

Technical Documentation

Data Sources, Methodology, Ground Truthing and Version Changes



DOCUMENT CONTENTS

1. Introduction
2. Methodology
 - Light Duty - *Power and Energy*
 - Medium-Heavy Duty- *Power and Energy*
3. Version Documentation

1.

Introduction



eRoadMAP uses a combination of EV adoption projections and measured trip data to estimate power and energy requirements from an increasing number of electric light-, medium-, and heavy-duty, on-road vehicles.

- EV adoption projections require assumptions and analysis around how rapidly different types of vehicles will transition to electric options, and how EVs will be distributed geographically over time.
- Estimating energy requirements for EVs from conventional vehicles requires assumptions and modeling around how EVs will be driven, their efficiency, where they will stop, for how long, and how they may be expected to recharge their batteries.

The following slides articulate the methodology, primary data sources, and key assumptions used to conduct this analysis for eRoadMAP V2.2. This tool will continue to evolve and improve as EPRI gathers additional data and new methodologies/assumptions become available.

While eRoadMAP data is critically important for understanding load growth over time, it does not replace the rigorous utility processes involved in planning utility upgrades. The data resulting from this analysis can be useful in highlighting areas where multiple customers may be clustered around one or two feeders and can enable utility and customer discussions to happen sooner rather than later in the planning process through early engagement.

The EPRI team is continuing to work with fleet operators, vehicle manufacturers, and charging providers to add more data sources to this work. Currently the eRoadMAP data set does not include the following transportation loads: transit buses and federal and municipal fleets. These loads will be added as EPRI gathers more data.

Additionally, as EPRI gathers more data, the confidence in the energy estimates at each hexagon will rise. However, *it should be noted that generally as one zooms in to smaller and smaller areas, the certainty will decrease as the data is reliant on the behavior of fewer vehicles rather than an aggregated number.*

INTRODUCTION – ACRONYMS

Acronym	Definition
BEV	Battery-Electric Vehicle
CEC	California Energy Commission
CV	Combustion Vehicle
EPRI	Electric Power Research Institute
FHWA	Federal Highway Administration
HEV	Hybrid Electric Vehicle
LD/LDV	Light-duty / Light-duty Vehicle
MDHD	Medium-duty Heavy-duty
NREL	National Renewable Energy Laboratory
OEM	Original Equipment Manufacturer
PEV	Plug-in Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
VIO	Vehicles in Operation

Vehicles Included in V2.2 eRoadMAP™

- **Personal light-duty vehicles**
 - Class 1-2 – passenger vehicles
- **Medium-duty trucks**
 - Class 3-6
- **Heavy-duty trucks**
 - Class 7-8

Future Enhancements

- **Transit buses**
- **Municipal fleets**
- **Government fleets**

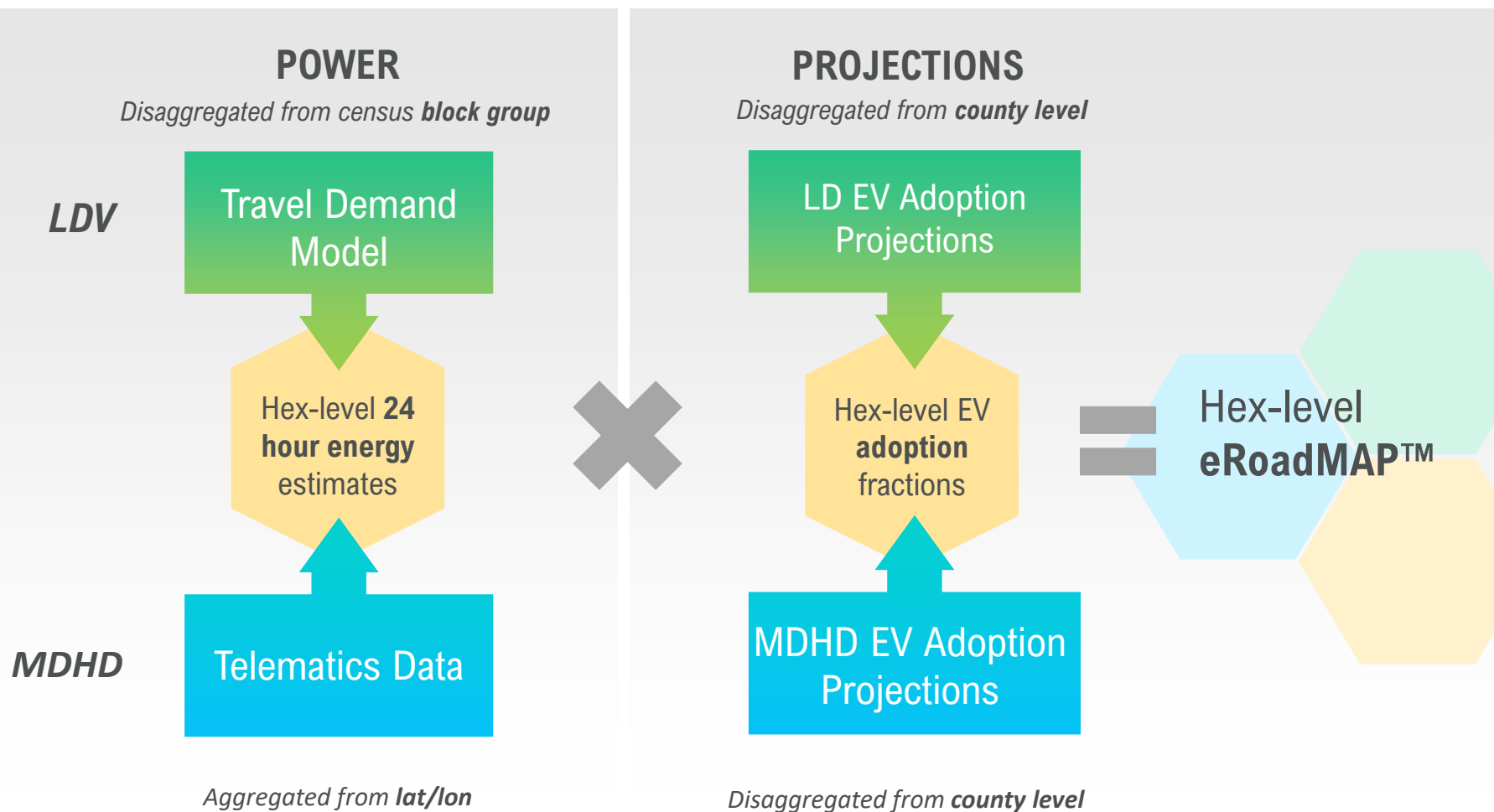
Added in this update: Ports and Airports

Note: EPRI has collected information from specific MDHD vehicle fleets where possible to enhance the confidence in the electrification plans and vehicle behavior. These include Daimler, Volvo, Navistar, Paccar, Amazon, Enterprise etc.

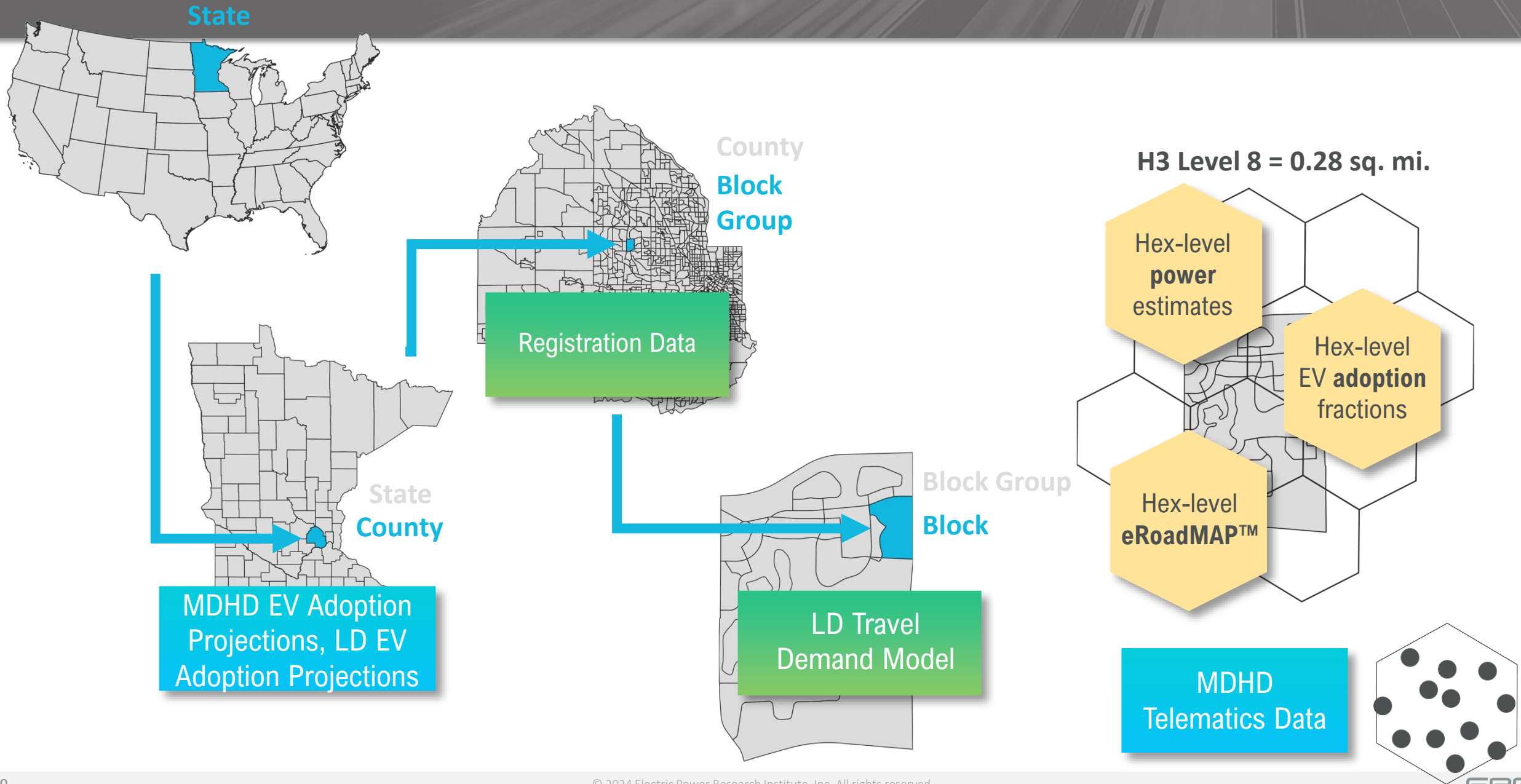
EPRI will update these lists as we incorporate additional data sets.

Adoption and Vehicle Behavior

Due to the variety of data sets and data resolution, each data set and projection had to be manipulated to be in a format that would allow integration with the other data sets. Below is a simplistic view of how the projections and data sets were pulled together.



Levels of Resolution Used in eRoadMAP





Data Partners

ANALYTICS



DATA

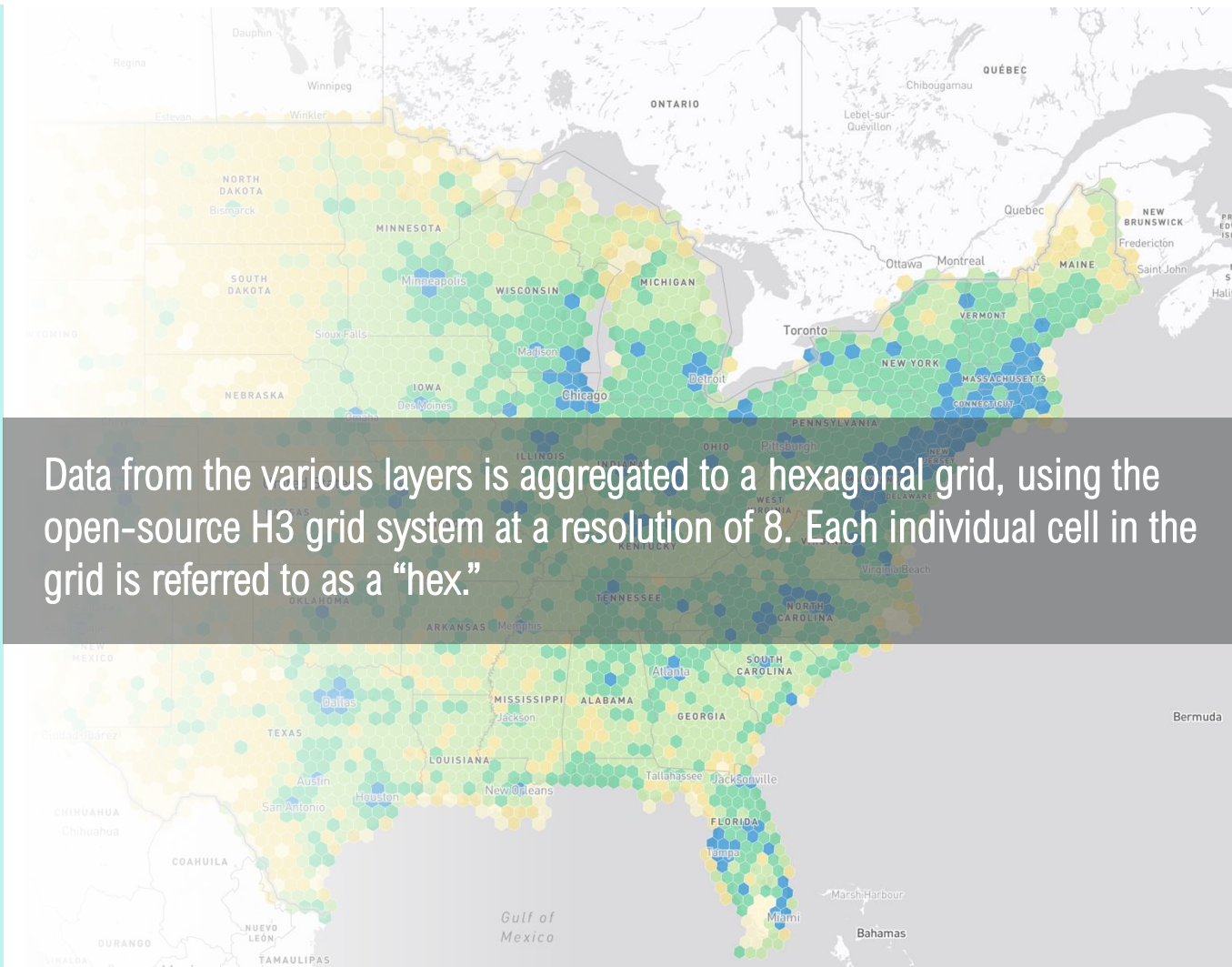


Sustainability in Action



Res	Average Hexagon Area (km ²)	Average Hexagon Area (mi ²)
0	4,357,449.42	1,682,419.93
1	609,788.44	235,440.54
2	86,801.78	33,514.34
3	12,393.43	4,785.13
4	1,770.35	683.53
5	252.90	97.65
6	36.13	13.95
7	5.16	1.99
8	0.74	0.28
9	0.11	0.04
10	0.0150	0.0058
11	0.0021	0.0008
12	0.0003	0.0001

H3 resolution levels
<https://www.uber.com/blog/h3/>



2.

Methodology



Light-Duty Vehicles



Light-Duty Vehicles

Introduction



The methods and data informing the LD power and energy needs were provided to eRoadMAP by RMI (Rocky Mountain Institute).

EPRI and RMI worked together to use RMI's GridUp modeling tool with custom eRoadMAP assumptions for vehicle efficiency and adoption over time. RMI provided the analysis and made the data available to EPRI and the eRoadMAP tool. Both the GridUp modeling tool and eRoadMAP will be updated over time to reflect updated industry information.

This light-duty section covers data sources as well as assumptions used to calculate energy and power over time.

Light-Duty Vehicles

Data Sources



The data for light-duty vehicles was informed by a travel model called **Replica**. Below some features of the dataset are outlined:

- It is a synthetic, high-resolution representation of movements and activities of people.
- The complete blend of data sources in Replica is proprietary but primary sources that are used to calibrate its data include:
 - U.S. Census population data (households)
 - Household travel surveys (households, vehicles, trip origins + destinations, trip distances, trip sequences)
 - Android cell pings (population, trip origins + destinations, trip distances, trip sequences)
- The Replica data includes the start and end times of a trip, the purpose of a trip and the distance traveled.

[Replica Travel Demand Model Link](#)

Light-Duty Vehicles

Data Sources



In addition to using Replica to capture LD vehicle behavior, EPRI collected information from Tesla and Enterprise to include energy and power needs for Tesla public charging and airport rental car lots respectively.

These additional loads have been added to the Light Duty data supplied by RMI.

Light-Duty Assumptions

General



In order to model the power and energy needs of an electrified vehicle fleet, general assumptions were made.

More detailed assumptions can be found in the respective sections.

General Assumptions

- **Feasibility:** All light duty vehicle trips are achievable by an electric vehicle. There is no threshold range to determine which trips are not electrifiable.
- **Behavior:** Driver behavior will not shift with the adoption of battery electric vehicles from internal combustion engines. Average weekday behavior is used for power needs as it has more coordinated charging behavior than weekends, resulting in higher peaks. The analysis is based on a representative 2023 Q2 weekday.
- **Efficiency:** Vehicle efficiency doesn't vary with weather; a bulk efficiency average is used. LD vehicles were assumed to have an efficiency of 0.42 kWh/mile. *Note that this likely will need to be revisited as technology improves and larger vehicles enter the market.*
- **Adoption:** Adoption over time aligns with EPRI's adoption trajectory (defined later in the slides).

Light-Duty Assumptions

Charging Behavior



Assumptions that directly pertain to charging behavior are listed below.

RMI's GridUp Model Assumptions

- Drivers will attempt to charge their vehicles enough to offset the day's energy use. This means that a driver will charge daily rather than every two or three days.
- Stop duration and destination information determine what kind of charger a driver would attempt to use during a stop.
- Whether a charger is available is decided probabilistically, with different probabilities for different charger categories or types.
- Drivers prefer charging during longer stops and at homes and workplaces. Charging opportunities are sorted by whether they are at home/work or not and in descending order of stop duration. The locations are then used in ranked order until the vehicle is charged.

Light-Duty Assumptions

Charger Power Level Assumed



The table below lists the power levels available at each charging station type within the RMI model. DCFC power levels are session averages.

EVSE Type	Power (kW)
DCFC 350 kW	227.5
DCFC 250 kW	162.5
DCFC 150 kW	136.5
Public L2	11.2
Single & Multi-Family Home L2	7.2
Civic L2	7.2
Work L2	7.2

Note: The assumed power levels per charger come from the US Department of transportation and are summarized in the following table. "Charger Types and Speeds," United States Department of Transportation, accessed July 9, 2024, <https://www.transportation.gov/rural/ev/toolkit/ev-basics/charging-speeds>.

DCFC session averages relative to nameplate power levels are based on commercial EV charging tests from the following table. "Edmunds EV Charging Test," Edmunds, accessed September 3, 2025, <https://www.edmunds.com/car-news/electric-car-charging.html>.

Light-Duty Assumptions

Probability of Charger Type



The table below lists the probability of finding a charger type at a location during the hour of peak demand within the RMI model. Off-peak probabilities increase in inverse proportion to the amount of demand..

EVSE Location	Probability
Single Family Home has L2	100%
MFH has L2	50%
Office workplace has L2	50%
Non-office workplace has L2	10%
Civic institutional has L2	50%
Long public stop has L2	100%
Quick public stop has DCFC 150	35%
Quick public stop has DCFC 250	30%
Quick public stop has DCFC 350	35%

Note: The probability that a driver finds a charger of a certain type can significantly impact when and where they charge. RMI's model made reasonable assumptions based on a study of real-world EV charging as well as best estimates of what charging availability will exist in the future. RMI's assumptions were informed by the below referenced paper. If a charger isn't available at a location, it is assumed that the vehicle charges at the next stop. Most vehicles are able to replenish the energy used each day.

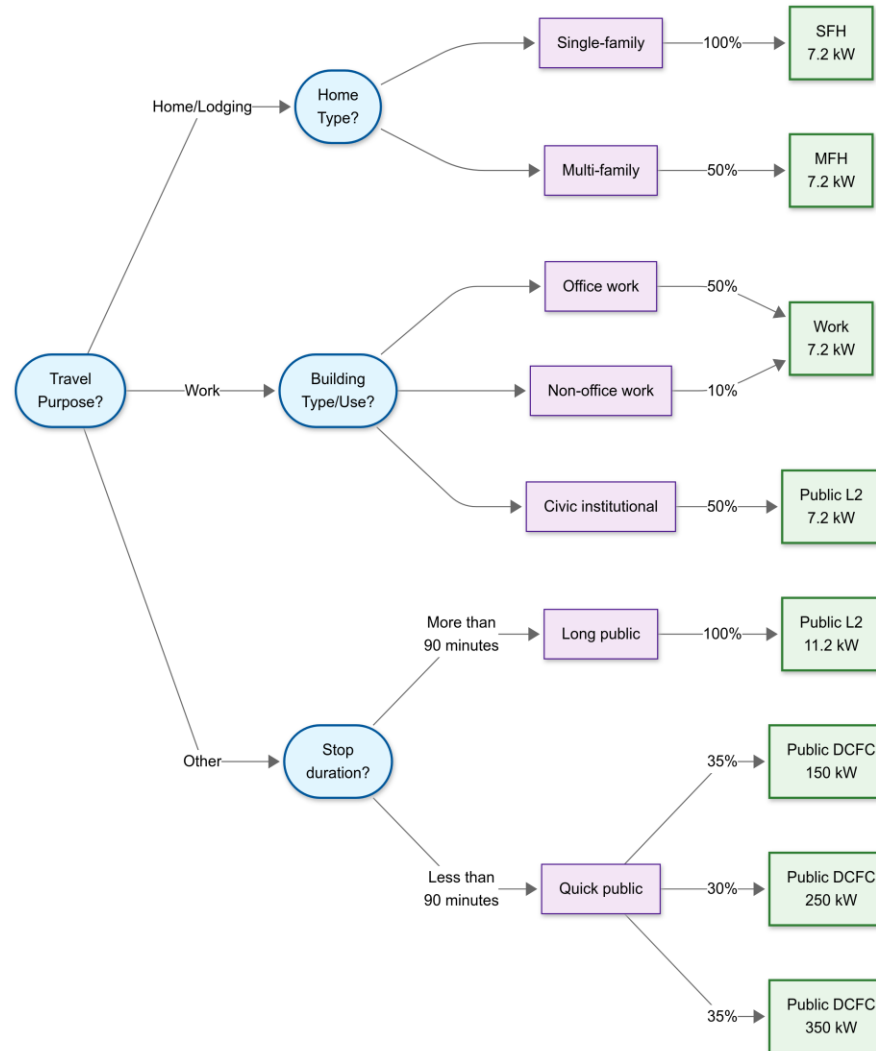
Sarah LaMonaca and Lisa Ryan, "The State of Play in Electric Vehicle Charging Services – A Review of Infrastructure Provision, Players, and Policies," *Renewable and Sustainable Energy Reviews* 154, (February 2022) <https://www.sciencedirect.com/science/article/pii/S1364032121010066>.

Light-Duty Assumptions

Charging Options and Probabilities



This is a visual showing both the charging options and probabilities



GridUp uses information on destination activities to decide what kind of charging may be available. The charger power levels and probabilities are shown in each case.

The model doesn't vary these charging levels or probabilities over time, but future versions may.

Light-Duty Assumptions

Managed and Unmanaged Charging

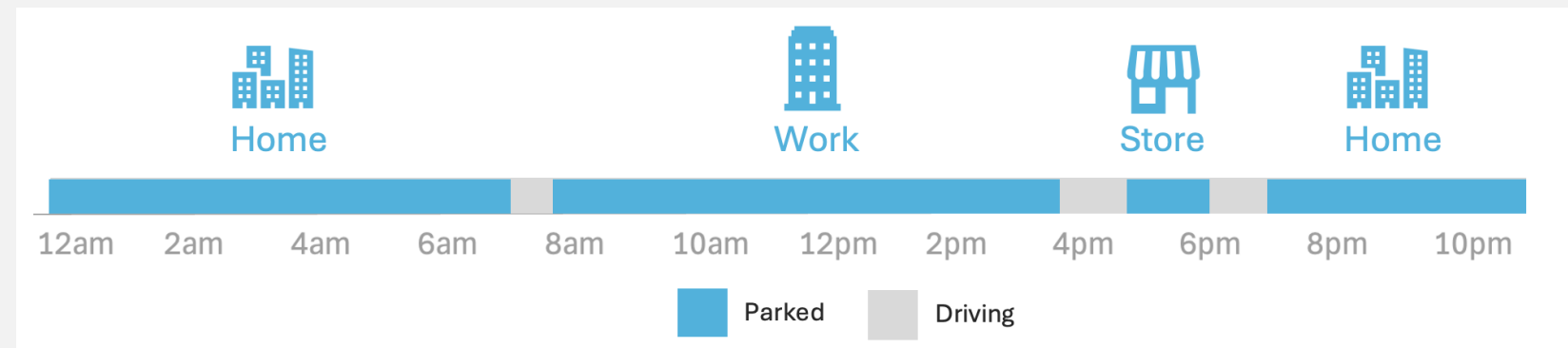


Both unmanaged and managed charging are shown in the eRoadMAP tool. In the unmanaged case, charging starts when the vehicle arrives at its destination and is done at nameplate charger power until energy demand is met or the vehicle leaves. In the managed case, the vehicle charges at the minimum power required to meet energy demand within the duration of the stop (see example on the next slide).

eRoadMAP provides average power for both managed and unmanaged charging scenarios. Note that the energy needed in both managed and unmanaged charging is the same.

Example

An EV owner commutes to their workplace from home on a particular day, stopping at a grocery store on the way back. They travel 40 miles in total, associated with 16.8 kWh of energy needs ($40\text{mi} * 0.42\text{kWh/mi}$). Their travel behavior looks like this:



Light-Duty Assumptions

Managed and Unmanaged Charging



Example (continued)

In the unmanaged case, if the EV owner lives in a single-family home, there is a 100% probability of finding a charger (7.2kW) at home. The car charges for 2.2 hours, from 7pm to 9.12pm ($16\text{kWh}/7.2\text{kW} = 2.2\text{h}$).

If the EV owner lives in an apartment building, there is a 20% probability of finding a charger (7.2kW) at home. If that does not happen, there is a 20% chance of charging (7.2kW) at work, where the car charges from 8am to 10.12am ($16\text{kWh}/7.2\text{kW} = 2.2\text{h}$). If not, they will charge at the store (19.2, 50, or 150 kW) during the hour that the vehicle is stopped there (example: $16\text{kWh}/19.2\text{kW} = 0.83\text{h}$).



Light-Duty Assumptions

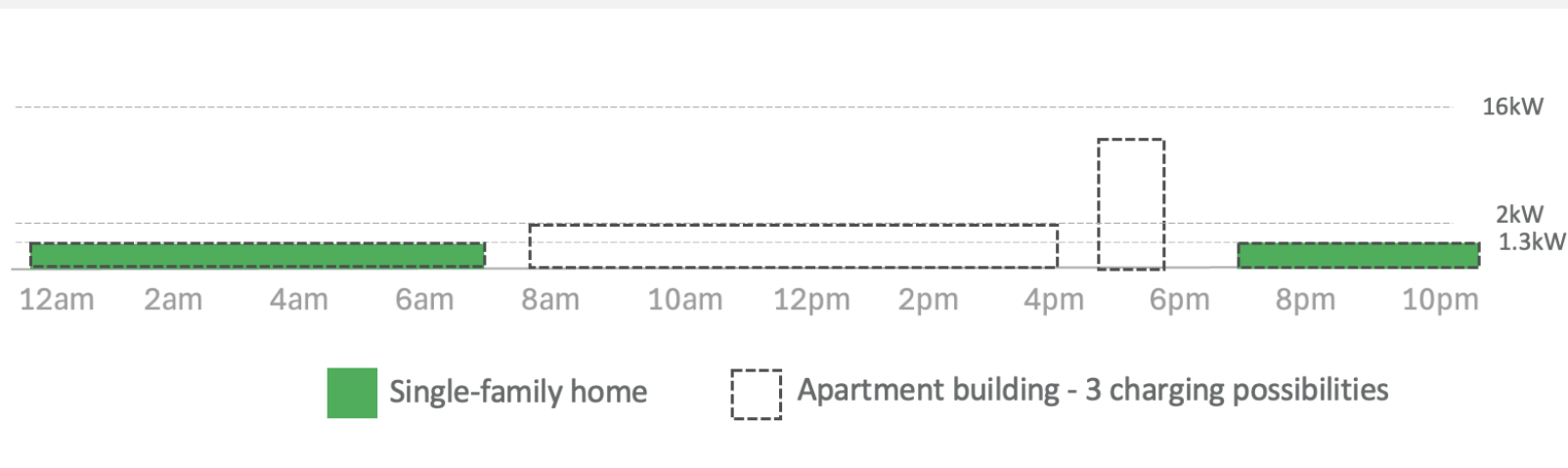
Managed and Unmanaged Charging



Example (continued)

In the managed case, if the EV owner lives in a single-family home, their energy needs are again fully met at home. But the car charges over 12 hours from 7pm to 7am, drawing 1.3kW of power ($16\text{kWh}/12\text{h} = 1.3\text{kW}$).

If they live in an apartment building, there is a 20% probability of finding a charger (7.2kW) at home. If that does not happen, they have a 20% chance of charging (7.2kW) at work, where the car charges for 8 hours, drawing 2kW of power ($16\text{kWh}/8\text{h} = 2\text{kW}$). If that doesn't happen, they will charge at the store (19.2, 50, or 150 kW) during the hour that the vehicle is stopped there (example: $16\text{kWh}/1\text{h} = 16\text{kW}$).

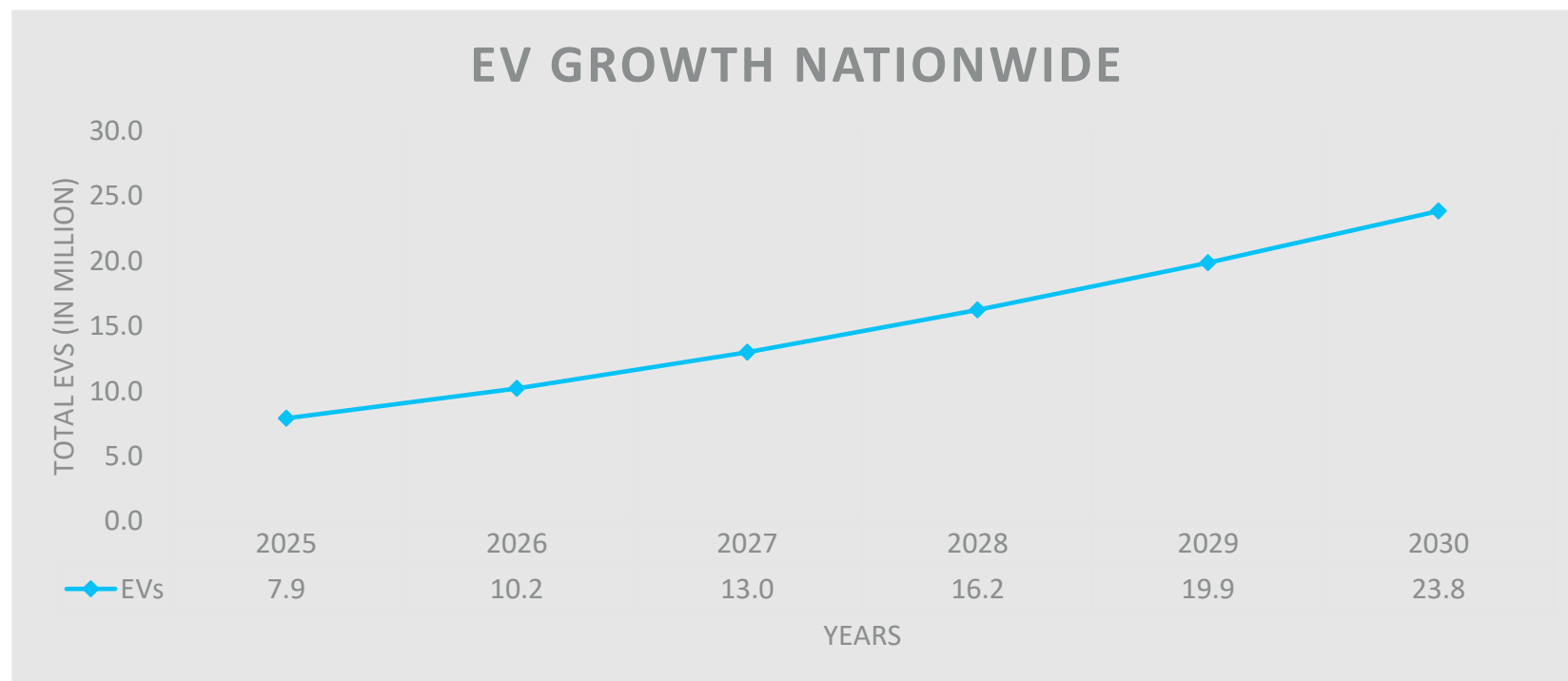


Light-Duty Adoption

Assumptions



EPRI's adoption scenario projects 24M EVs (out of ~243M total vehicles) in 2030. In 2030, 87% of EVs were BEVs and 13% were PHEV. This projected EV adoption over time takes into account factors such as adjustments to federal EV incentives and NEVI funding, individual state propensity to purchase EVs and state EV credits.



Note: EPRI plans to regularly review these assumptions over time to ensure they continue to accurately reflect consumer and market trends.

Light-Duty Adoption

Data Resolution



RMI's light duty vehicle behavior model and vehicle population size is based on household information. Households are assigned to block groups but draw power from stop locations at the hexagon level, blending two data resolutions.

NREL's light-duty adoption scenario (previous slide) is provided at the county level, which block groups nest perfectly inside of. Therefore, the NREL year-over-year county level adoption is uniformly assigned to each block group within the county.

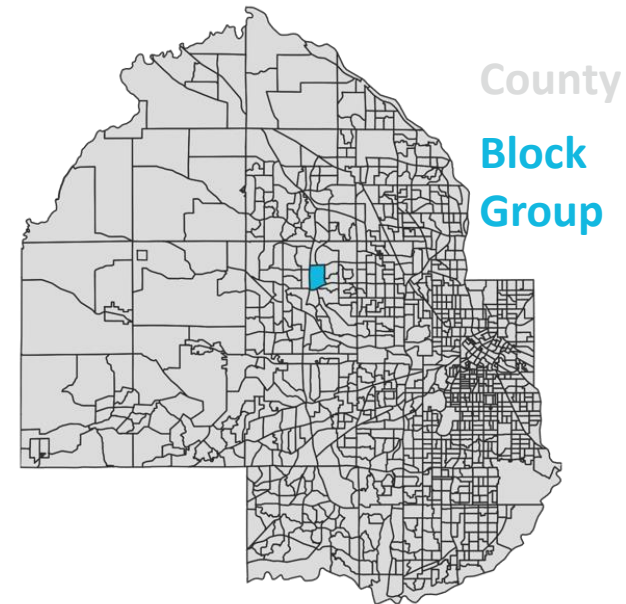


Illustration of block groups within a county

Medium- & Heavy-Duty Vehicles



Medium- & Heavy-Duty Vehicles

Data Coverage

Current combined data sets capture approximately 21% of the MDHD on road behavior. This data is then weighted to represent 100% of on road MDHD vehicles (see scaling section on weighting methods).

As EPRI collects more data, the percentage of data coverage will increase. Data collection from fleets adds data on vehicle behavior as well as data on EV adoption timelines. These fleet timelines replace modeled adoption assumptions as they are fleet specific plans.

This section covers data sources, data coverage, assumptions and data scaling for medium and heavy duty vehicles.

Medium- & Heavy-Duty Vehicles

Data Sources

The data for medium and heavy-duty vehicles combines OEM data, fleet data, and aggregated data from a variety of sources.

MDHD Data Type	Source
OEM	Volvo
OEM	Navistar
Fleet	Amazon
Aggregator	INRIX
Aggregator	Geotab

More data sets, such as PACCAR and Daimler, are in the process of being added to future version of the tool.

Medium- & Heavy-Duty Vehicles

EV ADOPTION PROJECTIONS

Overview

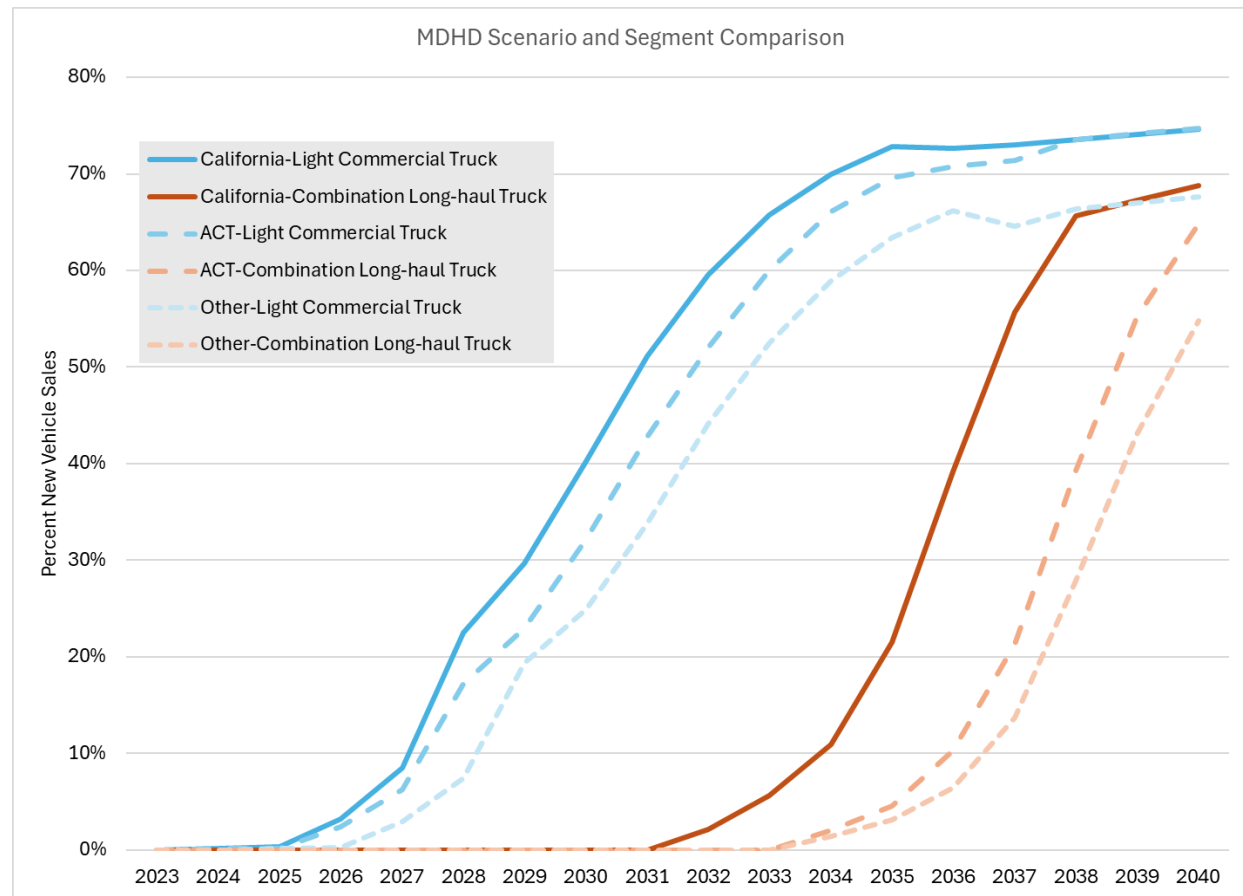
EPRI used NREL’s adoption scenarios as a basis for the MDHD adoption in eRoadMAP. For MDHD adoption, states were divided into three zones (as defined below) as different policies are applicable for each category.

California	ACT States	Rest of US
California has implemented a variety of policies and incentives to increase MCHC adoption. Even though ACT is currently withdrawn, California is expected to have higher adoption than other states.	10 other states have adopted the ACT rule (Oregon, Washington, Colorado, New Jersey, New York, Vermont, Massachusetts, Maryland, New Mexico, and Rhode Island). ACT adoption should significantly increase adoption.	In the rest of the U.S. there are a variety of incentives, goals, and market structure that will result in varying levels of adoption, but there are no formal wide-scale regulations.

The adoption trajectory is built on some NREL modeling drawing on the ‘Central’, ‘Advanced ICEV & HEV Technology’ and ‘NREL Conservative Electricity Price’ for the different zones defined above. Where EPRI has additional information on certain segments, those are individually tuned.

NREL MDHD Scenario Information: [https://www.cell.com/iscience/pdf/S2589-0042\(24\)00606-0.pdf](https://www.cell.com/iscience/pdf/S2589-0042(24)00606-0.pdf)
Data Available at: <https://data.nrel.gov/submissions/227>

Adoption Category Comparison



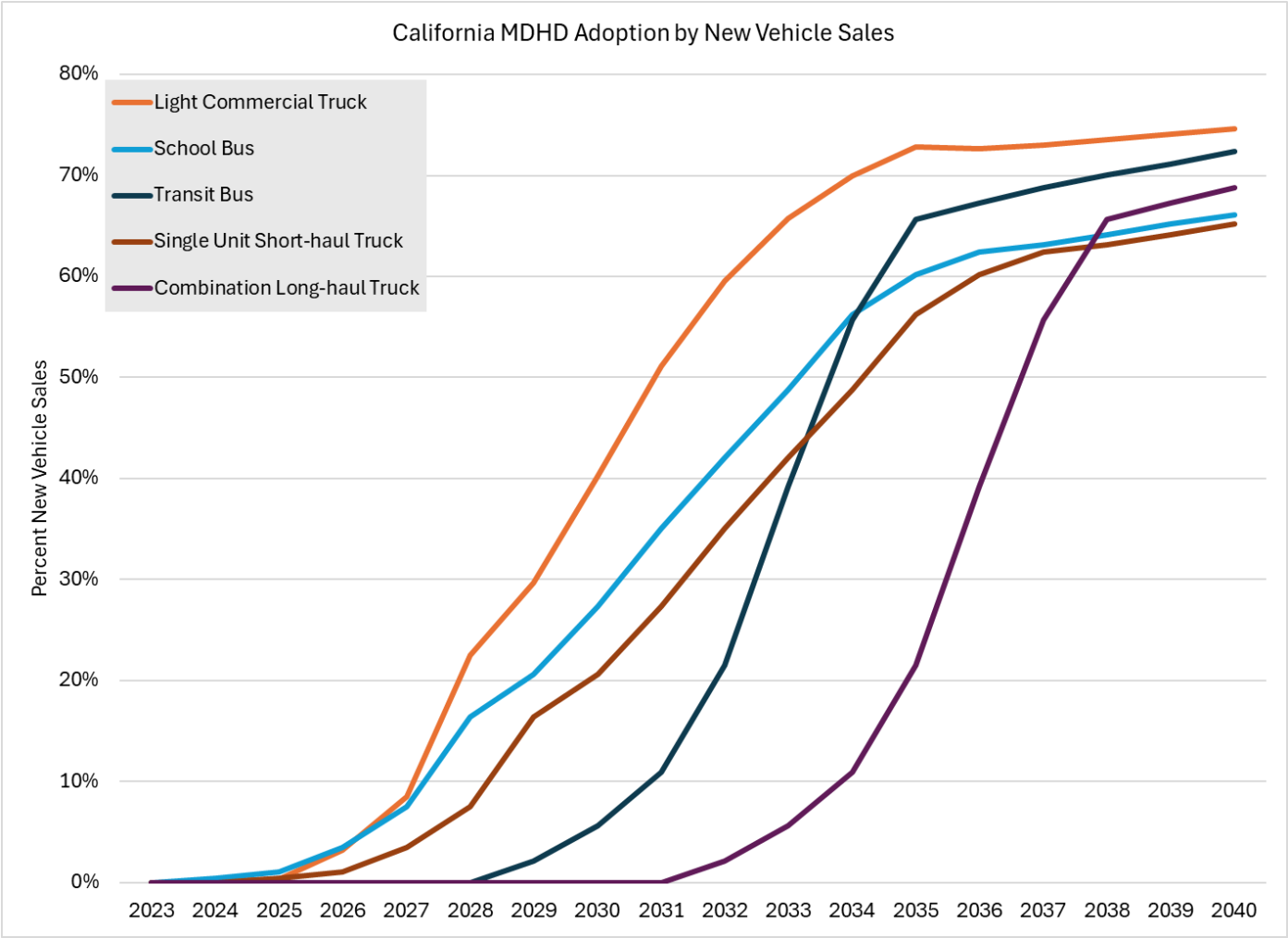
The above plot shows the difference in adoption for the three different state categories together with two vehicle segments- combination long haul and light commercial trucks.

There is a delay of approximately 6 years between the light commercial truck segment and the combination long haul segment in all state categories. The plot also shows a delay of 2 years for 'Other' states in comparison to California for light commercial trucks, which is lengthened to 3 years for combination long haul. Adoption curves for each state grouping are in the following slides.

Medium- & Heavy-Duty Vehicles

EV ADOPTION PROJECTIONS

California

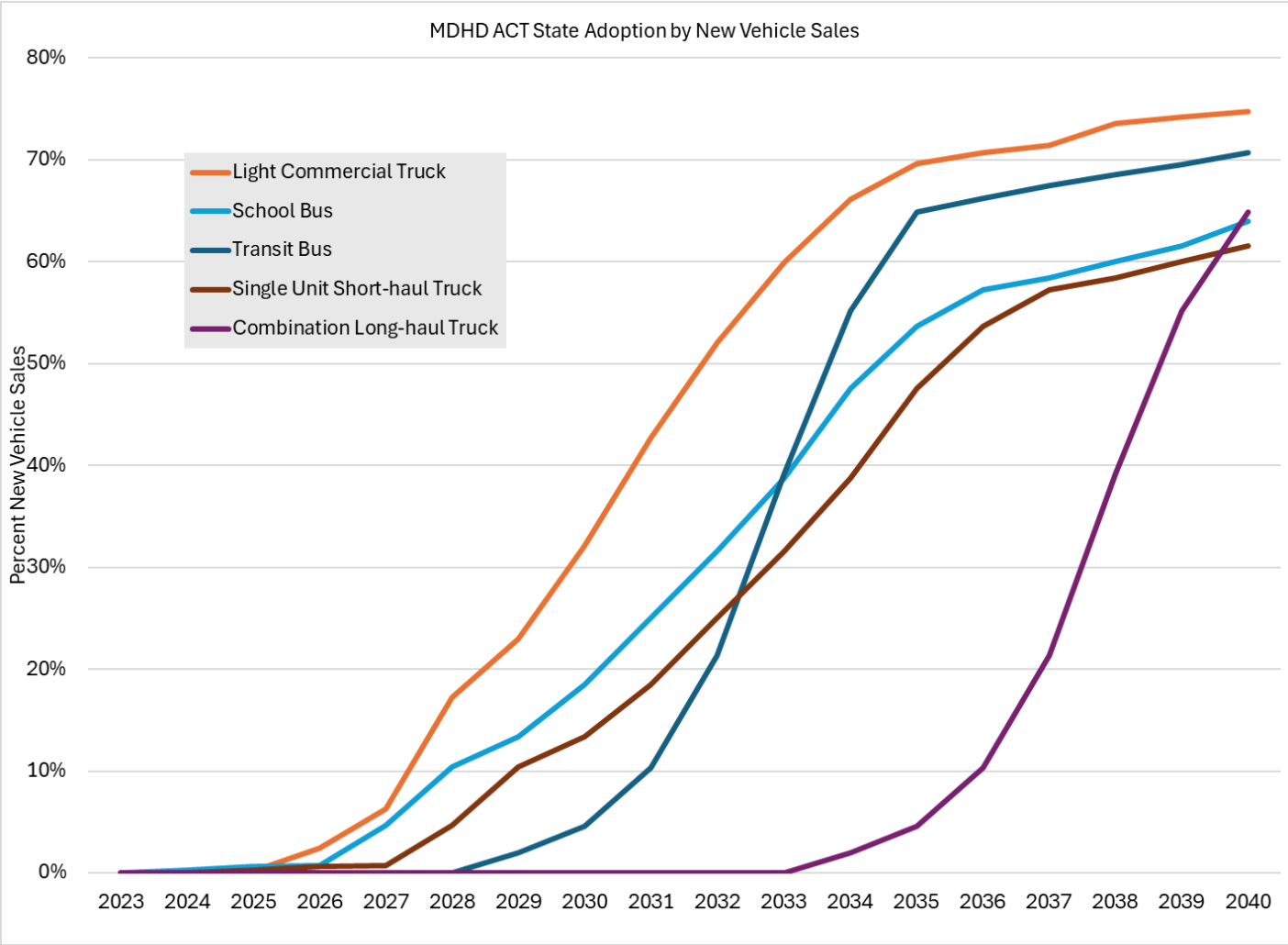


These adoption curves show the percent of new vehicle sales over time for California for a sample set of vehicle segments. Light commercial trucks are adopted much earlier than the combination long-haul, which only begin in 2031.

Medium- & Heavy-Duty Vehicles

EV ADOPTION PROJECTIONS

ACT States

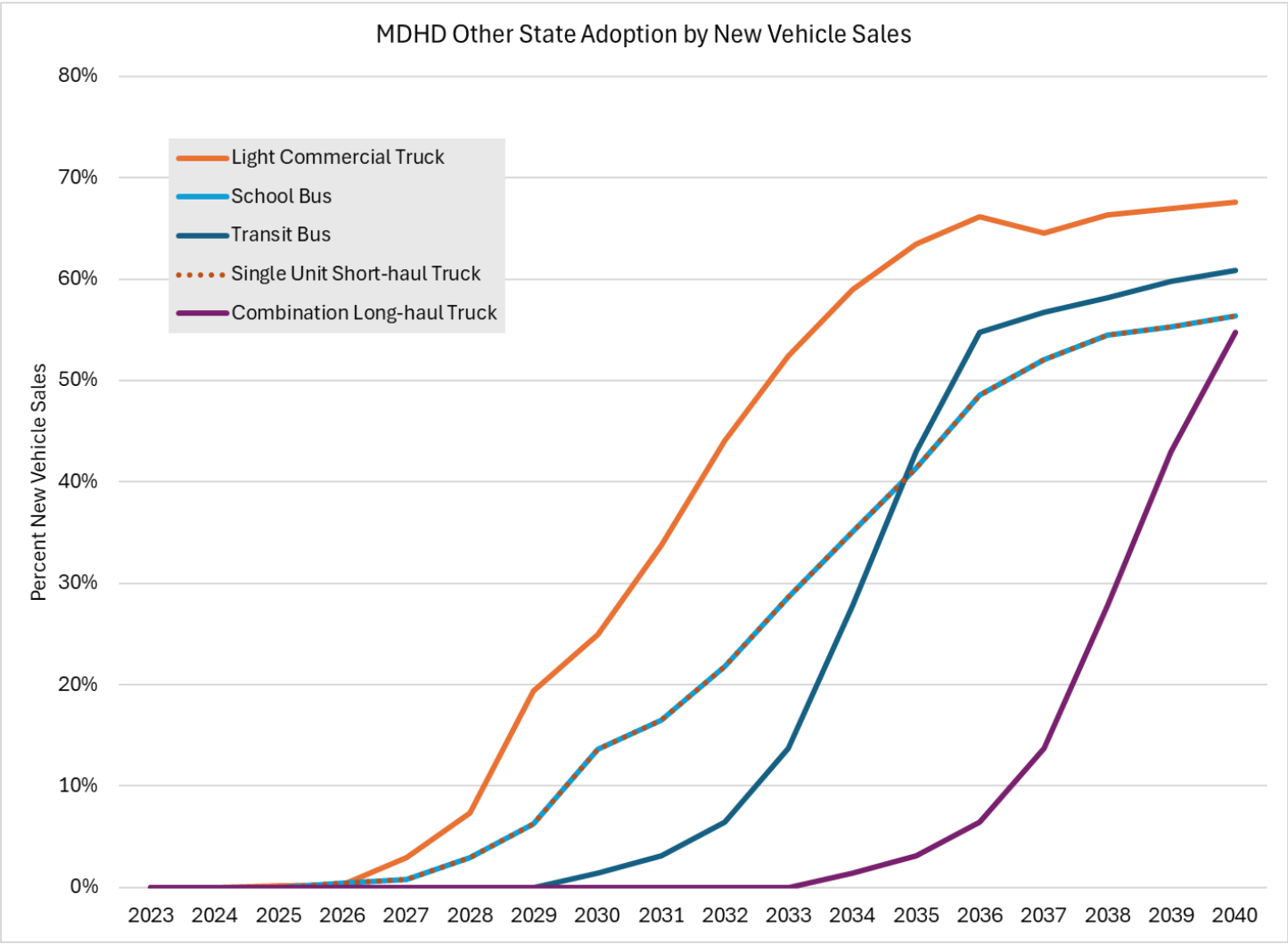


These adoption curves show the percent of new vehicle sales over time for the grouping of ACT states for a sample set of vehicle segments. Light commercial trucks are adopted much earlier than the combination long-haul, which only begin in 2034.

Medium- & Heavy-Duty Vehicles

EV ADOPTION PROJECTIONS

Other States



These adoption curves show the percent of new vehicle sales over time for the grouping of other states for a sample set of vehicle segments. Light commercial trucks are adopted much earlier than the combination long-haul, which only begin in 2034.

Medium- & Heavy-Duty Vehicles

EV ADOPTION PROJECTIONS

Adoption by Year and State Type

New Vehicle Market Share for Select Vehicle Classes for the different state types.
State type defined in a previous slide

State Type	Vehicle Class	2025	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
California	Light Commercial Truck	0%	3%	9%	22%	30%	40%	51%	60%	66%	70%	73%
California	School Bus	1%	3%	8%	16%	21%	27%	35%	42%	49%	56%	60%
California	Refuse Truck	0%	0%	0%	0%	2%	6%	11%	22%	39%	56%	66%
California	Transit Bus	0%	0%	0%	0%	2%	6%	11%	22%	39%	56%	66%
California	Single Unit Short-haul Truck	0%	1%	3%	8%	16%	21%	27%	35%	42%	49%	56%
California	Combination Short-haul Truck	0%	0%	0%	0%	0%	2%	6%	11%	22%	39%	56%
California	Combination Long-haul Truck	0%	0%	0%	0%	0%	0%	0%	2%	6%	11%	22%
ACT	Light Commercial Truck	0%	2%	6%	17%	23%	32%	43%	52%	60%	66%	70%
ACT	School Bus	1%	1%	5%	10%	13%	18%	25%	32%	39%	48%	54%
ACT	Refuse Truck	0%	0%	0%	0%	2%	5%	10%	21%	39%	55%	65%
ACT	Transit Bus	0%	0%	0%	0%	2%	5%	10%	21%	39%	55%	65%
ACT	Single Unit Short-haul Truck	0%	1%	1%	5%	10%	13%	18%	25%	32%	39%	48%
ACT	Combination Short-haul Truck	0%	0%	0%	0%	0%	2%	5%	10%	21%	39%	55%
ACT	Combination Long-haul Truck	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	5%
Other	Light Commercial Truck	0%	0%	3%	7%	19%	25%	34%	44%	52%	59%	63%
Other	School Bus	0%	0%	1%	3%	6%	14%	16%	22%	29%	35%	41%
Other	Refuse Truck	0%	0%	0%	0%	0%	1%	3%	6%	14%	28%	43%
Other	Transit Bus	0%	0%	0%	0%	0%	1%	3%	6%	14%	28%	43%
Other	Single Unit Short-haul Truck	0%	0%	1%	3%	6%	14%	16%	22%	29%	35%	41%
Other	Combination Short-haul Truck	0%	0%	0%	0%	0%	0%	0%	1%	3%	6%	14%
Other	Combination Long-haul Truck	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	3%

Medium- & Heavy-Duty Vehicles

ESTIMATING ENERGY NEEDS

Converting Activity to Energy

To model the amount of energy needed for each hexagon, the average daily miles driven was used together with an electric vehicle consumption rate. Unlike LD vehicles, there isn't a travel model that accurately reflects the average local mileage. EPRI has combined a number of data sources and weighted them to be able to estimate the number of miles that may need to be charged within a hexagon.

$$\text{Energy} \sim \text{Distance} \times \text{Consumption Rate}$$

Class 3-5: **1.1 kWh/mi** | Class 6-8: **1.8 kWh/mi**

Note: The electric vehicle consumption rate will be subject to refinement as more data becomes available.

ESTIMATING ENERGY NEEDS

To assign energy to charging locations, EPRI needed to convert between telematics data from a few different data sources and assign energy to specific locations.

- Departure times and locations
- Distances traveled
- Stop time and location

- Charging is assigned to the longest stop of the day, which is meant to be representative of depot charging.

A map of the Los Angeles metropolitan area with a network graph overlaid. The graph consists of black dots representing nodes and black lines representing edges. The nodes are distributed across the map, with a high concentration in the central and southern parts, particularly around the San Diego River and the Harbor area. The edges connect various nodes, forming a complex web. Major highways like I-5, I-10, I-15, and I-405 are visible in the background. Labels for various cities and areas are present, including Culver City, Inglewood, Hawthorne, Lawndale, Gardena, Compton, Lynwood, South Gate, Bell Gardens, Downey, Paramount, Bell, Lakewood, Signal Hill, Long Beach, Rolling Hills, and Rolling Hills Estates. The map also shows the Los Angeles International Airport (LAX) and the San Diego River.

Medium- & Heavy-Duty Vehicles

ESTIMATING ENERGY NEEDS

Assigning Energy to Charging Locations

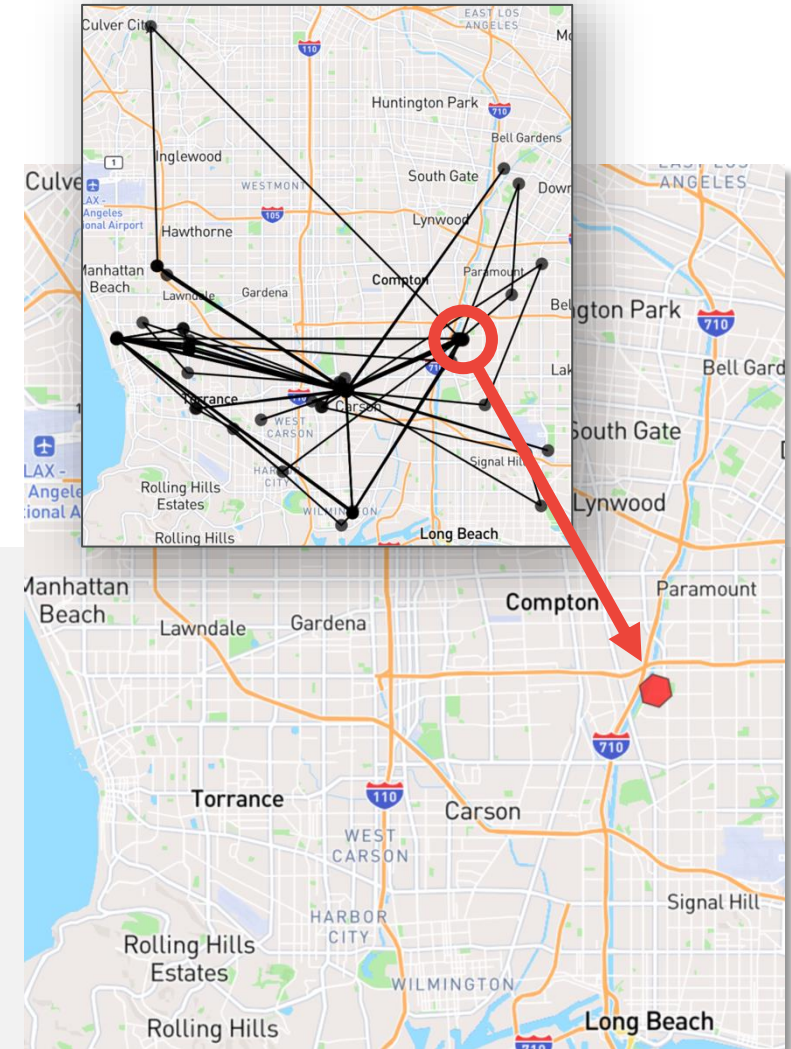
Assigning Energy for Depot Charging:

1) Find the location where every vehicle spends the most total time between trips *each day*; assume this location is its depot *for that day**.

2) Assume all energy consumed by the vehicle is replenished at depot.

*** By re-assigning depot every day, the “depot charging” mode can mean different things depending on vehicle behavior:**

- For vehicles that return to depot every day, this captures the intuitive sense of depot-based charging.
- For other vehicles, e.g., long-haul trucks, “depot” charging means charging during the longest stop each day, wherever that happens to be (often a truck stop).



Medium- & Heavy-Duty Vehicles

ESTIMATING ENERGY NEEDS

Long Haul Truck Segmentation

It is likely that shorter haul trucks will electrify before longer haul trucks as the batteries needed are smaller (less expensive) and the charging can be met with depot charging rather than charging at multiple locations along the route.

In order to segment out trucks that may have a longer timeline to electrification, a filter was added to eRoadMAP to remove trips that have a daily mileage of over 500 miles. This threshold was based on discussions with NACFE (North America Council for Freight Efficiency).

EPRI is working on further segmentation for future work.

Long mileage
trucks included



Long-Haul Trucks

Long mileage
trucks not included



Long-Haul Trucks

When landing on the eRoadMAP website, the default is to include longer mileage trucks. They can be removed with the radio button.

Medium- & Heavy-Duty Vehicles

ESTIMATING ENERGY NEEDS

Managed and Unmanaged Charging

Both managed and unmanaged charging were included in the MDHD analysis. In both scenarios, it is assumed that:

1. A charger is available for each vehicle and ports are not being shared.
2. The total average daily energy needed is the same. Average daily energy is calculated from the average daily mileage and assumed vehicle efficiency.

eRoadMAP provides average power for both managed and unmanaged charging scenarios. Note that the energy needed in both managed and unmanaged charging is the same.

Unmanaged
charging



Managed Charging

Managed
charging



Managed Charging

When landing on the eRoadMAP website, the default is unmanaged charging. Managed charging can be applied by pressing the radio button.

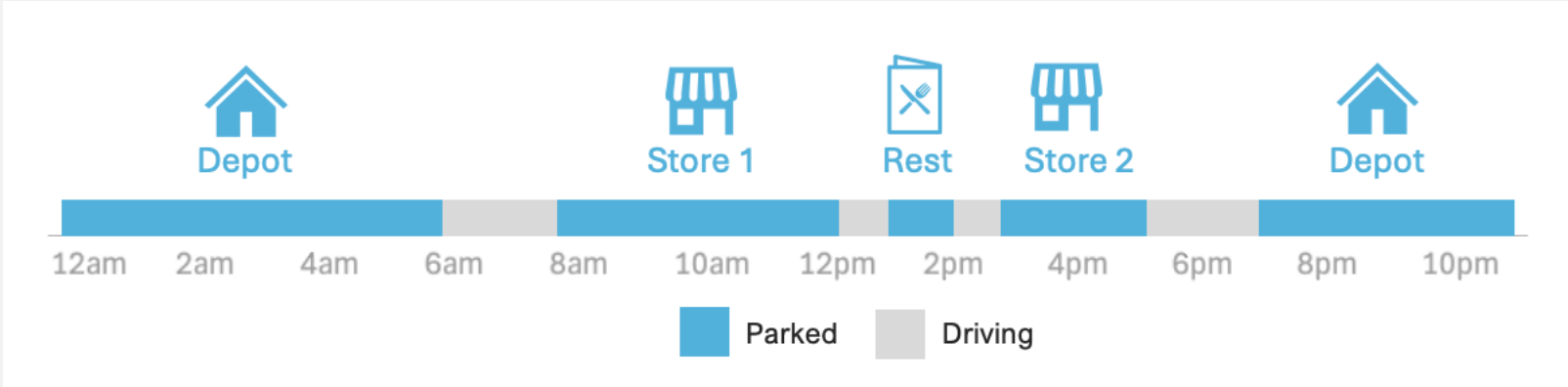
Medium- & Heavy-Duty Vehicles

ESTIMATING ENERGY NEEDS

Managed and Unmanaged Charging

Example

A Class 8 delivery truck departs from its depot, makes several stops, and returns to its depot on a particular day, travelling 250 miles in total. The truck's energy needs for the day are 450kWh (250 mi * 1.8kWh/mi). The travel behavior looks like this:



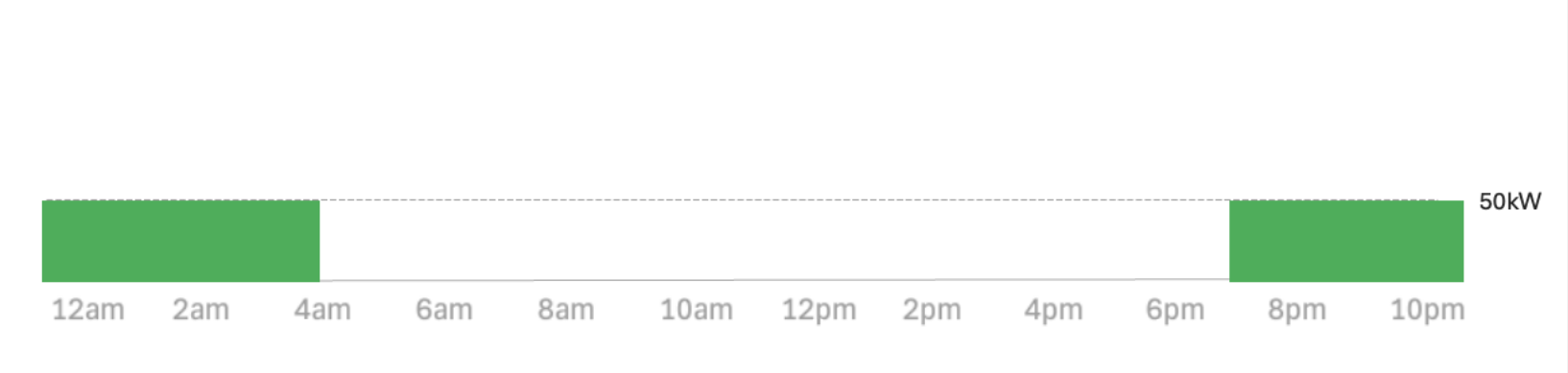
Medium- & Heavy-Duty Vehicles

ESTIMATING ENERGY NEEDS

Managed and Unmanaged Charging

Example (continued)

In the managed case, the energy needs are assigned to the longest dwell location*, which is the depot in this case. The smallest feasible charger is assigned**, which is a 50kW charger (closest to $450\text{kWh}/11\text{h}=41\text{kW}$). So, the truck charges for 9 hours from 7pm to 4am ($50\text{kW} \times 9\text{h} = 450\text{kWh}$).



*We assume that the longest dwell location has the highest possibility of being a depot/ similar location such as a highway rest stop where battery replenishment is likely.

**We assume that the appropriate charger (10kW, 19.2kW, 50kW, 150kW, 350kW, and 750kW) is available at the longest dwell location since fleet charger characteristics are currently unknown.

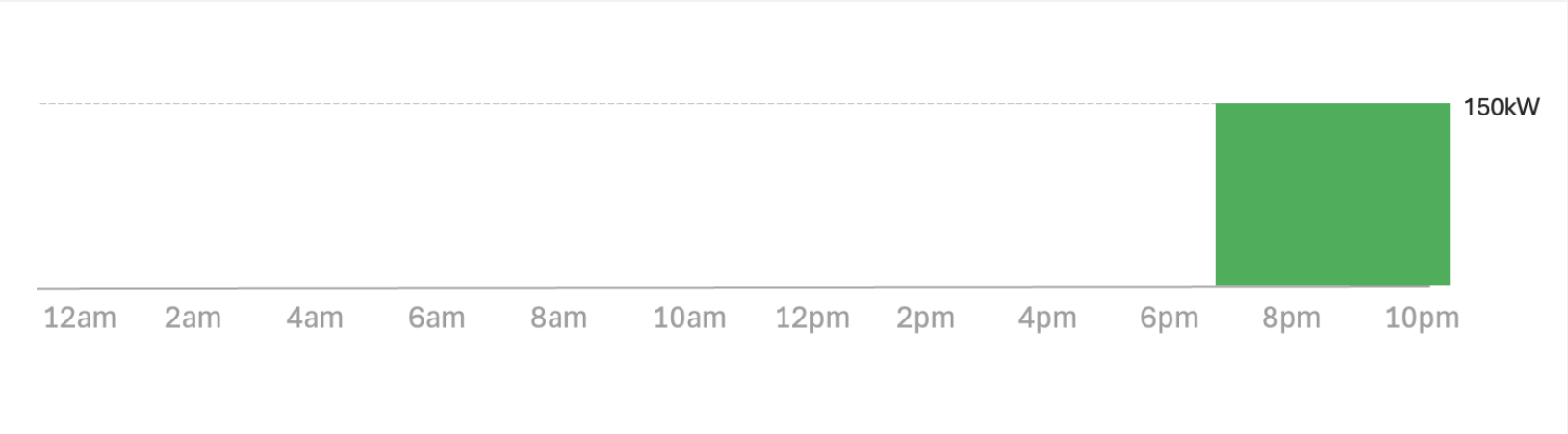
Medium- & Heavy-Duty Vehicles

ESTIMATING ENERGY NEEDS

Managed and Unmanaged Charging

Example (continued)

In the unmanaged case, we assign the next higher charger, which is a 150kW charger. So, the truck charges for 3 hours from 7pm to 10pm ($150\text{kW} * 3\text{h} = 450\text{kWh}$).



Medium- & Heavy-Duty Vehicles

ESTIMATING ENERGY NEEDS

MDHD Caveats & Future Research

Caveats

- **Granularity:** Due to combining data sets from many sources, the MDHD data is varies in format. Some of the data included latitude and longitude information while others were aggregated to an H8 hexagon. This means some of the assumptions were applied slightly differently.
- **Seasonality:** The data sets represent different periods of time, some including a months-worth of data while others are pre-aggregated to represent an average weekday. The resulting load shapes and peak power are from a representative weekday and don't include seasonal (weather or vehicle behavior) variations.

Future Research

- EPRI will be looking at load shape variability and adding additional OEMs and data sources to the map.

Medium- & Heavy-Duty Vehicles

ESTIMATING ENERGY NEEDS

Data Scaling

The eRoadMAP initial data set was built with INRIX. Depending on the region, INRIX can account for 10-15% of the full MDHD activity. To capture the full activity, the vehicle activity logged in INRIX needed to be locally weighted. As more data sets are collected and added to this map, the weighting will become less important as the data includes more vehicles.

- INRIX and Geotab data directly captures ~10% - 20% of MDHD vehicle activity combined. OEM data sets add another 5-8% of data coverage.
- This is scaled to represent 100% of estimated total energy demands
- Local validation process:
 - **Local** vehicle counts should be proportional to local *transportation-sector job counts*
 - **Aggregate** VMT must match total *measured VMT*

Medium- & Heavy-Duty Vehicles

ESTIMATING ENERGY NEEDS

Data Scaling

WEIGHTING STEPS OVERVIEW

- 1) **Scale** transportation jobs data to match *vehicles in operation* (VIO)
- 2) **Weight** telematics data to match the scaled *transportation jobs* data
- 3) **Calibrate** the weighted data to match measured *state-level vehicle miles traveled* (VMT)

Medium- & Heavy-Duty Vehicles

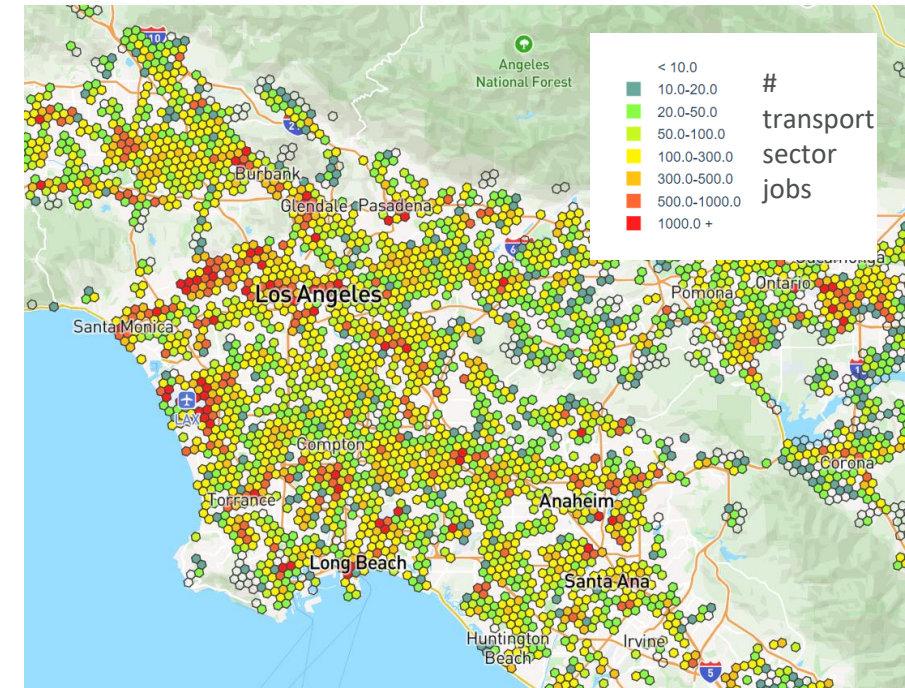
ESTIMATING ENERGY NEEDS

Data Scaling

DATA SCALING: VIO

- 1) **Scale** transportation jobs data to match *vehicles in operation* (VIO).
- 2) **Weight** telematics data to match the scaled *transportation jobs* data.
Cross validate the weighting/scaling process with registration and business census data in collaboration with the DOE labs.
- 3) **Calibrate** the weighted data to match measured *state-level vehicle miles traveled* (VMT).

Localized transportation job counts
(data from U.S. Census)



Medium- & Heavy-Duty Vehicles

ESTIMATING ENERGY NEEDS

Data Scaling

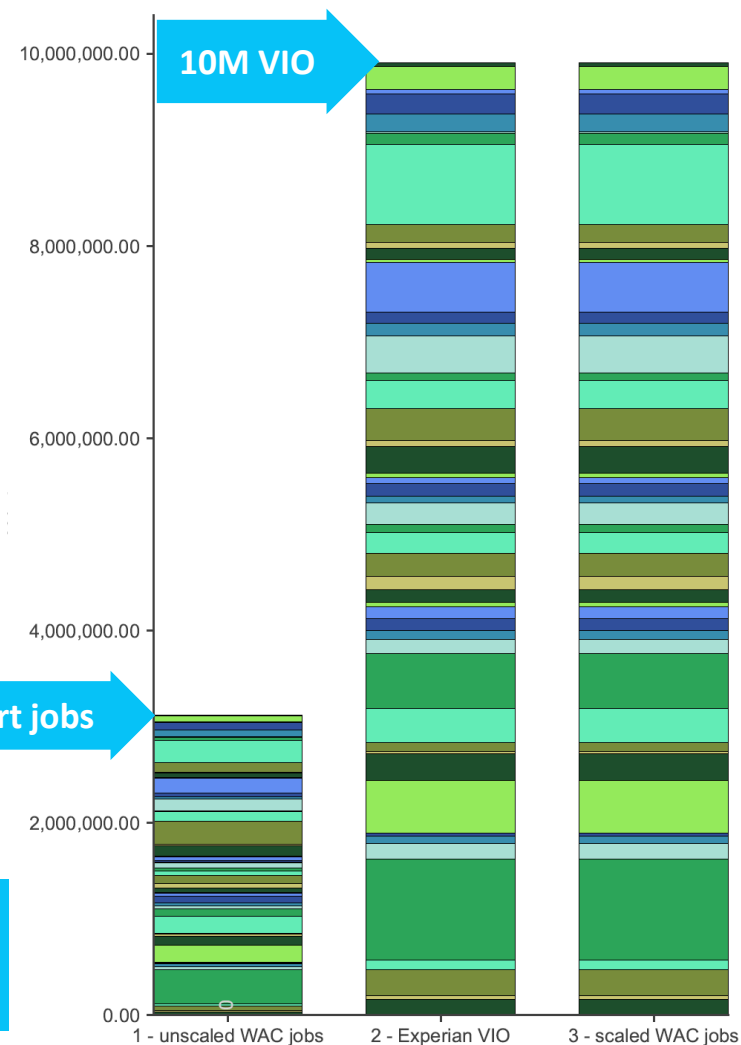
- 1) **Scale** transportation jobs data to match *vehicles in operation* (VIO).
- 2) **Weight** telematics data to match the scaled *transportation jobs* data. Cross validate the weighting/scaling process with registration and business census data in collaboration with the DOE labs.
- 3) **Calibrate** the weighted data to match measured *state-level vehicle miles traveled* (VMT).

*WAC = Workplace Area Characteristics

-- from LODES: LEHD (Longitudinal Employer-Household Dynamics) Origin Destination Employment Statistics

There are fewer transportation sector jobs than there are MDHD vehicles in operation

Solution: Scale job counts to match state-level VIO



Medium- & Heavy-Duty Vehicles

ESTIMATING ENERGY NEEDS

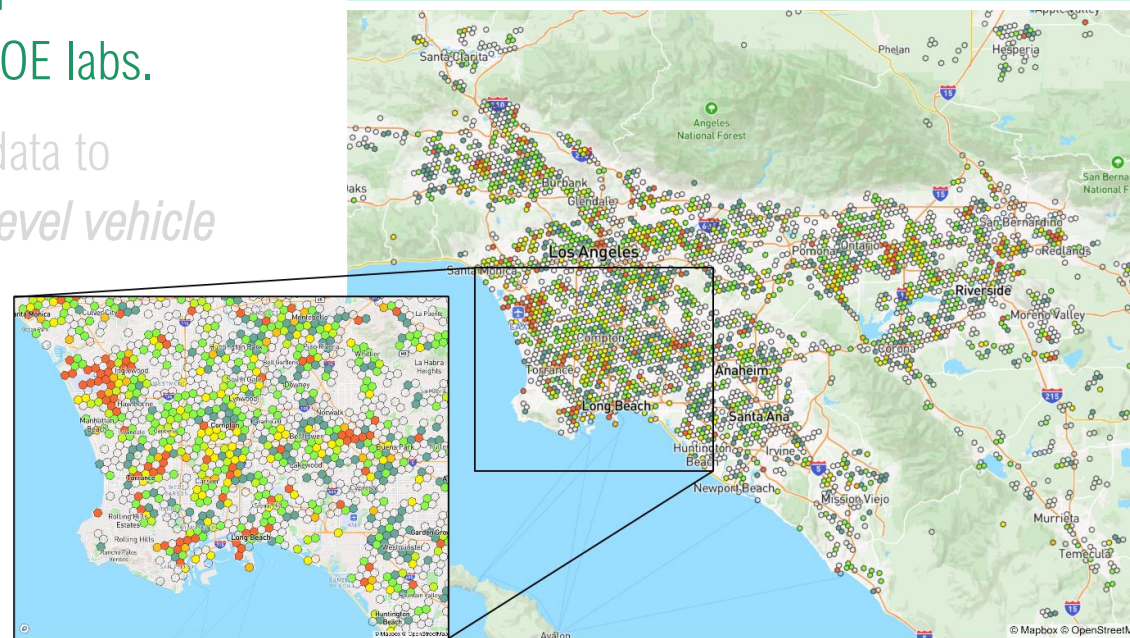
Data Scaling

DATA SCALING: VEHICLE WEIGHTING

- 1) Scale transportation jobs data to match *vehicles in operation* (VIO).
- 2) Weight telematics data to match the scaled *transportation jobs* data.
Cross validate the weighting/scaling process with registration and business census data in collaboration with the DOE labs.
- 3) Calibrate the weighted data to match measured *state-level vehicle miles traveled* (VMT).

Weight Applied to Each Vehicle in a Cell:

$$w = \frac{\# \text{ census jobs}}{\# \text{ telematics vehicles}}$$



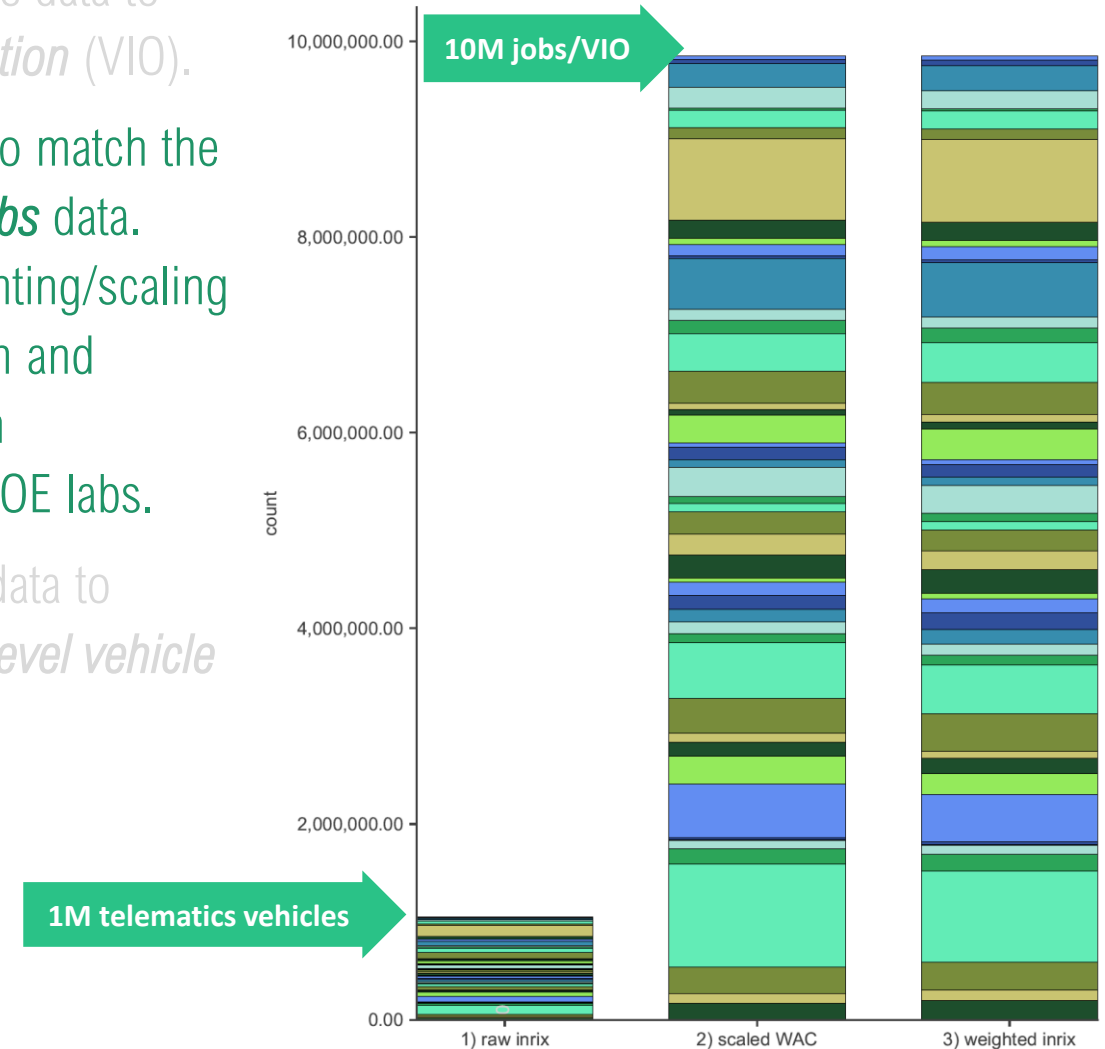
Medium- & Heavy-Duty Vehicles

ESTIMATING ENERGY NEEDS

Data Scaling

- 1) **Scale** transportation jobs data to match *vehicles in operation* (VIO).
- 2) **Weight** telematics data to match the scaled *transportation jobs* data. Cross validate the weighting/scaling process with registration and business census data in collaboration with the DOE labs.
- 3) **Calibrate** the weighted data to match measured *state-level vehicle miles traveled* (VMT).

After localized weighting, the vehicle counts are scaled up in aggregate to match VIO.



Medium- & Heavy-Duty Vehicles

ESTIMATING ENERGY NEEDS

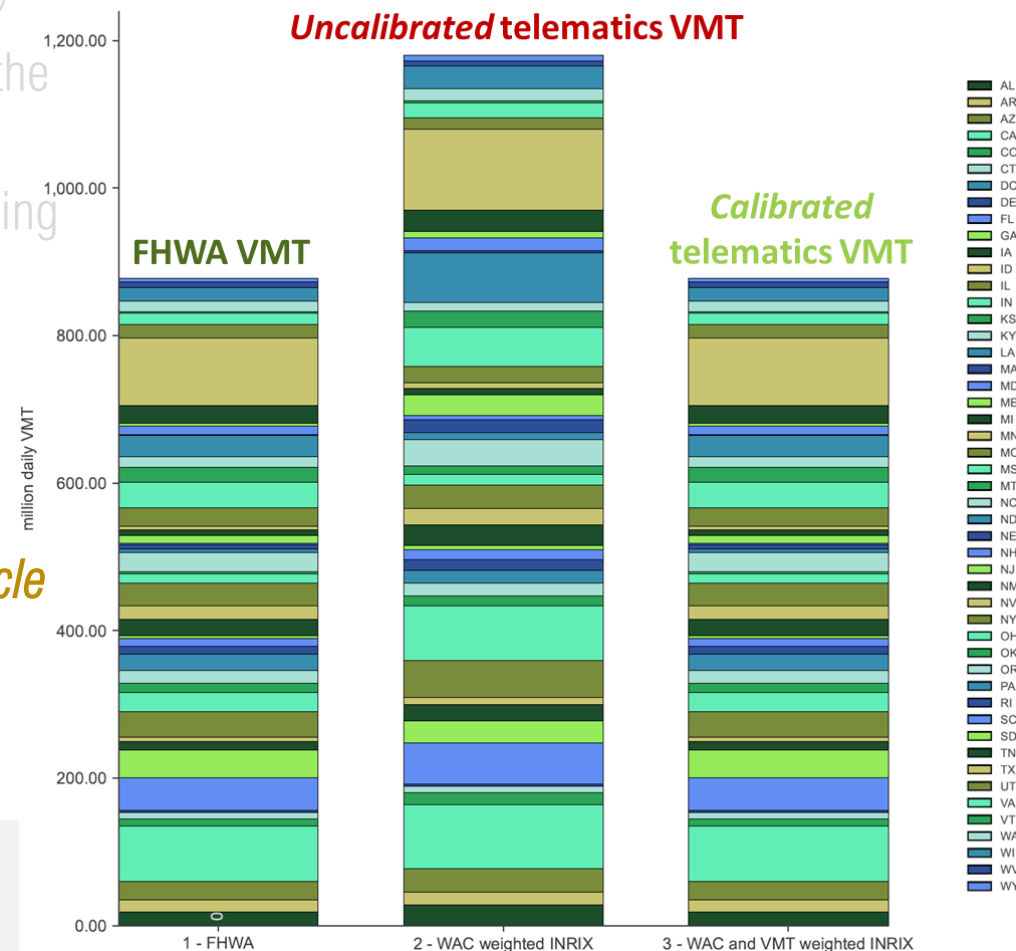
Data Scaling

- 1) Scale transportation jobs data to match *vehicles in operation* (VIO).
- 2) Weight telematics data to match the scaled *transportation jobs* data. Cross validate the weighting/scaling process with registration and business census data in collaboration with the DOE labs.
- 3) Calibrate the weighted data to match measured *state-level vehicle miles traveled* (VMT).

Note: There is no precise method of counting vehicles in INRIX. If the INRIX vehicles are under-counted, scaling to jobs/total VIO will result in systematic over-weighting. Thus, this correction is to be expected.

DATA SCALING: VMT

Calibrate weights based on state-level VMT from FHWA



3.

Version Documentation



Version Name	Release Date
eRoadMAP™ 2.2	2025 09 05
eRoadMAP™ 2.1	2025 04 10
eRoadMAP™ 2.0	2024 11 18
eRoadMAP™ 1.2	2024 08 02
eRoadMAP™ 1.1	2024 03 11
eRoadMAP™ 1.0	2023 11 28



DOCUMENTED eRoadMAP™ SUMMARY OF INCLUDED DATASETS

Type	Dataset	Month added
Light-duty (LD)	Tesla	2024 05
	Enterprise Mobility	2024 03
	Replica	2023 09
Medium- and heavy-duty (MDHD)	School Buses (WRI)	2025 04
	Garbage Trucks	2025 09
	Ports	2025 09
	Airports	2025 09
	Pitt Ohio	2025 04
	Navistar	2024 08
	Geotab	2024 08
	INRIX	2023 09
	Volvo	2023 09
	Daimler	2023 09
	Amazon	2023 09

DOCUMENTED eRoadMAP™ SUMMARY OF INCLUDED DATASETS

Type	Dataset	Month added
Supporting*	LODES	2023 09
	FHWA Vehicle Miles Traveled	2023 09
	Experian	2023 09

** Datasets supporting key analysis for eRoadMAP but not represented directly in the tool.*

Note: eRoadMAP also displays several additional layers, such as hosting capacity, that can be toggled on or off to view information relevant to EV decision-making. The documentation for these additional layers can be found here: [link](#)

Version	eRoadMAP™ 2.2		
Release date	2025 09 05		
Modelling & assumptions updates	The adoption trajectory was adjusted to reflect changing state and federal policies. Compared to the previous adoption trajectory, adoption over time will be delayed. This will impact larger vehicles the most and will likely delay electric vehicle adoption by 2-8 years.		
Website functionality updates	New utilities added to the load capacity maps- PECO.		
Data updates	New datasets added:		
	Dataset	Month added	Description
	Ports	2025 09	Modeled Electricity Demand for Electric Cargo Handling Equipment (eCHE) for top 25 U.S. container ports by total tonnage.
	Airports	2025 09	Modeled Electricity Demand for Electric Ground Support Equipment (eEGSE) at top 50 U.S. commercial airports (NREL)
	Garbage Trucks	2025 09	Nationwide Garbage Truck Load. Behavioral data from a private fleet comprising 15% of the full garbage truck fleet.



Version	eRoadMAP™ 2.1		
Release date	2025 04 10		
Modelling & assumptions updates	-		
Website functionality updates	Grid Capacity visualized in heatmap format in addition to the existing feeder line capacity.		
Data updates	New datasets added:		
	Dataset	Month added	Description
	School Buses (WRI)	2025 04	Nationwide School Bus Fleet
	Pitt Ohio	2025 04	North-East Trucking Fleet

Version	eRoadMAP™ 2.0		
Release date	2024 11 18		
Modelling & assumptions updates	Added average maximum power to capture power needs in addition to energy needs. Included managed and unmanaged charging options.		
Website functionality updates	Added the 'Power' tab to show average maximum power. Added a filter for long-haul vehicle mileage (500+ miles driven per day).		
Data updates	Added additional utilities to the Hosting Capacity layer.		
	Dataset	Month added	Description
	-	-	-

Version	eRoadMAP™ 1.2		
Release date	2024 08 02		
Modelling & assumptions updates	-		
Website functionality updates	-		
Data updates	New datasets added:		
	Dataset	Month added	Description
	Navistar	2024 08	MDHD fleet data set
	Geotab	2024 08	Data Aggregator representing 5% of the full MDHD fleet.



Version	eRoadMAP™ 1.1		
Release date	2024 03 11		
Modelling & assumptions updates	Corrected LD dataset for adjust for prisons. Added additional layers that can be toggled on/ off to support EV decision-making, such as: Areas of Air Quality Concern, Truck Stops, EV Charging Stations, Hosting Capacity (PG&E + SCE), Justice 40 Census Tracts and Transportation Disadvantage Areas.		
Website functionality updates	Added filter to MWh and added satellite map layer.		
Data updates	New datasets added:		
	Dataset	Month added	Description
	Tesla	2024 05	Existing Public charging growth plans.
	Enterprise Mobility, scaled for full rental fleet	2024 03	Fleet behavior and electrification plans



Version	eRoadMAP™ 1.0		
Release date	2023 11 28		
Modelling & assumptions updates	First release of the dataset.		
Website functionality updates	First launch of the website.		
Data updates	New datasets added:		
	Dataset	Month added	Description
	Replica	2023 09	LD travel model based on cell phone data
	INRIX	2023 09	Data Aggregator representing 10-15% of the full MDHD fleet.
	Volvo	2023 11	MDHD fleet data set.
	Daimler	2023 11	MDHD fleet data set.
	Amazon	2023 11	Delivery fleet behavior and electrification timeline data set.