ERCOT EV ALLOCATION STUDY

METHODOLOGY FOR DETERMINING EV LOAD IMPACT AT THE SUBSTATION LEVEL

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Executive Summary

Introduction

- The Brattle Group was retained by ERCOT to develop a repeatable process for forecasting electric vehicle load impacts at the substation level out to 2029, for use in their System Planning Assessment
- ERCOT requested that Brattle provide an interactive "tool" that could be used to easily replicate and update the analysis in the future
- Brattle has conducted a thorough review of ERCOT's existing electric vehicle assumptions, allocated those forecasts to ERCOT substations using Texas-specific and publicly accessible data, and generated representative 24-hour load profiles at each substation for 8 years, 4 seasons, and 2 day types
- Brattle has also corresponded at length with several of ERCOT's Transmission and Distribution Service Providers to leverage their existing work and experience in understanding local impacts of EVs
- This presentation details Brattle's approach in carrying out the analysis from start to finish, and includes a summary of the final results
- The Excel-based interactive tool will be passed off to members of ERCOT's Transmission Planning team at the conclusion of the engagement

Methodology Overview

Brattle applied a 3-step approach to its analysis of EV load impacts at the ERCOT substation-level:

1 Establish Light, Medium, and Heavy-Duty EV Adoption Forecasts for 2022-2029

- Update and improve upon ERCOT's existing adoption assumption for LDV penetration.
- Build out adoption forecast for a more granular list of Medium and Heavy-Duty (MHDV) EVs

2 Allocate Adoption Forecasts to ERCOT Substations

- Separate methodologies for LDV and MHDV allocation
- Vehicles first allocated to the zip-codes and then to the substations using data from ERCOT, the Census, and Moody's.

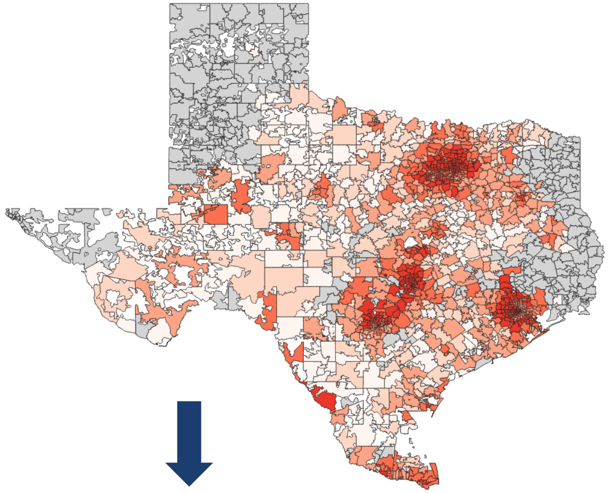
3 Calculate Load Impacts at the Substation-Level

- Calculate 64 representative load profiles for each substation, showing load throughout 4 seasons, 2 day types, and 8 years.
- Develop interactive tool that generates profiles for each substation and can be easily updated in the future.

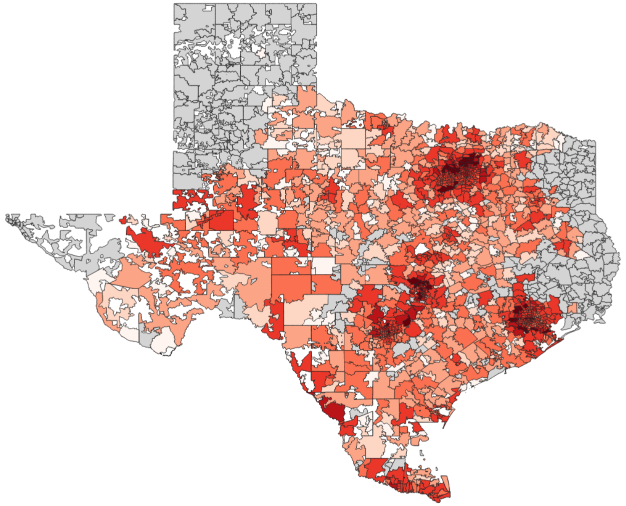
Summary of Results

- **System-wide adoption and load impacts:**
  - ~770,000 LDVs and ~160,000 MHDVs are projected to be electric in Texas by 2029, representing about **4%** of LDV stock and **4%** of MHDV stock and therefore **4%** of all vehicles on the road. Approximately **96%** of these electrified vehicles will be registered within ERCOT's service territory.
  - The total EV charging load in 2029 is approximately **6 TWh**, adding 1.25% of load to ERCOT's electric load forecast in 2029 up from 0.2% in 2022
- **Allocation to substations:**
  - LDV allocation is developed based on metrics capturing future propensity for adoption. Allocation is concentrated primarily in urban and suburban zip codes surrounding major cities such as Austin, Houston, DFW, San Antonio.
  - MHDV allocation is established by multiple bottom-up models for key use cases. Delivery vehicles and regional and long haul trucks add load to substations in the city outskirts and major highways. Buses, pickup trucks, and certain regional trucks will increase load in urban and suburban areas

2022 EV Adoption



2029 EV Adoption



Step 1: Forecasting ERCOT EV Adoption

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Forecasting Approach

- The results of this analysis rely on carefully developed EV adoption forecasts
- After benchmarking ERCOT's existing adoption assumption against other jurisdictions around the U.S., Brattle determined that a "refresh" of ERCOT's existing assumption was needed to ensure that the resulting allocations to substations were accurate
- Brattle performed a thorough review of ERCOT's existing stock turnover models, which forecast Light-Duty (LDV) and Medium-Heavy-Duty (MHDV) Electric Vehicle adoption out to 2037
  - Brattle identified several areas for potential improvement of ERCOT's LDV stock turnover model and applied these to arrive at a "refreshed" LDV adoption forecast.
  - Improvements to the MHDV model were more substantial, as Brattle developed forecasts for more granular MHDV use-cases.

LDV Stock Turnover Methodology Adjustments

LDV Stock = **Existing LDV Registrations** + **New Sales** - **Retirements**

Existing LDV Registrations

ERCOT Approach:
- Actual historical sales data from 2015-2021 sourced from ERCOT.

Brattle Approach:
- No change.

New Sales

ERCOT Approach:
- Apply market share forecast from *2020 BNEF Electric Vehicle Outlook* to a static estimate of Texas-level vehicle sales.
- Apply 4-year delay to resulting forecast to match actual sales trajectory.

Brattle Approach:
- Apply market share forecast from *2021 BNEF Electric Vehicle Outlook* to Passenger Sales Forecast from *2022 EIA Annual Energy Outlook, Table 38* (scaled down to TX-level).
- Apply 3-year delay to match actual sales trajectory.

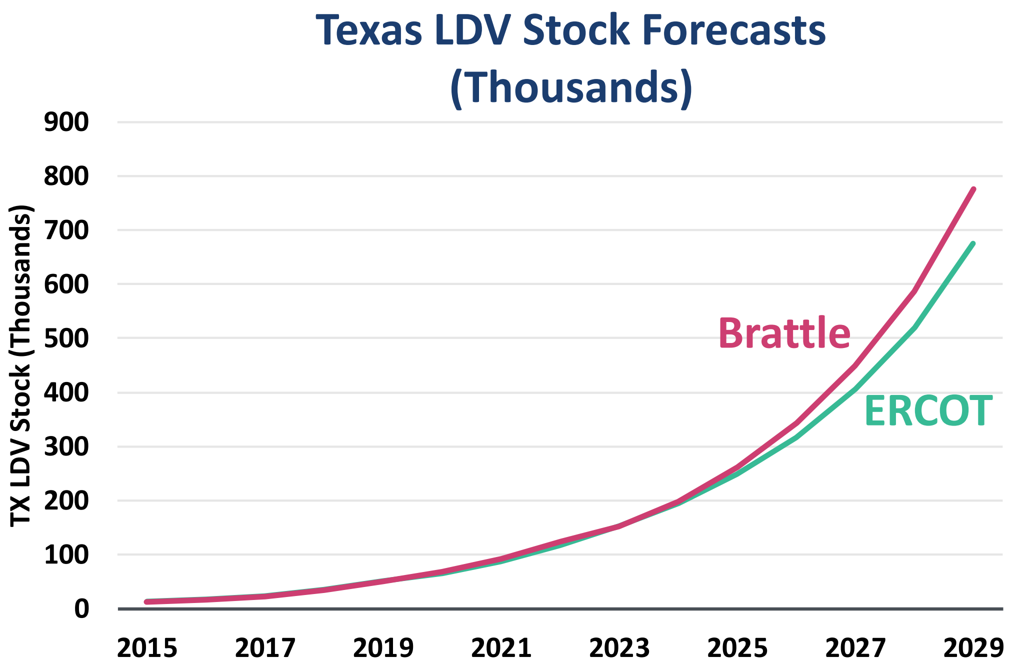
Retirements

ERCOT Approach:
- Assume 50% of vehicles sold in a given year retire after 10 years.

Brattle Approach:
- Apply annual retirement analysis using Survivability Data from National Highway Traffic Safety Administration.

Updated LDV Stock Forecast

- **Brattle's updated LDV stock forecast exceeds ERCOT's original assumption by about 100,000 vehicles in 2029 for several reasons:**
  - The AEO forecast of total LDVs sold in 2029 is higher than ERCOT's static assumption.
  - Brattle's light truck sales forecast exceeds ERCOT's.
  - These increases are somewhat offset by Brattle's retirement approach, which results in more vehicles retired by 2029 than in ERCOT's forecast, but the resulting stock forecast is still higher.



Electric MHDV Adoption is Currently Low in Texas

MHDV electric vehicle adoption is currently much less advanced than LDV adoption.

- There were only 50 registered electric MHDVs in 2021.
- In class 2B, the largest MHDV class in our study, no EVs were registered in 2021.
- This poses a challenge for forecasting the adoption and allocation of vehicles
  - There is no historical adoption trend.
  - There is a high level of uncertainty about the development of these advanced technologies.

Medium and Heavy Duty Vehicles are Segmented into Classes

We group MHDVs into 5 classes, which largely align with the Federal Highway Administration's gross vehicle weight ratings (FHWA GVWR) and ERCOT's vehicle class segmentation.

- These classes were selected to align with the classes used for EV sales adoption forecasts in Brattle's Delphi Survey.
- We add additional granularity to ERCOT's breakdown by adding more categories to their Local HD class.
- We consider buses and school buses separately from the weight classes.

<table>
<tr><th>Weight less than or equal to (lbs)</th><th>6,000</th><th>8,500</th><th>10,000</th><th>14,000</th><th>16,000</th><th>19,500</th><th>26,000</th><th>33,000</th><th>60,000</th><th>over 60,000</th></tr>
<tr><td>FHWA GVWR Vehicle</td><td>Class 1</td><td colspan="2">Class 2</td><td>Class 3</td><td>Class 4</td><td>Class 5</td><td>Class 6</td><td>Class 7</td><td colspan="2">Class 8</td></tr>
<tr><td rowspan="2">ERCOT Vehicle Classes</td><td colspan="3" rowspan="2">Light Duty Trucks and Cars</td><td colspan="7">Local HD</td></tr>
<tr><td colspan="5"></td><td colspan="2">Long Distance HD</td></tr>
<tr><td rowspan="2">Brattle Vehicle Classes</td><td colspan="2" rowspan="2"></td><td rowspan="2">Class 2B</td><td colspan="2" rowspan="2">Class 3-4</td><td colspan="2" rowspan="2">Class 5-6</td><td colspan="3">Class 7-8 Regional</td></tr>
<tr><td colspan="3">Class 7-8 Long Haul</td></tr>
</table>

Forecasting Electric MHDV Adoption

We implement a stock turnover model to forecast electric MHDV adoption levels in each class.

- In this model, we use initial vehicle numbers sourced from EV Hub for 2021, which are very few.
- We then project vehicles in subsequent years by assuming a certain number of new vehicles enter, based on the assumed initial sales and sales growth rate projection.
- Vehicles are expected to retire after their expected lifetime (10-12 years for MHDVs), but this is longer than the study period from 2022-2029, so the model assumes no electric vehicles retire.
- The share of new vehicles that are EVs is forecasted based on the forecasted EV sales adoption rate.

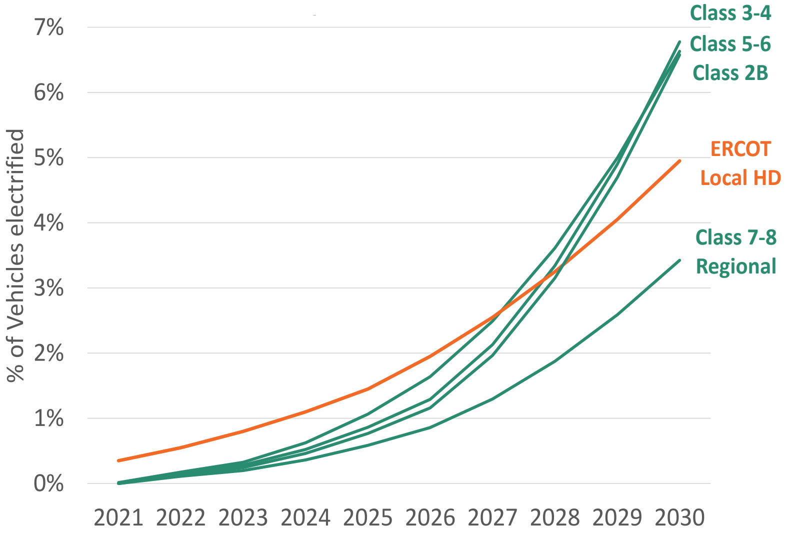
Electric MHDV Stock	=	Existing Electric MHDV Registrations	+	New Sales	-	Retirements
		Because electric MHDV technology is new, these vehicles are assumed to have age 0 in 2021.		New sales are calculated as forecasted MHDV sales in the class times forecasted EV sales share for the class.		Because vehicle lifetimes are assumed to be longer than the study period (to 2029), retirements are 0.

Forecasting Electric MHDV Adoption

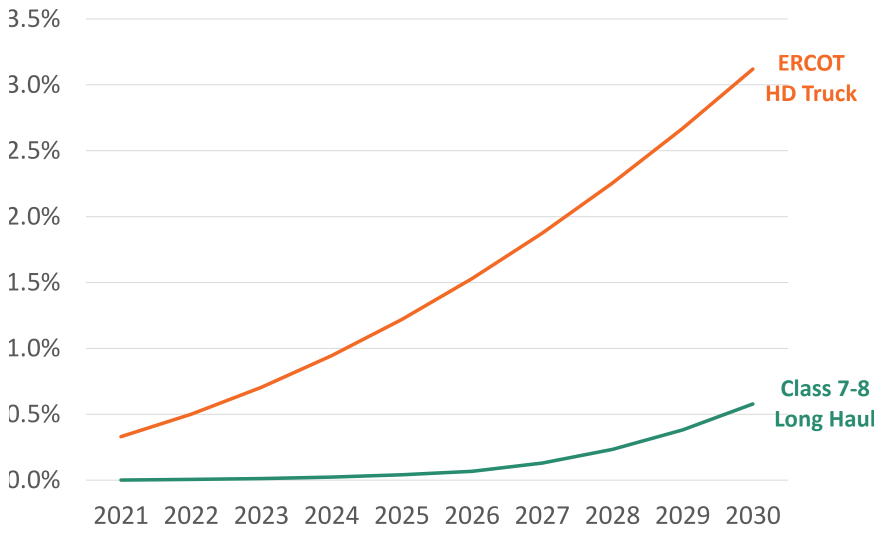
Forecasts are based on data from a Delphi Survey conducted by Brattle in late 2020.

- A panel of experts was asked to predict MHDV sales adoption across classes in 2025, 2030, and 2035. Their responses were then aggregated into high, base, and low scenarios.
- We use the base forecast for buses, and the low forecast for other vehicle types.
- We benchmark the stock adoption forecasts derived from these sales adoption forecasts through the stock turnover model against ERCOT's assumptions, which are less granular.

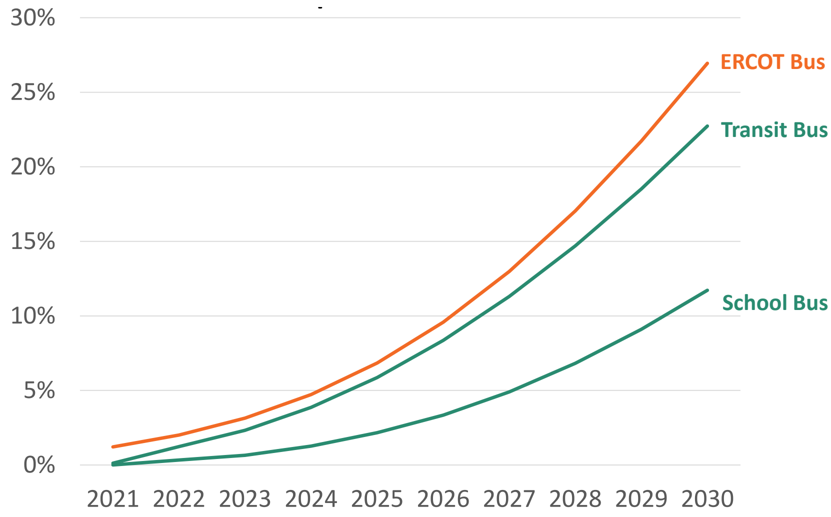
EV Stock Adoption Forecast: Local HD



EV Stock Adoption Forecast: Long Haul HD



EV Stock Adoption Forecast: Buses



Step 2: Allocating EV Adoption to ERCOT Substations

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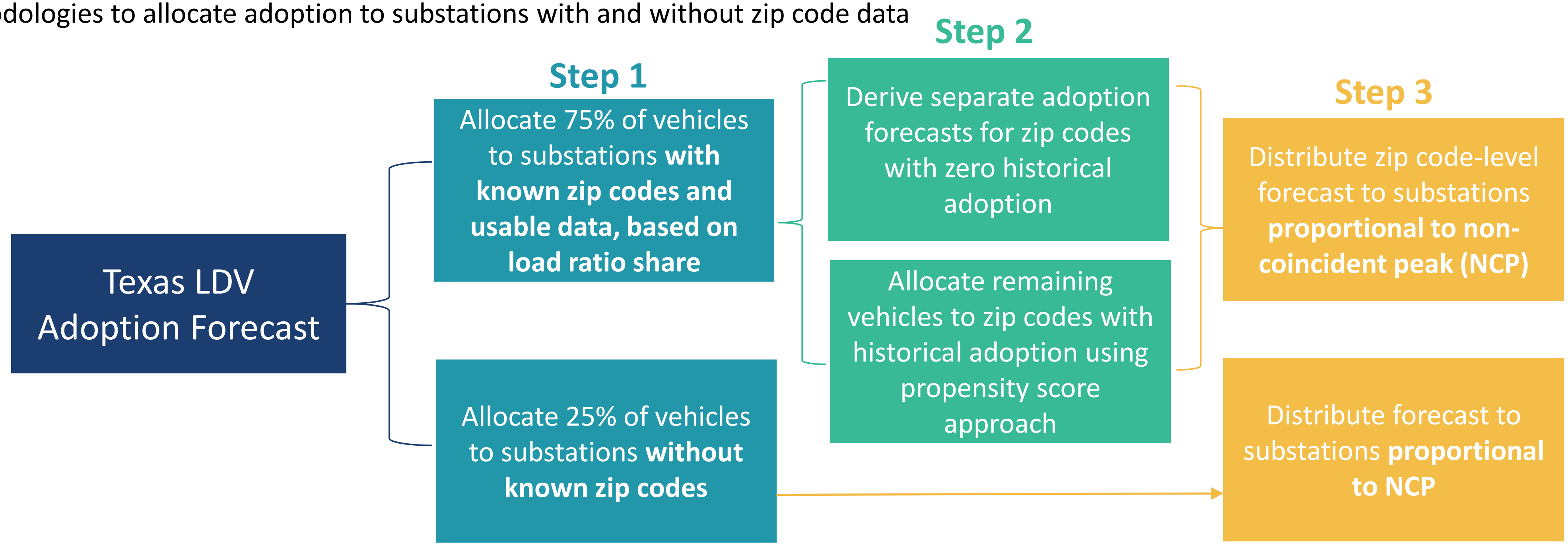
- Develop interactive tool that generates profiles for each substation and can be easily updated in the future.

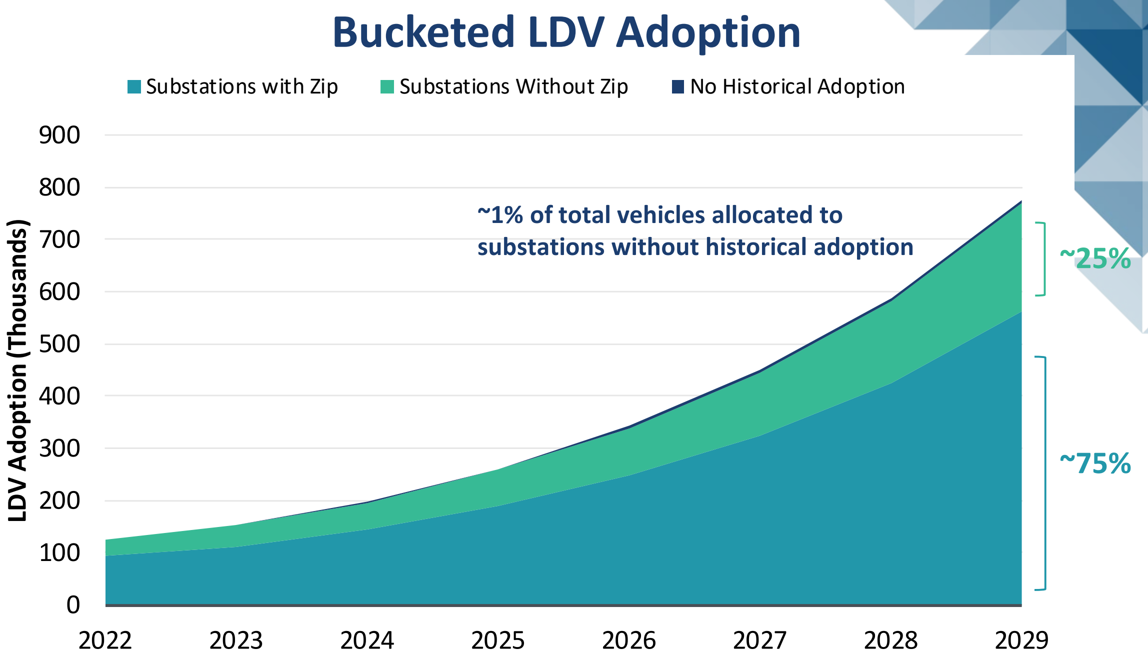
LDV Allocation Methodology

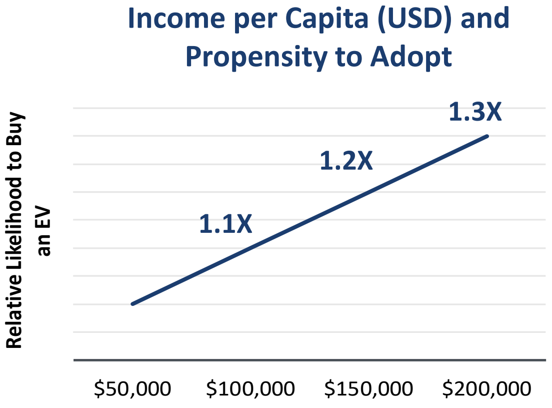
- The objective of this step in the analysis is to allocate our Texas-level LDV forecast to each of ERCOT's substations.
  - We first allocate adoption to all zip codes in ERCOT's service territory, and then further allocate to the substations serving each zip code.
- ERCOT Substations fall into three categories:
  - **ESIID Substations** – Existing ERCOT substations with loads associated with competitive choice areas within ERCOT.
  - **NOIE Substations** – Existing ERCOT substations with loads associated with Non Opt-In entities within ERCOT.
  - **Planned Substations**
- From ERCOT, we received a mapping of ESIID substations to the zip codes they serve, as well as non-coincident peak forecasts (in MW) for each substation. ERCOT does not track the zip codes served by Non Opt-In Entities (NOIE) or Planned substations. For this reason, we applied varying methodologies to allocate adoption to substations with and without zip code data

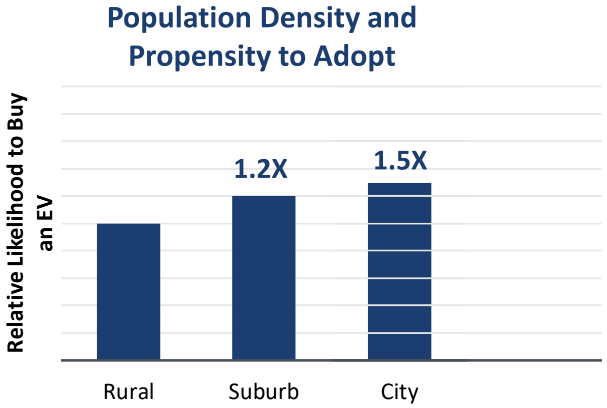


LDV Allocation Methodology

- **Step 1: In the absence of zip code data for all of ERCOT's substations, we first separate our LDV adoption forecast into two "buckets,"** so we could allocate one bucket to substations with zip code data, and one bucket to substations without zip code data.
  - We allocated **75%** of our forecasted LDV adoption to these substations and the **remaining 25%** to the substations without associated zip code data.
- **Step 2: Assign a "propensity score" to all Texas zip codes, indicating the relative likelihood of EV adoption in each zip code.** We rely on this metric to determine where LDV adoption is most likely to occur across Texas in each of our forecasted years and translate this into a share of Texas-wide adoption.
  - **Propensity Score = Income per Capita Score × Population Density Score × Historical Adoption × Total Vehicle Registrations**
  - Approximately **1%** of the LDV forecast is allocated to zip codes *without historical adoption*, using a set of "rules" that detail when EV adoption is expected to occur, and how quickly it will ramp up (see Appendix).
- **Step 3: Allocate LDVs from zip codes to the substations that serve them, proportional to each substation's non-coincident peak (NCP).**
  - NCP serves as a proxy for the relative "popularity" of a substation – a substation with a higher NCP can be expected to serve more EV load.
  - Our propensity score calculation considers the impact of existing economic conditions, the prevalence of vehicle ownership, and historical EV adoption in each zip code.







Source: McFadden et. al., The Impact of Incentives on Electric Vehicle Adoption: National Average Results. EPRI 2019.

Example Allocation to Zip Code with Historical Adoption

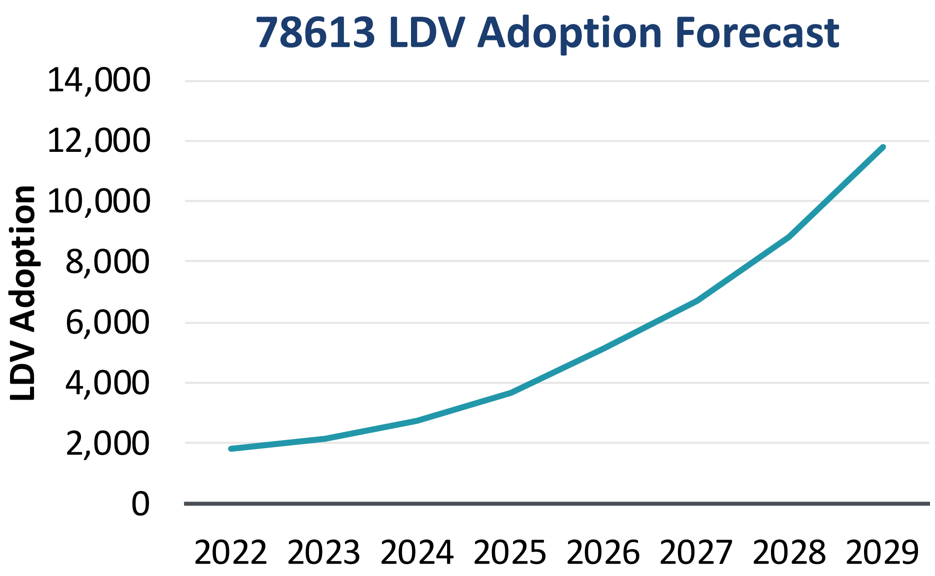
1. **78613** is a zip code located in the Austin metro area, primarily in Williamson County.
    - Population 2022: 65,099 (U.S. Census Bureau).
    - Land Area: 28 sq. miles (U.S. Census Bureau).
    - Population Density: ~2,351 residents per sq. mile ("Urban").
    - Income per capita 2022: $43,375 (U.S. Census Bureau).
    - Approx. Total Registered Vehicles 2022: 30,490.
    - Current LDV Adoption, as of April 2022: 1,130 vehicles (Atlas EV Hub).

2. **2022 Propensity Score = (Income Score = 1) * (Pop. Density Score = 1.5) * 30,940 * 1,130 = 51,681,225**

3. Propensity Score Share of Total = **1.9%** (Share of forecast allocated to this zip code)

4. Vehicles Allocated in 2022 = **1,843**

We repeat this process for all Texas zip codes with historical EV adoption.



Note: Adoption ramps up in later years due to increasing forecasted income per capita in this zip code, which increases its Income Score from 1 to 1.05 and boost its propensity score relative to other zip codes.

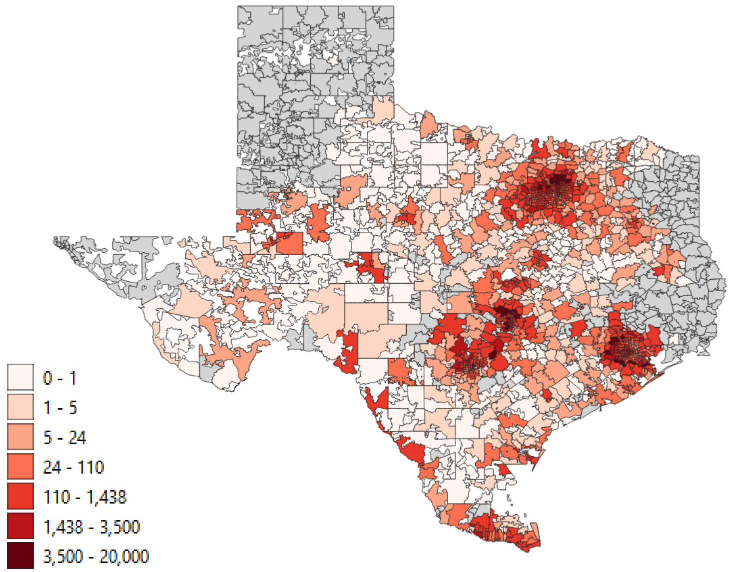
LDV Allocation: Summary of Results

- Our resulting allocation concentrates adoption primarily in urban and suburban zip codes surrounding major cities. The highest adoption zip codes in 2029 all started out with relatively high adoption in 2022.
  - Note that these values do not include additional adoption that may be served by NOIE or Planned substations.
  - Once the TX zip codes are pared down to just ERCOT zip codes, we find that **95%** of LDVs adopted in TX will fall in ERCOT's service territory.

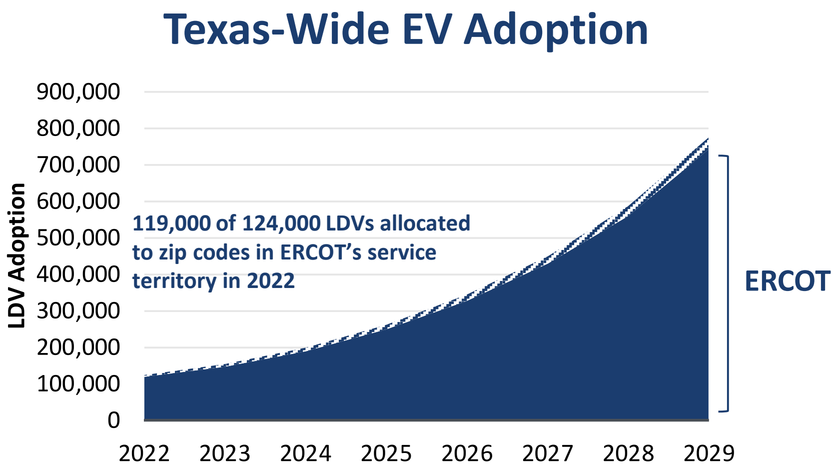
Top 10 Zip Codes by LDV Adoption in 2029

Rank	Zip Code	Current (2022) Adoption Level	2029 Adoption	Nearest City
1	77479	1,401	15,883	Houston
2	78613	1,130	11,934	Austin
3	75034	959	10,792	Dallas
4	75035	1,438	10,581	Dallas
5	77494	1,027	9,625	Houston
6	78660	892	8,344	Austin
7	75070	709	8,199	Dallas
8	78665	642	6,997	Austin
9	77584	589	6,726	Houston
10	78704	1,068	6,408	Austin

2029 LDV Allocation by Zip Code



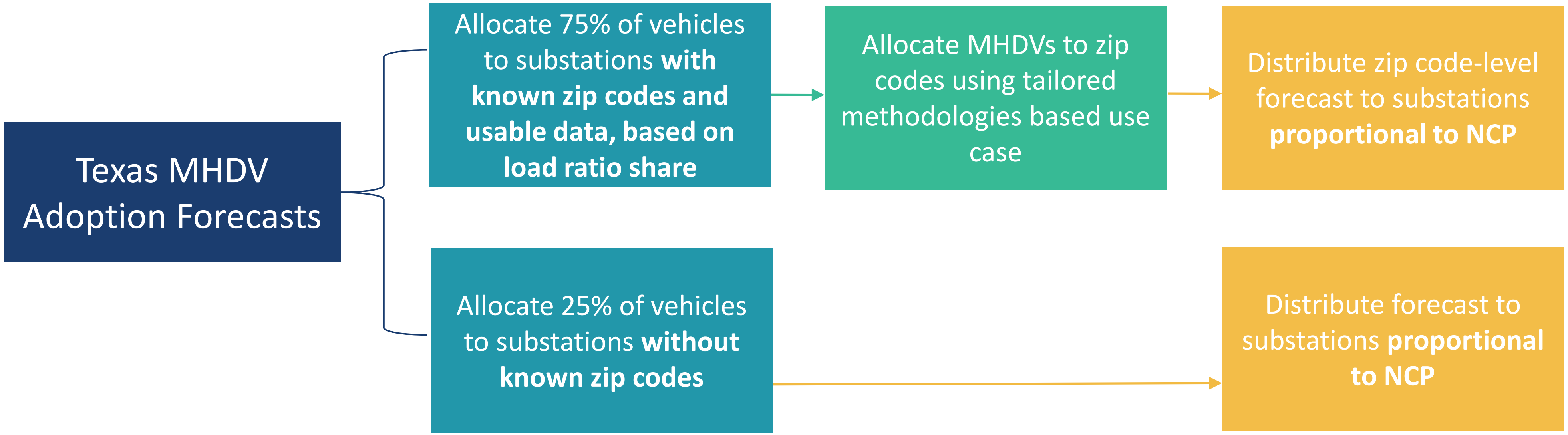
Note: Figure is only showing adoption allocated to substations with zip code mappings. Adoption allocated to NOIE and Planned substations is not included, which is likely why some zip codes show 0 adoption.



MHDV Allocation Methodology: Overview

As in the LDV methodology, we allocate 25% of vehicles directly to the NOIE substations proportionally to the NCP load served by those substations, because ERCOT does not track the zip codes served by these substations.

For the remaining 75% of vehicles, we developed a 4-step methodology to allocate MHDVs to zip codes and then to substations.



MHDV Allocation Methodology: Overview

Step 1:	Step 2:	Step 3:	Step 4:
Identify primary use cases within each class	Identify proxies for number of vehicles at a given location	Allocate system-wide vehicle numbers to locations	Assess results and model limitations

We developed a 4-step methodology to allocate MHDVs to substations.

1. In the first step, we identify the primary use cases of each vehicle weight class.
2. Understanding use cases is key to elucidating the economic factors that affect MHDV locations, driving patterns, and electrification likelihood, which is Step 2.
3. We develop quantitative metrics to allocate vehicles in each class to zip codes and then substations, by using the proxies and corresponding data sources identified in Step 2.
4. Lastly, we produce data visualizations and assess the results in the context of acknowledged model limitations.

Step 1: Composition of Vehicle Classes

By identifying a set of primary use cases in each vehicle class, we group the vehicles into categories that share similar geographic distributions and driving patterns.

- These groups combine vehicle types whose charging locations are expected to depend on common factors and proxies.
- We develop seven "Allocation Methods," A-G, for these key use case groups.

Vehicle Class	# EVs projected by 2029	Primary Use Cases	Share of Vehicles in Class in 2021	Allocation Method
Class 2B	95,592	Pickup Truck	78%	A: Pickup Trucks
		Cargo Van	22%	B: Regional Delivery Vehicles
Class 3-4	40,390	Pickup Truck	83%	A: Pickup Trucks
		Dump Truck	9%	C: Dump Trucks
		Cargo Van	4%	B: Regional Delivery Vehicles
		Straight Truck	4%	B: Regional Delivery Vehicles
Class 5-6	9,643	Straight Truck	57%	B: Regional Delivery Vehicles
		Dump Truck	40%	C: Dump Trucks
		Step Van	4%	B: Regional Delivery Vehicles
Class 7-8 Regional	4,044	Dump Truck	38%	C: Dump Trucks
		Tractor	33%	D: Regional Heavy Duty Trucks
		Straight Truck	29%	D: Regional Heavy Duty Trucks
Class 7-8 Long Haul	841	Tractor	58%	E: Long Haul Heavy Duty Trucks
		Straight Truck	42%	E: Long Haul Heavy Duty Trucks
Buses	3,476	Transit Bus	100%	F: Transit Buses
School Buses	5,609	School Bus	100%	G: School Buses

Step 2: Identify Proxies for MHDV Location and EV Adoption

We identified public data sources that inform estimation of:

1. Where MHDVs are located
2. Where EV MHDV adoption is likely

We use these identified proxies to develop a quantitative allocation metric for each method, A-G.

Allocation Method	1. Proxies for Vehicle Location	2. Proxies for EV Adoption Likelihood
A: Pickup Trucks	1. Population Density 2. Number of LDVs	1. Population Density 2. Income
B: Regional Delivery Vehicles	1. Employment in the transportation and warehousing industry	1. Distribution center locations
C: Dump Trucks	1. Employment in mining and construction industries	1. Assumed uniform adoption likelihood across zip codes
D: Regional Heavy Duty Trucks	1. Employment levels in the transportation and warehousing industry 2. Truck traffic on roads 3. Corridor charging station locations	1. Distribution center locations
E: Long Haul Heavy Duty Trucks	1. Truck traffic on major roads 2. Corridor charging station locations	1. Assumed uniform adoption likelihood across zip codes
F: Transit Buses	1. Buses registered at a transportation authority level 2. Population	1. Population density 2. Income
G: School Buses	1. Population of school aged children 2. Population density	1. Population density 2. Income

Step 3: Allocation Vehicles to Locations

Step 1: Identify primary use cases within each class	Step 2: Identify proxies for number of vehicles at a given location	Step 3: Allocate system-wide vehicle numbers to locations	Step 4: Assess results and model limitations

Using the identified proxies, we transform the available data to estimate at a zip code level:

1. The current number of vehicles in each class and use case
2. The relative rate of EV adoption

These two metrics are then combined to calculate the number of forecasted EVs at a zip code

Lastly, we convert zip code level vehicle projections to substation level projections based on the non-coincident peak load of each substation.

→ In the following slides, we will describe two of the allocation methods (B and F). Our full report will cover all of the methods in detail.

Example: Allocation Method B for Regional Delivery Vehicles

Estimate distribution of 2022 vehicles (all fuel types) at zip code level for each category and class

Develop metric to represent rate of EV adoption in category at a zip code level for 2022-2029

Allocate EV forecast to zip codes

Map forecast from zip codes to substations

Estimate the number of regional delivery vehicles per zip code by considering employment level in the transportation & warehousing industry as a proxy. Calculate:

a. An estimate of transportation & warehousing employment by workplace zip code
   - Found by converting census tract level employment data by industry (Census) to zip codes using US Housing & Urban Dev. geographic mapping data.

b. A sum of Texas-wide employment in transportation & warehousing

c. Divide (a) by (b) to obtain relative estimated shares of 2022 vehicles in each zip code.

Model high vs low EV adoption zip codes based off whether the zip code has a warehouse of a major company expected to be an early EV adopter.

a. Identified warehouse coordinates using Google Maps.

b. Mapped coordinates to zip codes using Census zip code locations.

c. Flagged zip codes with one of the identified warehouses.

1. *Zip codes with warehouses:* Allocate Brattle **base case** EV stock adoption forecast proportionally to the zip code's employment share
2. *Zip codes without warehouses:* Allocate Brattle **low case** EV stock adoption forecast proportionally to the zip code's employment share
3. Rescale forecasts so that they sum to the Brattle low case forecast across all zip codes.

Allocate vehicles from zip codes to substations proportionally to substations' non-coincident peak load.

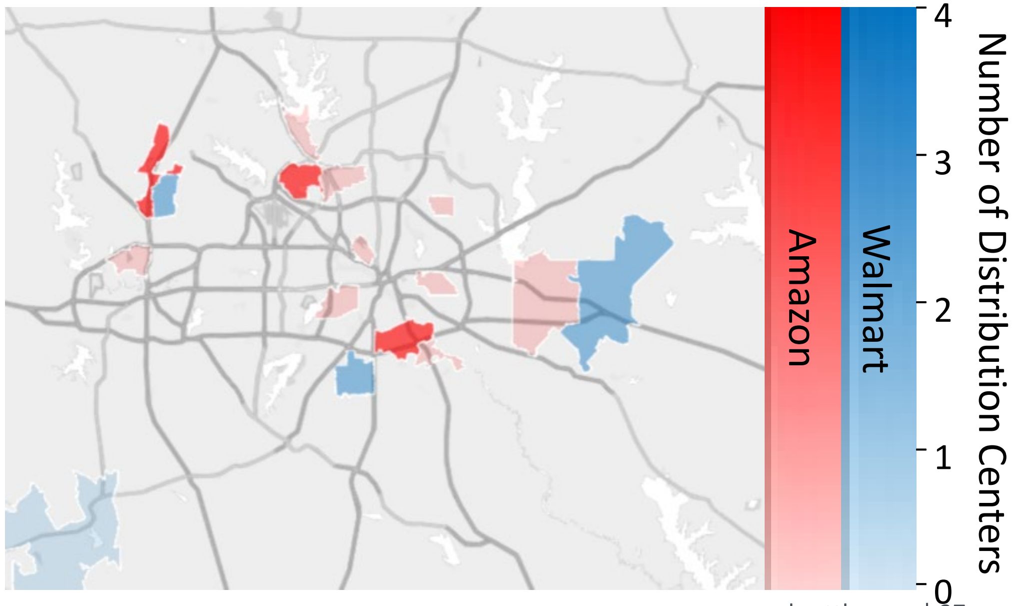
Example: Allocation Method B – Detail on Identifying Zip Codes

- We identified companies in Texas expected to be early or major adopters of EVs based on information from TDSPs and ERCOT.
- For straight truck allocation, we consider the warehouses of Walmart, HEB, Frito Lay, Amazon, UPS, and FedEx. For cargo and step van allocation, we only consider Amazon, UPS, and FedEx locations.

Expected Early or Major Adopters of Electric Trucks by TDSPs

	CPS	Oncor	TNMP	Austin Energy
Consumer Goods	Walmart, AT&T, Verizon, Ikea	Amazon	Amazon	Amazon, Ikea, Staples, J.B. Hunt
Food	Frito Lay, Pepsi	Frito Lay		Frito Lay, Coca Cola, Pepsi, Nestle
Transport	UPS	FedEx, UPS, Ryder		DHL, UPS, FedEx, USPS

Amazon and Walmart Distribution Center Density in DFW Area

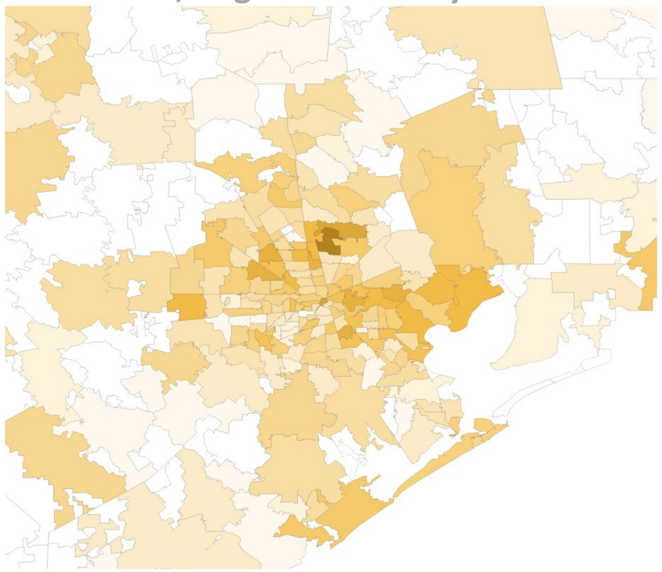


Results: Regional Delivery Vehicles

Electric regional delivery vehicle adoption is projected to occur around city outskirts and along major highways where distribution centers tend to be located.

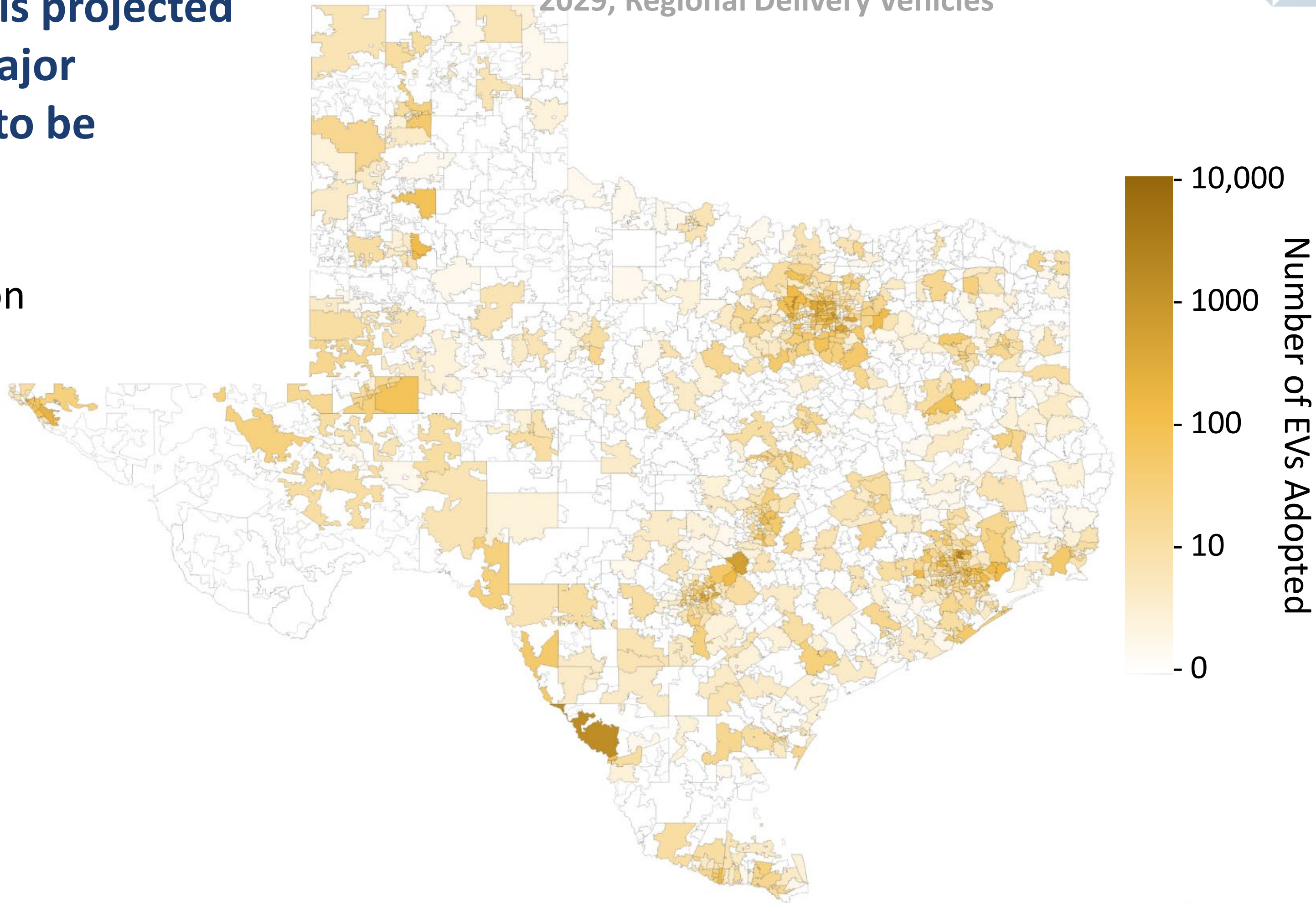
Forecasted EVs by Zip Code Detail: Houston

2029, Regional Delivery Vehicles



Texas Forecasted EVs by Zip Code

2029, Regional Delivery Vehicles



Example: Allocation Method F for Transit Buses

Estimate total 2022 transit buses (all fuel types) at zip code level → **Develop metric to represent rate of EV adoption at a zip code level for 2022-2029** → **Allocate EV forecast to zip codes** → **Map forecast from zip codes to substations**

Estimate the number of transit buses per zip code through the following steps:

1. Obtain number of buses by transportation authority (TX DOT)
2. Estimate number of buses by city (urban areas) or county (rural areas) based on transportation authority to county and city mappings (TX DOT)
3. Estimate number of buses by zip code based on county to zip code mappings (US Housing & Urban Dev.) and city to zip code mappings (USZip.com), allocating to zip codes based on the relative numbers of addresses in each zip code (US Housing & Urban Dev.)

Estimate relative likelihood of EV adoption conditional on number of buses in each zip code for 2022-2029 by multiplying (a) and (b):

a. Income adoption propensity score (mapped from census zip code income data)
b. Population density adoption propensity score (mapped from census zip code population density data)

1. Calculate EV transit bus adoption propensity scores for 2022-2029 by multiplying total transit buses per zip code by relative likelihood of EV adoption conditional on number of buses in each zip code
2. Allocate Brattle **base case** EV stock adoption forecast to zip codes proportional to metric calculated in (1)

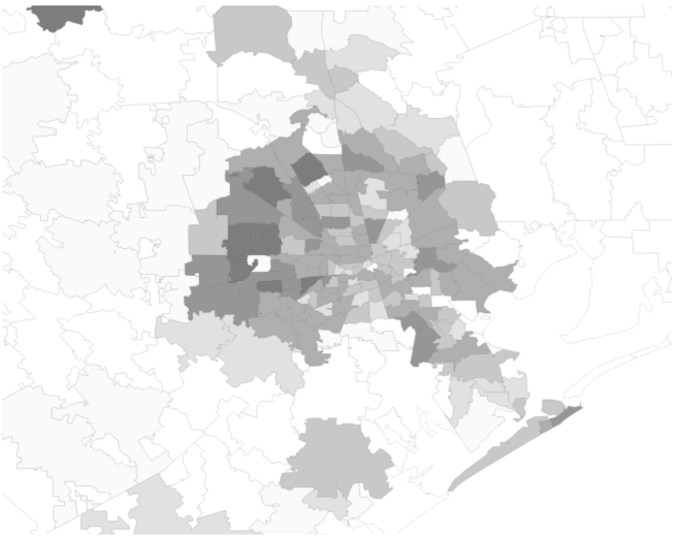
Allocate vehicles from zip codes to substations proportionally to substations' non-coincident peak load.

Results: Transit Buses

Electric transit bus adoption is expected to occur primarily in cities and areas with higher average income. Because depot charging locations were not identified, charging was assumed to occur where bus driving occurs.

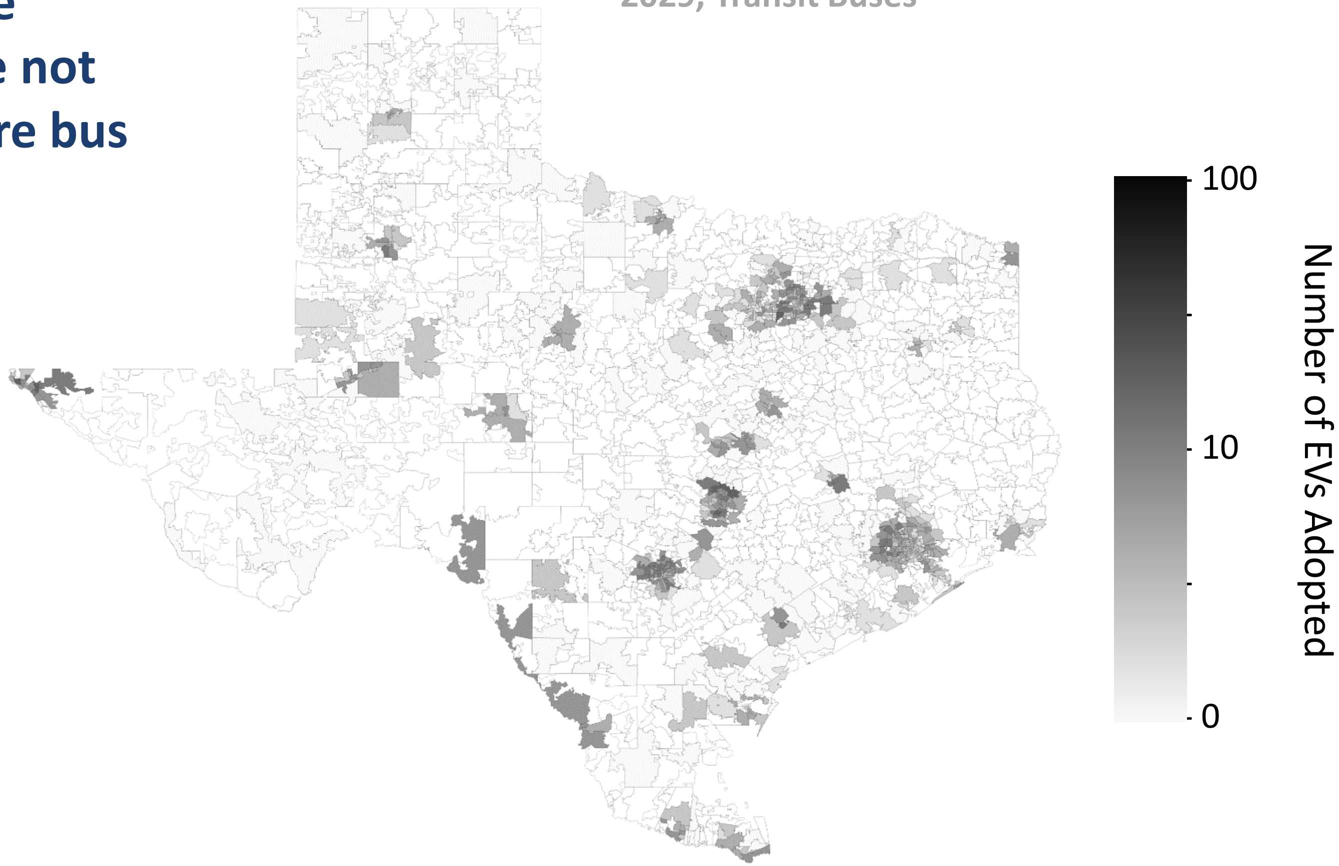
Forecasted EVs by Zip Code Detail: Houston

2029, Transit Buses



Texas Forecasted EVs by Zip Code

2029, Transit Buses



Example: Allocation Method G for School Buses

Estimate the relative shares of 2022 school buses (all fuel types) between zip codes → **Develop metric to represent rate of EV adoption at a zip code level for 2022-2029** → **Allocate EV forecast to zip codes** → **Map forecast from zip codes to substations**

Estimate the relative shares of 2022 school buses (all fuel types) between zip codes

Use number of children who ride the school bus in a zip code as a proxy for the number of school buses (assume equal school bus to child ratio across zip codes).

Estimate the relative share of school buses per zip code by multiplying (a) and (b):

a. An estimate of school bus ridership rate by zip code
   - Find by joining data on school bus ridership rate among children reported for different population density ranges within Texas (Census) with population density data by zip code (Census)

b. Data on the number of school aged children by zip code (Census)

Develop metric to represent rate of EV adoption at a zip code level for 2022-2029

Estimate relative likelihood of EV adoption conditional on number of school buses in each zip code for 2022-2029 by multiplying (a) and (b):

a. Income adoption propensity score (mapped from census zip code income data)

b. Population density adoption propensity score (mapped from census zip code population density data)

Allocate EV forecast to zip codes

1. Calculate EV transit bus adoption propensity scores for 2022-2029 by multiplying total school buses per zip code by relative likelihood of EV adoption conditional on number of buses in each zip code
2. Allocate Brattle **base case** EV stock adoption forecast to zip codes proportional to metric calculated in (1)

Map forecast from zip codes to substations

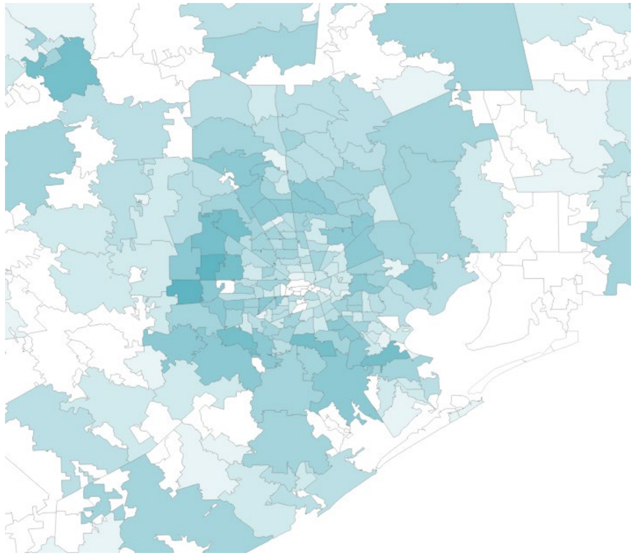
Allocate vehicles from zip codes to substations proportionally to substations' non-coincident peak load.

Results: School Buses

We project the most electric school bus adoption in suburban areas where children are more likely to ride the school bus and where there may be more public support for EV adoption among higher income people living in high density zip codes.

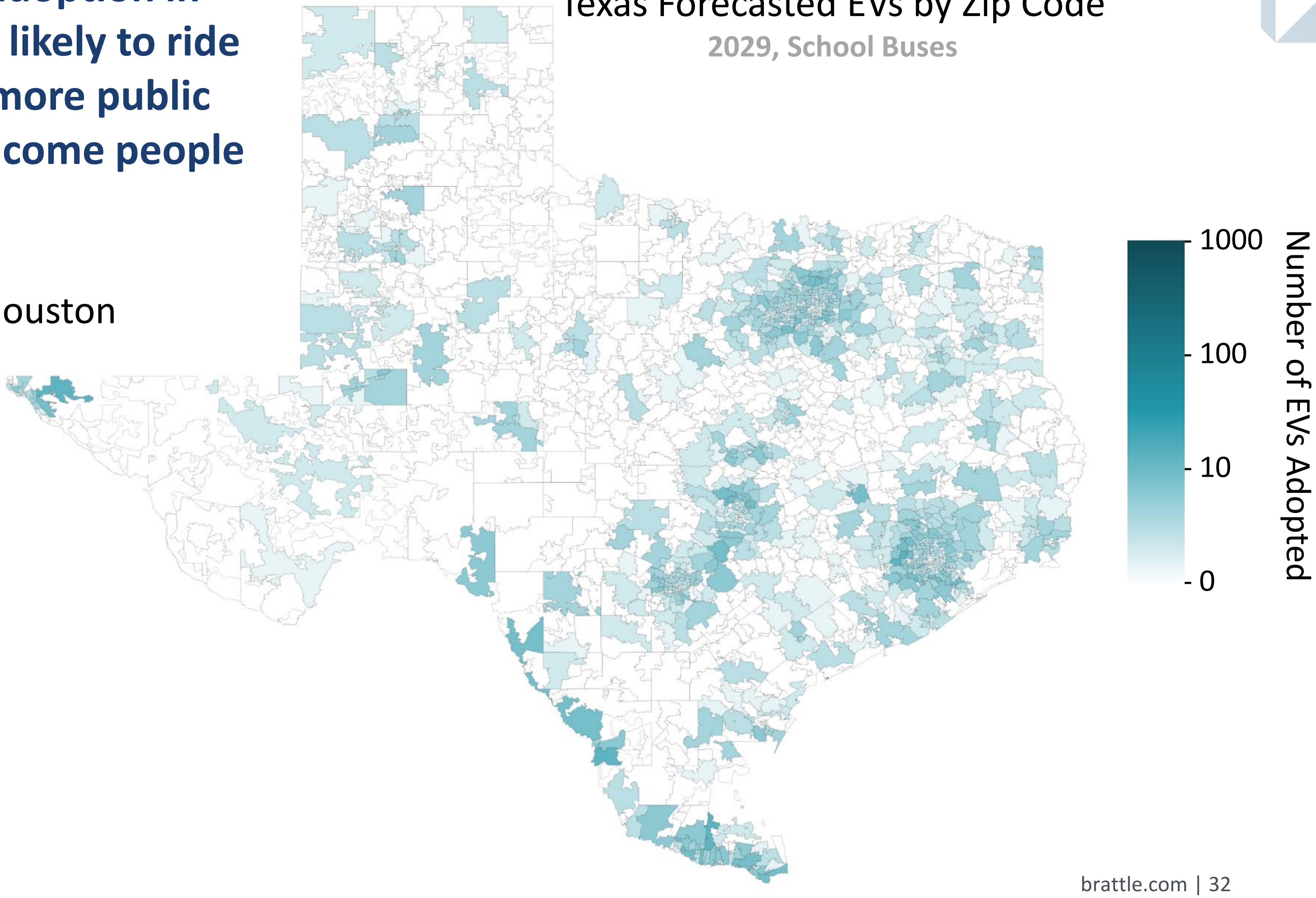
Forecasted EVs by Zip Code Detail: Houston

2029, School Buses



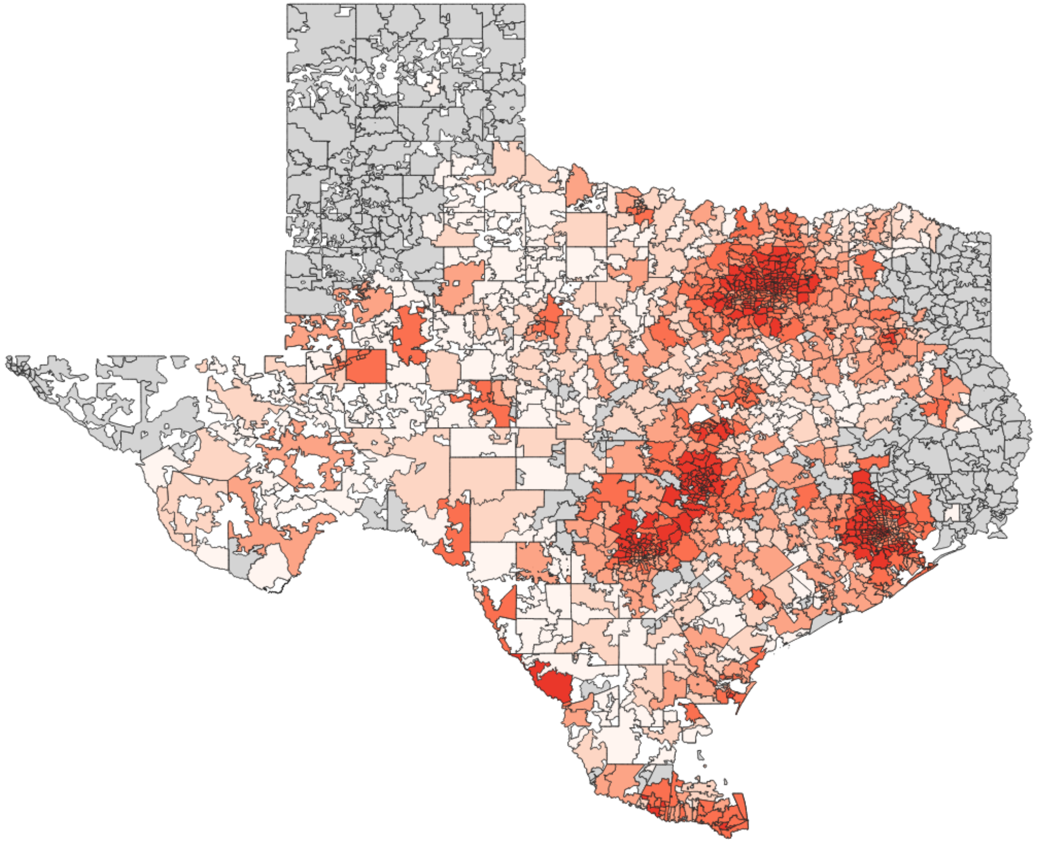
Texas Forecasted EVs by Zip Code

2029, School Buses



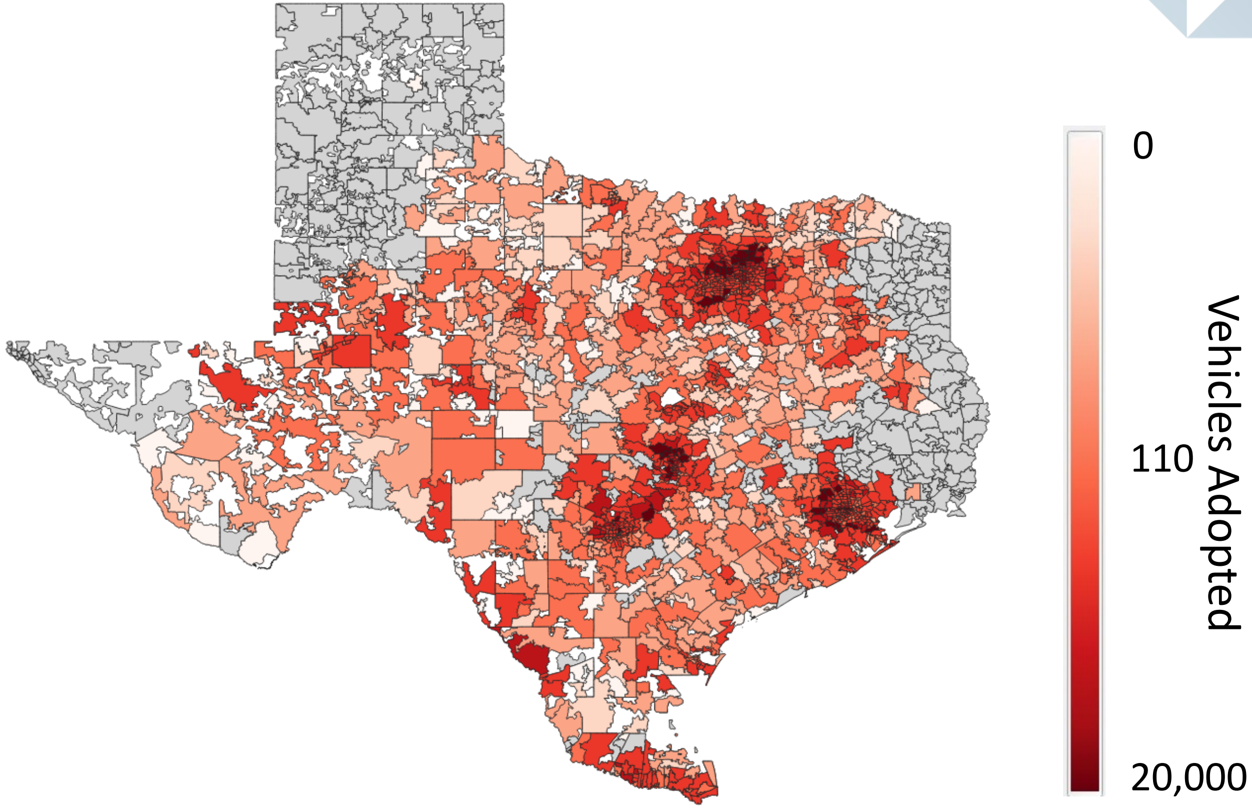
Final Electric Vehicle Allocation to ERCOT Zip Codes

2022 Electric Vehicle Adoption



Note: Showing actual LDV adoption as of April 2022 via Atlas EV Hub. MHDV adoption is currently very low in TX (~50 EVs total) and is not shown on the figure.

2029 Electric Vehicle Adoption



Note: Showing modeled LDV and MHDV adoption in 2029. LDV adoption includes only vehicles allocated to ESIID substations (75% of forecast). Due to data limitations we cannot show the location of LDVs allocated to NOIE/Planned substations serving these zip codes.

Step 3: Load Impact Analysis

Step 3: Load Impacts at the Substation-Level

1 Establish Light, Medium, and Heavy-Duty EV Adoption Forecasts for 2022-2029

- Update and improve upon ERCOT's existing adoption assumption for LDV penetration.
- Build out adoption forecast for a more granular list of Medium and Heavy-Duty (MHDV) EVs

2 Allocate Adoption Forecasts to ERCOT Substations

- Separate methodologies for LDV and MHDV allocation
- Vehicles first allocated to the zip-code level and then to the substation-level using data from ERCOT, the Census, and Moody's.

3 Calculate Load Impacts at the Substation-Level

- Calculate 64 representative load profiles for each substation, showing load throughout 4 seasons, 2 day types, and 8 years.
- Develop interactive tool that generates profiles for each substation and can be easily updated in the future.

EV Load Profile Model Flow

Primary Texas-specific inputs:
- Total EVs
- Mix of EV types (Battery Electric (BEV)/Plug-in Hybrid (PHEV), sedan/SUV, battery size)

Daily Electric Vehicle Miles Traveled (VMT) (per vehicle, quarter, day)

Inputs:
- % electric miles for PHEV
- Daily VMT for TX LDV drivers
- Seasonal VMT (% of annual)
- Weekday vs weekend VMT

→ **Daily Energy Demand** (per vehicle, quarter, day)

Inputs:
- Vehicle average efficiency
- Seasonal ambient temperature by Weather Zone
- Efficiency vs temperature

→ **Daily Energy Charger Demand** (per vehicle, quarter, day)

Inputs:
- % of demand by location, for each vehicle, season, and day

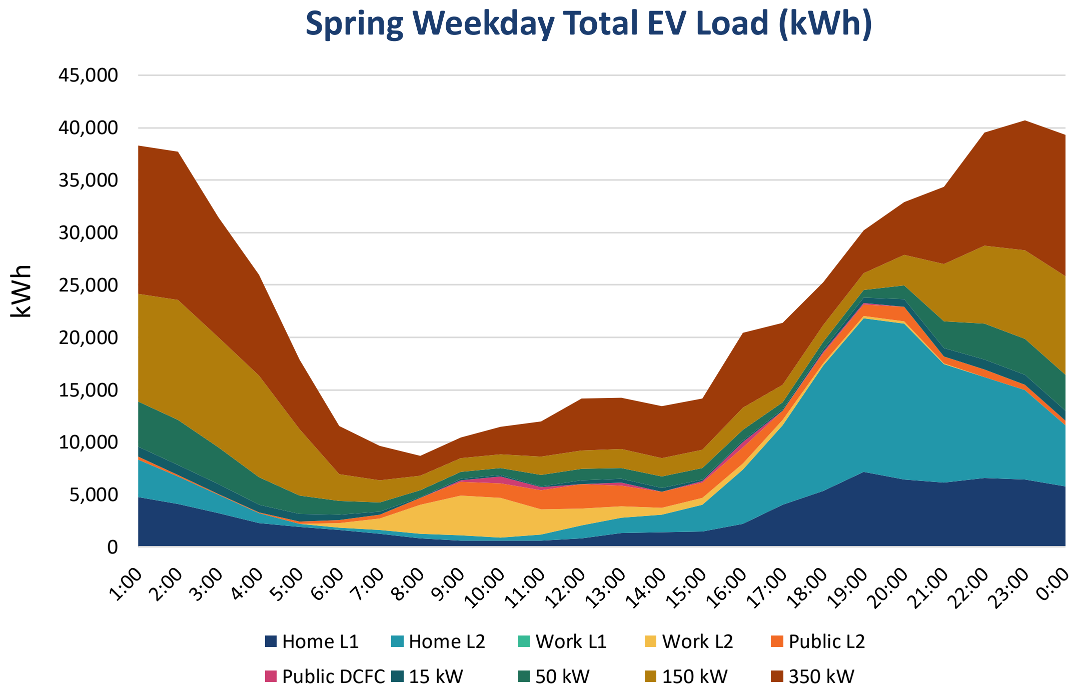
→ **24-hr Energy Charger Demand** (per vehicle, season, day)

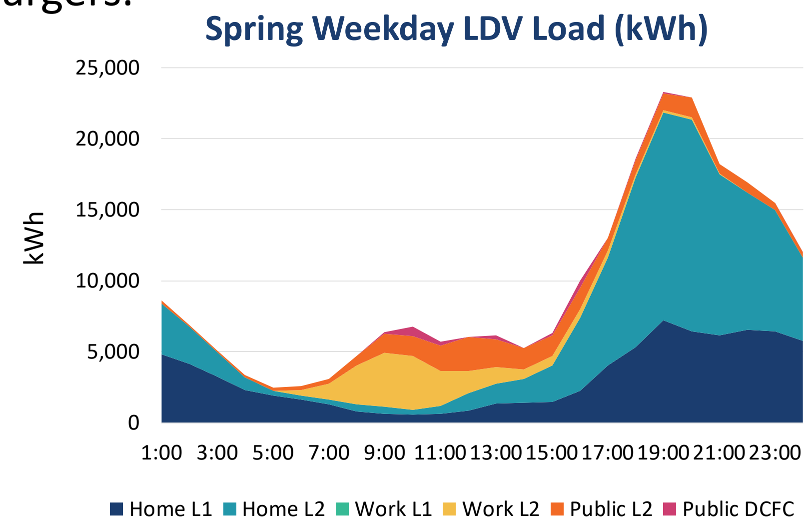
Inputs:
- 24 hour normalized demand by charger type for each vehicle and day

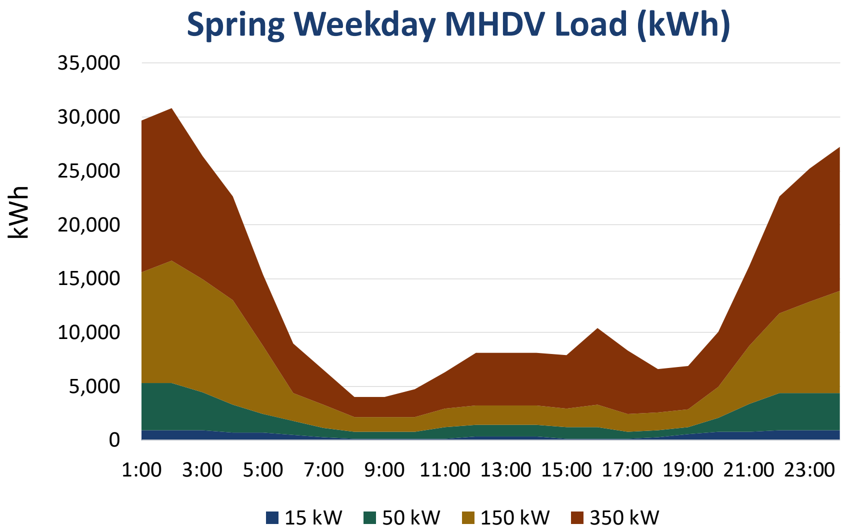
Output:
- Total hourly EV demand at each substation by season/day
- Can break down load by location/charging type

Example Load Profiles

Takeaways: Our load profiles assume that substations will serve high levels of evening and overnight load due to charging from Long Haul trucks and LDVs plugging in at Home L2 chargers.

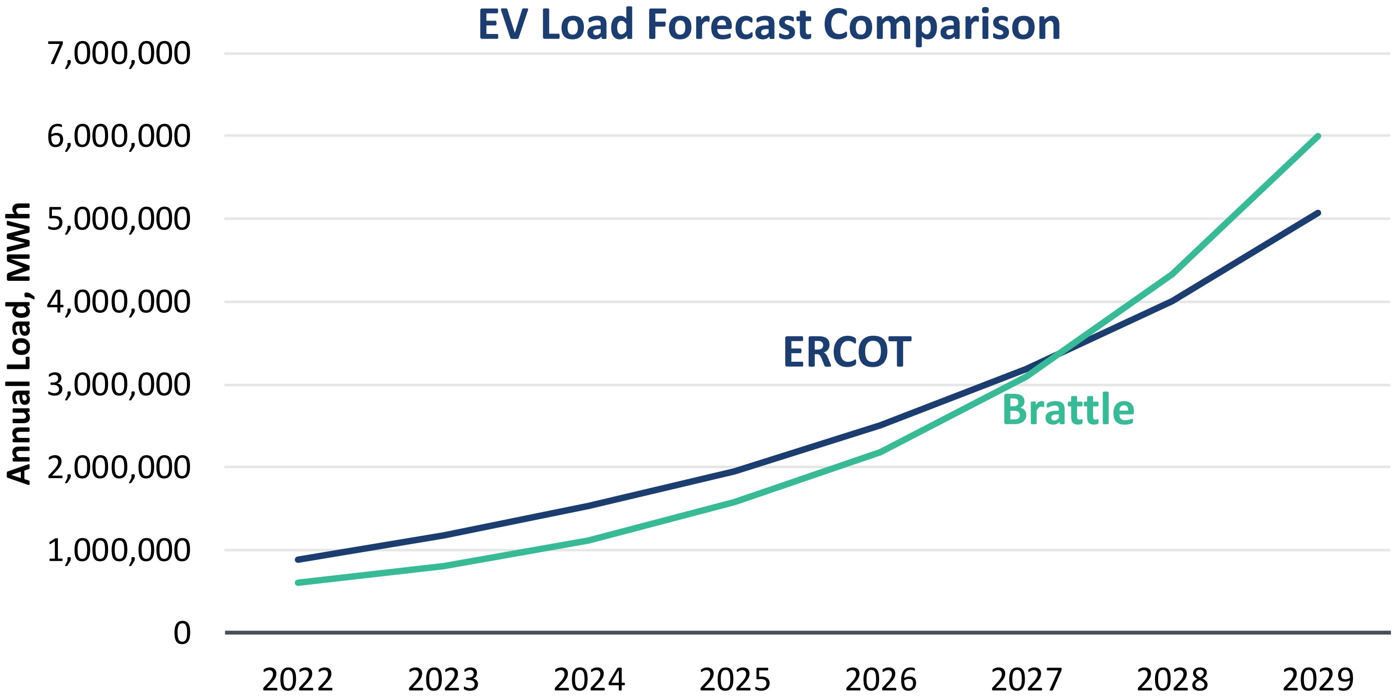






Comparison to ERCOT Load Forecast

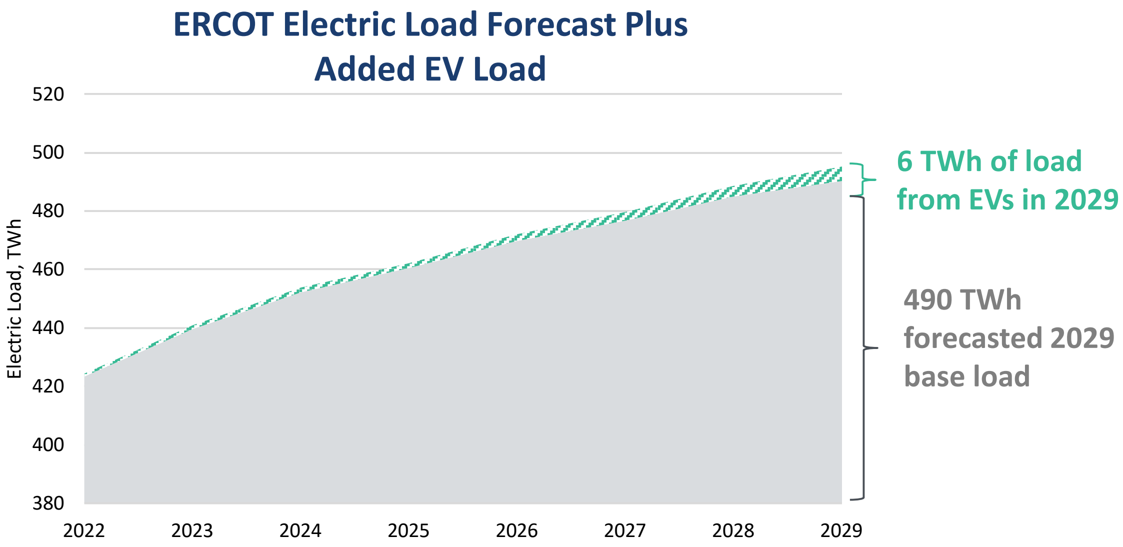
- Brattle's annual EV load forecast aligns closely with ERCOT's original load impact assumption at the system level.
- ERCOT's assumption reports an annual total system load impact of approximately **5.1 TWh** in 2029, while Brattle's approach comes in slightly higher at **6 TWh**.

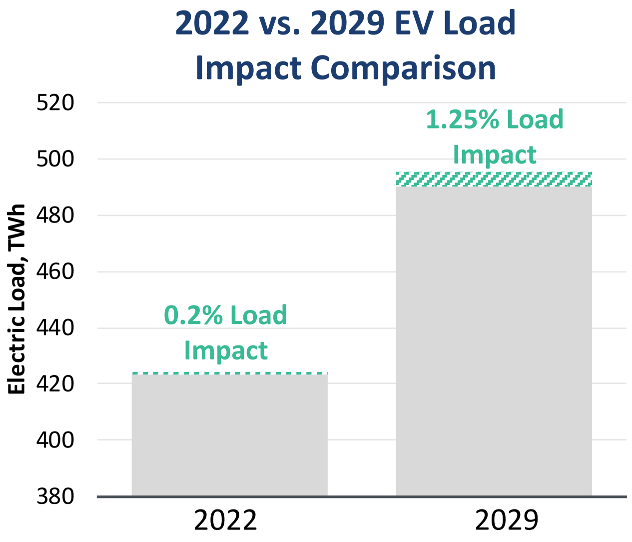


ERCOT EV Load Forecast Impacts

- EV adoption across all ERCOT substations is expected to add about 0.2% of load to ERCOT's electric load forecast in 2022 and about 1.25% of load in 2029.
  - By 2029, EV load will add approximately **6 TWh** of load to ERCOT's base load forecast.
  - This is the combined charging load estimated to come from **~750,000 LDVs** and **~130,000 MHDVs.**
- ERCOT's electric load will grow at a rate of **2.1%/year** without EV load, and **2.3%/year** with EV load.

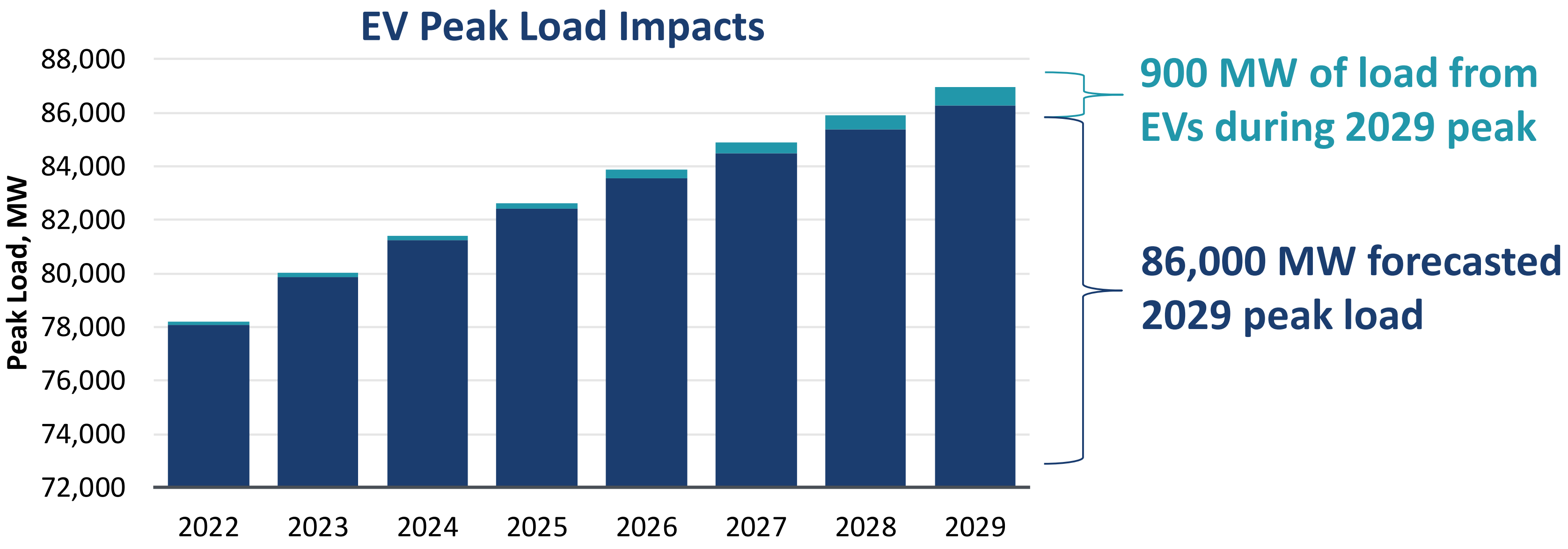
Vehicle Type	Annual MWh
Passenger BEV	3.4
Passenger PHEV	2.0
Passenger Light Truck	3.9
MHDV Pickup Truck	7.4
Transit Bus	188
School Bus	17
Regional Delivery Truck	25
Dump Truck	6
HD Regional Truck	106
HD Long Haul Truck	488





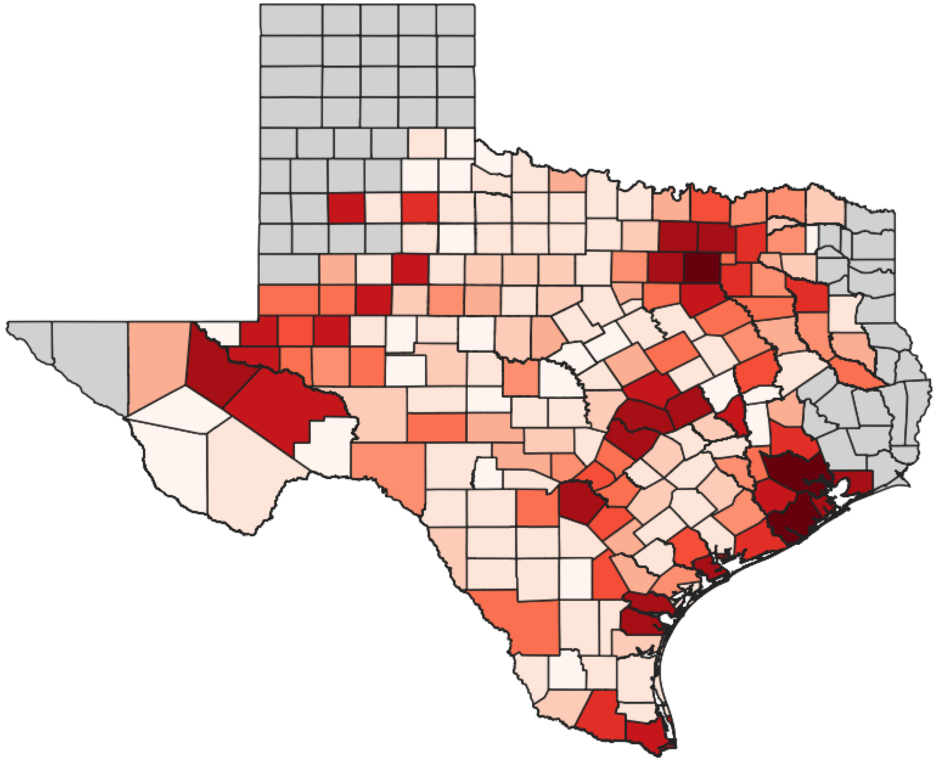
Peak Load Impacts

- According to 2021 4-CP calculation, ERCOT's coincident peak occurred on Tuesday, August 24th at Hour Ending 17.
  - We see that at the system level, CP impacts are quite similar to total load impacts, totaling roughly 1% of the annual coincident peak in all years.
  - With EV load, ERCOT's peak load cumulative annual growth rate (CAGR) will increase from **1.4%/year** to **1.6%/year**.

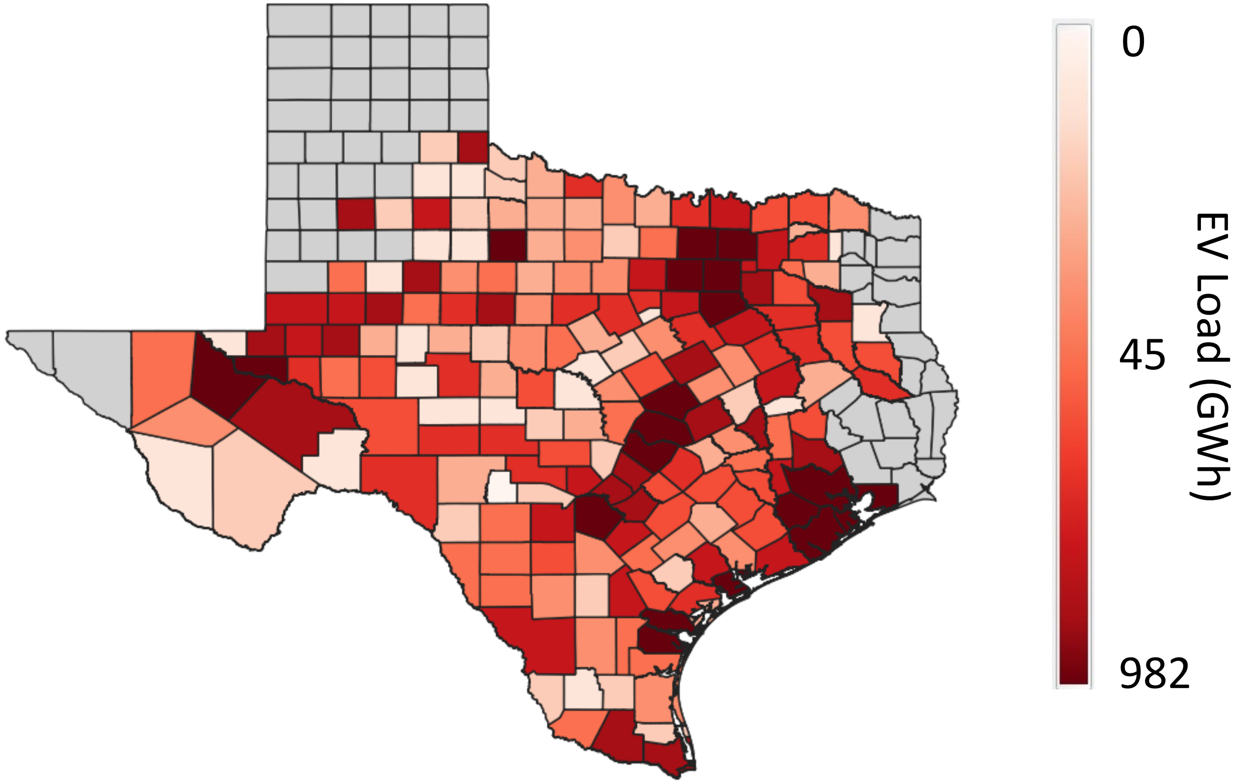


Total EV Load Distribution by County

2022 (Modeled) EV Load Impacts



2029 (Modeled) EV Load Impacts



Note: Based on modeled 2022 adoption of LDVs and MHDVs. Historical load impacts unavailable.

Recap

- Brattle team developed a new methodology to allocate light, medium and heavy duty vehicles to ERCOT substations to understand the extent of additional load on substation peaks
- We utilized the most recent and best available information to guide our methodology, largely relying on publicly available data sources
- We took into account the characteristics as well as use cases for each vehicle category for defining an allocation method for that category
- This is still a very nascent research area, and there are not publicly available precedents to the allocation of EVs to more granular locations
- While our allocation method resulted in allocations consistent with a priori expectations (i.e. higher LDV allocations to urban and suburban zip codes surrounding major cities such as Austin, Houston, DFW and higher allocations of delivery vehicles and regional and long haul trucks add load to substations in the city outskirts and major highways), the accuracy of the approach should be evaluated periodically and adjusted as more data becomes available

Key Limitations

- Lack of zip code data for all substations causes us to make approximations for load at substations for which we do not know the associated zip code
- Approximation of adoption at zip codes with no historical adoption is speculative and assumes no-historical-adoption zips will experience adoption at a faster rate than zips with historical adoption
- List of active zip codes in TX and appropriate mappings to counties, census tracts, etc. has had inconsistencies across sources
- Propensity score approach could capture more economic variables in future iterations to produce more granular and diverse results across zips

MHDV Analysis Key Limitations

Allocation Method	Limitations and Areas for Future Development
Pickup Trucks	• Did not have pickup truck registrations at a county or zip code level- estimated based on a population density relationship.
Regional Delivery Vehicles	• In the future, could consider additional companies, distribution center size, and the specifics of expected announced adoption timelines.
Dump Trucks	• Did not identify centers where dump trucks are likely to charge • In the future, could add differentiation of EV adoption rates of dump trucks by zip code
Heavy Duty Trucks	• Assumed charging stations will be deployed as forecasted by the Texas DOT charging plan. • Assumed MHDV chargers will be deployed at the same rate and in the same locations as LDV chargers – MHDV report will be released this fall. • Assumed regional trucks will charge 50% along roads where they travel and 50% at distribution centers. • Assumed long haul vehicles will only charge along major highways.
Transit Buses	• Did not have information on bus depot and charging locations. • In the future, could incorporate information about which areas have announced electric bus adoption plans.
School Buses	• Did not have data on actual school bus registrations by zip code- estimated based on population density relationship. • Did not identify school bus charging locations or depots.

Appendix

Zip Codes with No Historical EV Adoption

- Approximately **1%** of our LDV vehicle forecast in each year is allocated to zip codes with **0 historical adoption**. These zip codes require a different allocation method, since there is little precedent to be able to predict adoption here.
- A primary limitation of the propensity score approach is that it assigns a score of 0 to the 428 zip codes with zero historical EV adoption.
  - Excluding the historical adjustment from the propensity score equation results in an unrealistic ramp-up rate for zip codes with 0 EVs.
- We derive standardized adoption forecasts for each of these zip codes separately, using the following “rules”:

1. Identify most common level of EV entry using EV Hub historical data

- We find it is most common for 1 EV to enter at a time across one year and ramp up from there

2. Identify a “rule” that will dictate the first year of entry for the first EV

- We find that the majority of zip codes with existing EV adoption in 2022 had propensity scores over 1,000. So we assign each no adoption zip code with a propensity score over 1,000 one EV in 2022. We work backwards from there, zip codes with prop scores from 500-1000 see adoption starting in 2023, and prop scores from 0-500 start in 2024.

3. Set a limit on the maximum number of EVs that can be electrified in a given no adoption zip code in 2029

- The system-wide electrification level we forecast with our ERCOT-wide forecast is 5% of total registrations by 2029.
- We cut this in half to account for delayed adoption in these zip codes.

4. Calculate linear growth from the year that the first EV comes online to the maximum adoption level

Example Allocation to Zip Code without Historical Adoption

- **79512** is a zip code located in the Abilene – Sweetwater metro area, primarily in Mitchell County.
  - Population: 8,197 (U.S. Census Bureau).
  - Land Area: 599 sq. miles (U.S. Census Bureau).
  - Population Density: ~14 residents per sq. mile (“Rural”).
  - Income per capita 2022: $21,658 (U.S. Census Bureau).
  - Approx. Total Registered Vehicles 2022: 3,872.
- 2022 Propensity Score = 1 * 1 * 3,872 = **3,872**
  - Propensity score exceeds 1,000, so we assign 1 EV to be adopted in this zip code by end of 2022.
- Forecasted total registered vehicles in 2029 = **3,960**
- 3,960 * 2.5% EV penetration = **99** EVs adopted by 2029
- We use this approach for all 428 zero-adoption zip codes and add up the total number of EVs forecasted to be adopted in each year.
  - We find that this results in roughly 1% of LDVs being allocated to these zip codes by 2029.