriers

To predict the renter barrier for commercial properties, the required leasing data was not available. The two main types of commercial leases are gross and net, which can greatly influence the ability to pursue electrification. In a gross lease, the landlord pays for operating expenses like the energy bill while the tenant pays a fixed rate. In a net lease, the tenant is responsible for operating expenses. A future iteration of the BIG database could include commercial property leasing data and add the barrier for commercial properties.

Expanding Data Granularity: Solar and Battery Storage

Energy Solutions sees an opportunity to increase the granularity of load forecast data, particularly for solar generation, battery storage, and EV charging. Energy Solutions used the Renewable Energy Integration and Optimization (REopt) tool, a software tool developed by NREL, to optimize planning of generation, storage, and controllable loads to maximize the value of integrated distributed energy systems for buildings. REopt offers the potential to size solar and battery systems to achieve the desired combination of energy cost savings, resilience, and clean energy.

The analysis could also be expanded to include hourly load profiles for a PV solar and battery system for sites based on their features. This could be achieved by using available data to generate site-specific inputs for each climate zone, vintage, and building type, which would be fed into REopt to produce solar and battery projections for each of these combinations. REopt also allows custom load profiles, which would enable the visualization of hourly electric demand versus the potential solar hourly generation. Energy Solutions could leverage the meter data and BEopt load profiles to estimate the load profile for each site. This approach would be computationally heavy but would allow the development of hourly load profiles, which would be useful to model the effects of solar and battery resources on grid load.

Expanding Data Granularity: Electric Vehicles

Energy Solutions calculated the average kWh/mile for an EV, and then multiplied that number by the average annual miles driven to get the total extra electric consumption from charging an EV. In future phases, Energy Solutions recommends expanding this calculation to include the aggregate hourly load profile for electric cars by leveraging EV-specific modeling tools such as EV Pro, which is a tool developed through a collaboration between NREL and the CEC, with additional support from the US Department of Energy. The tool uses detailed data on personal vehicle travel patterns, EV attributes, and charging station characteristics in bottom-up simulations to estimate the quantity and type of charging infrastructure necessary to support regional adoption of EVs.

Conclusion

This paper highlights the imperative for utilities to use granular data and harness building stock insights when developing strategic plans for beneficial electrification and ensuring equitable program implementation. Electrifying existing buildings, particularly multifamily and commercial properties, necessitates enhanced program design and delivery to overcome barriers. Moreover, robust electrification programs must address grid impacts that are more effectively modeled and quantified with detailed data. By analyzing building characteristics, ESJ factors, energy consumption data, and electrification barriers, the project team pinpointed optimal locations and measures for electrification efforts in Los Angeles County and Orange County and observed the overlap with ESJ-designated areas.

This planning effort exemplifies a data-driven approach to designing an equitable electrification program across a utility's service territory. Valuable insights were gained by leveraging comprehensive data and visualizing the relationships between building characteristics, customer attributes, ESJ considerations, climate zones, and electrical distribution circuit characteristics. These insights not only inform power service availability strategies but also provide lessons on how to handle limited data availability by collecting from multiple sources and through use of imputation.

This paper underscores the significance of leveraging available data to develop equitable electrification strategies and emphasizes the importance of informed decision-making in shaping electrification initiatives. Data showing the higher prevalence of electrification barriers for low-income households and ESJ-designated areas can empower utilities to budget for addressing these prominent barriers. Moving forward, utilities and stakeholders can draw upon the methodologies and insights presented here to advance their own electrification efforts, contributing to a more sustainable and equitable energy future.