

### **Attachment 3-1: Incremental Demand Accounting for the On-the-books EPA OTAQ GHG Rules**

Electricity demand in EPA 2023 Reference Case is based on AEO 2023 reference case for the non-EV portion. AEO's EV demand does not reflect the full forecasted zero emission vehicle (ZEV) adoption in its reference case. Therefore, EPA developed the appropriate EV demand to be used in EPA 2023 Reference Case.

Relative to AEO 2023, EPA's Office of Transportation and Air Quality (OTAQ) models increased Light-Duty Battery Electric Vehicle (LD BEV) adoption from EPA's Revised 2023 and Later Model Year Light-Duty Vehicle Greenhouse Gas Emissions Standards (LD GHG 2023-2026, 86 FR 74434) and increased HD ZEV adoption from California's Advanced Clean Trucks rule (ACT, 88 FR 20688). ACT is effective in California and several other states that have adopted it under CAA section 177.<sup>1</sup> OTAQ also models some increased HD ZEV adoption from market forces in states which have not adopted ACT.

This incremental demand is nearly consistent with what is used as baseline in OTAQ's analysis of recently finalized rules in Spring 2024; however, it is not identical. EPA 2023 Reference Case inputs were finalized prior to OTAQ finalizing their baseline (or no action case). EPA 2023 does not reflect the latest (Spring 2024) OTAQ rules because at the time this version of EPA Reference Case was finalized those rules were not final.

OTAQ developed incremental electricity demand inputs separately for the light-and-medium-duty vehicles and heavy-duty vehicles. OTAQ used EPA's OMEGA model to estimate battery electric vehicle (BEV) adoption in light and medium-duty vehicles. To estimate heavy-duty ZEV adoption, OTAQ used MOVES4.R1, an updated version of MOVES relative to MOVES4.0.0.<sup>2</sup>

#### **Modeling Plug-in Electric Vehicle Charging Demand and Inputs to IPM**

As plug-in electric vehicles<sup>3</sup> (PEVs) are projected to represent a significant share of the future U.S. light- and medium-duty vehicle fleet, EPA has developed new approaches to estimate the power sector<sup>4</sup> demand and resulting emissions due to PEV charging. EPA has combined the use of three analytical tools to incorporate power-sector-related emissions from PEV charging demand from light- and medium-duty vehicles:

- OMEGA manufacturer compliance model
- A suite of electric vehicle infrastructure modeling tools (EVI-X) developed by the National Renewable Energy Laboratory (NREL)
- The Integrated Planning Model (IPM)

EPA's manufacturer compliance model, OMEGA, is described in detail in Chapter 2 of EPA's Regulatory Impact Analysis for the Multi-Pollutant Emissions Standards for Model Years 2027 and Later Light-Duty and Medium-Duty Vehicles Final Rule (or LMDV-RIA) (U.S. EPA 2024). A separate analysis of heavy-duty Class 4 through 8 PEV regionalized charge demand due to the California's ACT program (State of California, Air Resources Board 2021) was also conducted by EPA using the EPA (MOVES) model (U.S. EPA 2024b). Regionalized light- and medium duty PEV demand from OMEGA/EVI-X and heavy-duty PEV and hydrogen electrolysis demand from MOVES were then combined into hourly transportation power sector demand projections from 2028 through 2055 for use in EPA 2023

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<sup>1</sup> At the time of our analysis, seven states had adopted ACT in addition to California. Oregon, Washington, New York, New Jersey, and Massachusetts adopted ACT beginning in MY 2025 while Vermont adopted ACT beginning in MY 2026 and Colorado in MY 2027. Three other states, New Mexico, Maryland, and Rhode Island adopted ACT (beginning in MY 2027) in November and December of 2023 and have not yet been incorporated into our analysis.

<sup>2</sup> Mo, Tiffany. Memorandum to Docket EPA-HQ-OAR-2022-0829. "Revisions to MOVES for Air Quality Modeling to support the FRM for the Multi-Pollutant Emissions Standards for Model Years 2027 and Later Light-Duty and Medium-Duty Vehicles". February 15, 2024.

<sup>3</sup> Plug-in electric vehicles is defined here as both battery electric vehicles and plug-in hybrid electric vehicles combined.

<sup>4</sup> Power sector is defined here to include electricity generation, transmission, and the distribution system, which typically ends at a service drop at a customer's premises.

Reference Case. EPA’s use of OMEGA and EVI-X to determine light- and medium-duty regional power sector demand is described in more detail below.

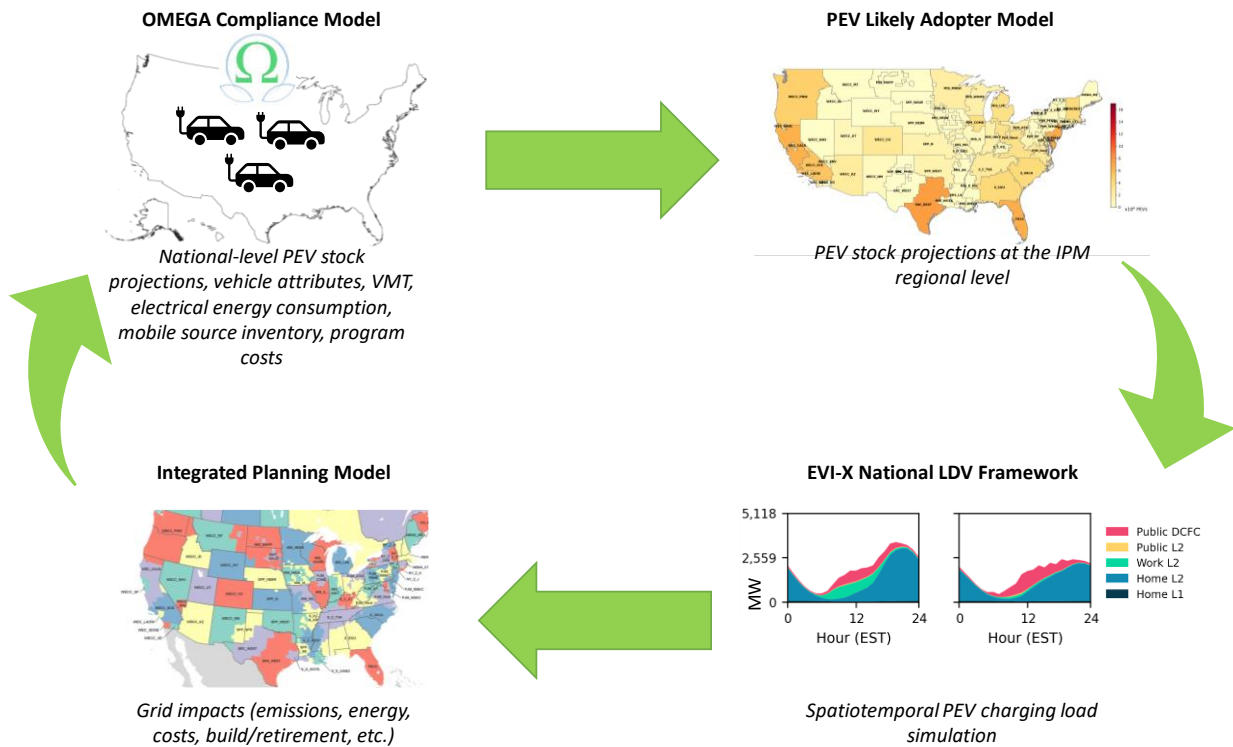
### **Modeling PEV Charge Demand and Regional Distribution**

Under an Interagency Agreement between EPA and the U.S. Department of Energy, NREL has developed a suite of electric vehicle infrastructure modeling tools (EVI-X) and methods for simulating PEV charging infrastructure requirements and associated electricity loads from best available data (U.S. EPA 2022b). EVI-X tools have informed multiple national, state, and local PEV charging infrastructure planning studies (E. Wood, C. Rames, et al. 2017) (E. Wood, C. Rames, et al. 2018) (Alexander, et al. 2021), including a national vehicle charging infrastructure assessment through 2030 (E. Wood, B. Borlaug, et al. 2023) and the Multi-State Transportation Electrification Impact Study of distribution-level impacts of vehicle electrification (E. Wood, B. Borlaug, et al. 2024).

In order to determine PEV charging demand, EVI-X models were used to translate scenario-specific forecasts of national light-duty vehicle stock and annual energy consumption from the OMEGA model into spatially disaggregated hourly load profiles required for subsequent power sector modeling using IPM for each of the 67 IPM regions. The primary components of the process flow from OMEGA outputs to IPM inputs is shown in Figure 1. IPM outputs also flow back into EPA mobile-source inventory analyses used within OMEGA as PEV emissions factors (U.S. EPA 2024).

### **PEV Disaggregation and Charging Simulation**

The OMEGA model evaluates the cost of compliance for meeting EPA vehicle emissions standards. Each OMEGA run produces projections of national vehicle sales, vehicle stock, vehicle technologies used to meet emissions standards, vehicle energy consumption, and tailpipe emissions. For EPA 2023 Reference Case, an OMEGA modeling run was conducted in May 2023 to generate projections from the U.S. light- and medium-duty vehicle fleet representing compliance with the Revised 2023 and Later Model Year Light-Duty Vehicle Greenhouse Gas Emissions Standards (2023+ LD-GHG) (86 FR 74434 2021) and the Greenhouse Gas Emissions and Fuel Efficiency Standards for Medium- and Heavy-Duty Engines and Vehicles— Phase 2 (HDP2) (86 FR 73478 2016). Vehicle sales and vehicle shares modeled include light-duty vehicles and trucks up to, and including, medium-duty passenger vehicles (MDPV); and medium-duty vehicles up to and including Class 3 pickup trucks, vans and incomplete vehicles.

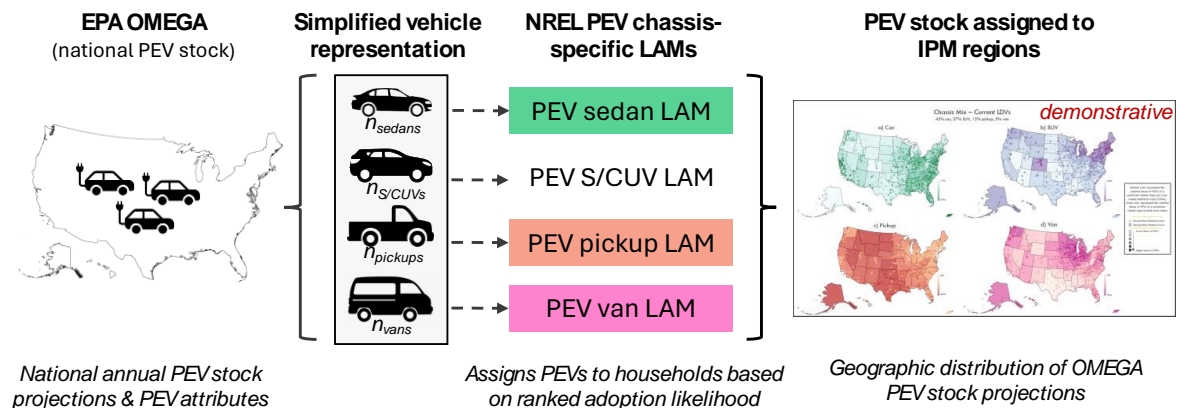


**Figure 1: Modeling process flow highlighting the primary components for translating OMEGA’s national PEV stock projections and PEV attributes into hourly load profiles.**

The OMEGA compliance modeling incorporated the anticipated impacts on light- and medium-duty vehicle electrification due to the Inflation Reduction Act (Public Law 117–169 2022) and thus the OMEGA results have increased PEV vehicle shares and increased PEV charging demand compared to the regulatory impact analyses for 2023+ LD-GHG or HDP<sup>5</sup>. Within the OMEGA compliance modeling, tailpipe emissions are zero in the case of BEVs and are zero during the charge-depleting operation of plug-in hybrid electric vehicles (PHEVs) and OMEGA provides an estimate of annual fleet charging demand based upon electrical energy consumption of individual PEVs represented within the OMEGA model. To produce estimates of the spatiotemporal charging loads needed for power sector emissions modeling, the national PEV stock from OMEGA needed to be disaggregated regionally.

The framework developed for PEV disaggregation leverages a likely adopter model (LAM) adapted by NREL (Ge, et al. 2021) to rank vehicles in the private light-duty fleet for their likelihood to be replaced by a PEV based on publicly available demographic data, including housing type, income, tenure (rent or own), state policies (ZEV states), and population density. The model was trained on the revealed preferences of 3,772 survey respondents (228 PEV owners) across the United States as described in (Ge, et al. 2021). Vehicle registration data from June 2022 (Experian Automotive 2022) was used to develop a set of chassis-specific LAMs for disaggregating PEV sedans, S/CUVs, pickups, and vans within the national light- and medium-duty vehicle fleet based on current regional vehicle type preferences. This process is outlined in Figure 2.

<sup>5</sup> PEV vehicle shares and charging demand used in EPA 2023 Reference Case is close to but not identical to those used to represent the “no action case” within the Light- and Medium-duty Multipollutant Final Rule and the Heavy-duty Phase 3 GHG Final Rule. This is due to the timing of the different analyses. OTAQ has further improved their electricity demand analysis after we have finalized EPA 2023 Reference Case inputs.



**Figure 2: Procedure for disaggregating OMEGA national PEV stock projections to IPM regions.**

Vehicle models represented within OMEGA are first assigned to a simplified chassis type (i.e., sedan, S/CUV, pickup, van). Next, the total number of vehicles for each chassis type are input into to each of the four chassis-specific LAMs to disaggregate PEVs into IPM regions based on regional vehicle type preferences and the likelihood of PEV adoption.

The OMEGA model generates vehicle adoption projections for thousands of unique PEV models over time. Conducting detailed charging simulations for each of these models would be computationally prohibitive and produce results that do not meaningfully differentiate from those generated by a reduced set of representative PEV models. Thus, a clustering approach was used to generate these representative PEV models for simulation from the complete set of OMEGA vehicles. K-means clustering was performed over each PEV’s respective battery capacity (kWh) and energy consumption rate (kWh/mi.) parameters as specified by OMEGA. A silhouette analysis was used to determine the appropriate number of clusters (k=6 for BEVs, k=2 for PHEVs) and OMEGA vehicles are assigned to clusters that minimize the Euclidean distance to the centroids of the two normalized (Z-score) parameters. These assignments are retained and used to map OMEGA vehicles to the most similar synthetic representative PEV model. The cluster centroids are used to produce the battery capacity and energy consumption rate parameters for the eight representative PEVs required for subsequent charging simulations. An additional parameter, the max DC charge acceptance, is defined as a PEV’s maximum effective charging rate over a typical 20 percent to 80 percent SOC DC fast charging (DCFC) window. This was required to simulate DCFC for BEVs and was not directly specified by the OMEGA model. PHEVs are assumed to not use DCFC. For modeling light-duty BEV DCFC, a simple heuristic was applied such that pre-2030 model years (Gen 1 batteries) would be capable of 1.5C charging on average while model year 2030 and later BEVs would be capable of charging at 3C (Gen 2 batteries).<sup>6</sup> The key parameters for simulating charging for each of the representative PEVs are shown in Table 1.

**Table 1: Representative PEV examples for charging simulations.**

Sim vehicle	Powertrain + EV Range [mi.]	Energy cons. rate [kWh/mi.]	Max AC accept. [kW] (Gen 1 / Gen 2)	Max DC accept. [kW] (Gen 1 / Gen 2)
BEV1	BEV 300	0.27	9 / 12	134 / 267
BEV2	BEV 300	0.31	9 / 12	154 / 308
BEV3	BEV 300	0.34	9 / 12	171 / 342
BEV4	BEV 300	0.38	9 / 12	191 / 383
BEV5	BEV 300	0.42	9 / 12	212 / 424
BEV6	BEV 300	0.47	9 / 12	236 / 471

<sup>6</sup> C-rate (or  $C_r$ ) is a measure of the rate at which a battery is charged/discharged relative to its maximum energy storage capacity. It is related to charge/discharge current in amperes (I) and maximum energy storage capacity in amp-hours (E) by the equation  $I = C_r \cdot E$ .

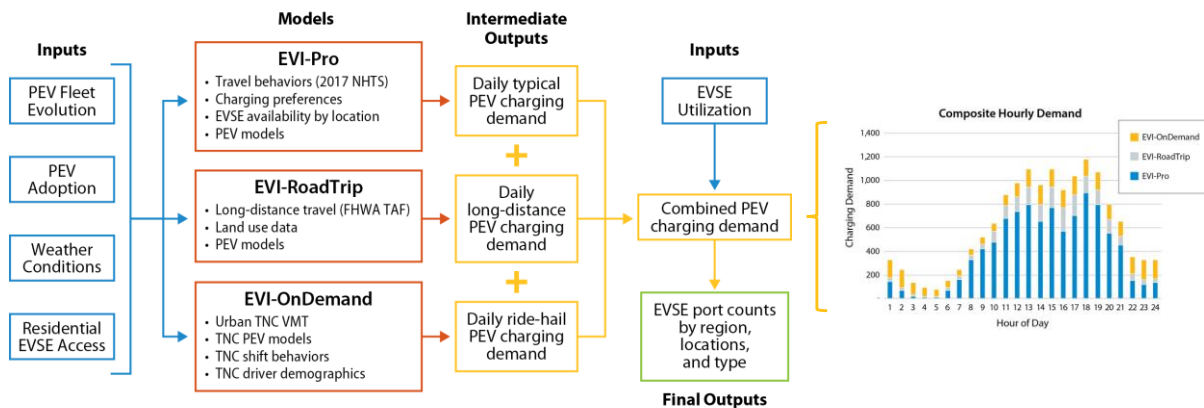
Sim vehicle	Powertrain + EV Range [mi.]	Energy cons. rate [kWh/mi.]	Max AC accept. [kW] (Gen 1 / Gen 2)	Max DC accept. [kW] (Gen 1 / Gen 2)
PHEV1	PHEV 50	0.29	9 / 12	-
PHEV2	PHEV 50	0.38	9 / 12	-
MD BEV1	BEV 150	0.54	12	300
MD BEV2	BEV 300	0.62	12	300
MD PHEV	PHEV 75	0.7	12	

The modeling of regionalized light-duty PEV charging demand builds on a foundation of research and collaboration with NREL, most notably the recently published 2030 National Charging Network report (E. Wood, B. Borlaug, et al. 2023). A brief explanation of this modeling approach is provided here; readers are directed to this previous work for more detailed explanations of the modeling approach and assumptions.

The core tools used for modeling light-duty vehicle (LDV) charging demands in this were:

- EVI-Pro: For typical daily charging needs
- EVI-RoadTrip: For fast charging along highways supporting long-distance travel
- EVI-OnDemand: For electrification of transportation network companies.

Each individual LDV model was integrated into a shared simulation pipeline (Figure 3). Models were provided with a self-consistent set of exogenous inputs that prescribe the size, composition, and geographic distribution of the national PEV fleet; technology attributes of vehicles and charging infrastructure; assumed levels of residential/overnight charging access; and regional environmental conditions. Each model used these inputs in bottom-up simulations of charging behavior by superimposing the use of a PEV over travel data from internal combustion engine vehicles. By relying on historical travel data from conventional vehicles, these models implicitly design infrastructure networks capable of making PEVs a one-to-one replacement for internal combustion engine vehicles, effectively minimizing impacts to existing driving behavior and identifying the most convenient network of charging infrastructure capable of meeting driver needs. (E. Wood, B. Borlaug, et al. 2023).



**Figure 3: EVI-X National light-duty vehicle framework simulation showing spatiotemporal EV electricity demands for three separate use cases: typical daily travel (EVI-Pro), long-distance travel (EVI-RoadTrip), and ride-hailing (EVI-OnDemand). Adapted from Wood et al. (2023) with permission.**

The independent (but coordinated) simulations produced a set of intermediate outputs estimating daily charging demands for typical PEV use, long-distance travel, and ride-hailing electrification. These intermediate outputs were then indexed in time (hourly over a representative 24-hour period) and space (core-based statistical area or county level) and were aggregated into a composite set of charging demands across multiple use cases. Once combined, the peak hour for every combination of charging type (e.g., Level 1 [L1], Level 2 [L2], direct current [DC]), location type (e.g., home, work, retail), and geography (e.g., core-based statistical area) was identified for the purpose of charging network sizing. Rather than sizing the simulated charging network to precisely meet the peak hourly demand in all

situations, the simulation pipeline used an assumed network-wide utilization rate in the peak hour to “oversize” the network by a margin that accounts for the fact that charging demands tend to vary seasonally and around holidays.

The simulation of medium-duty vehicles (MDVs) leveraged the EVI-X LDV pipeline with some key updates, namely:

- MDVs were disaggregated from the national level to counties in a manner proportional to existing registrations, as observed through data licensed from Experian. This contrasts the LDV approach, which relies on a set chassis-specific LAMs to assign PEVs to households with characteristics shown to correlate with PEV adoption.
- MDV travel patterns were derived from two sources based on chassis type: (1) vans were simulated based on data from NREL’s FleetDNA database, and (2) pickups were simulated based on data licensed from Wejo. This contrasts the LDV approach, which relies on the 2017 National Household Travel Survey (NHTS).
- Because MDVs are owned by a variety of businesses, both in terms of company size and business type, and are often used for both personal and commercial use, medium-duty PEVs in this study were assumed to be domiciled during off-shift periods at either a commercial property (e.g., a depot) or a private residential property (e.g., a single-family home). This study assumes that 75% of medium-duty PEVs are domiciled at depots and 25% at single-family homes. Note that further research into the domicile locations of MDVs is warranted since data on this topic are scarce, especially at the national level.

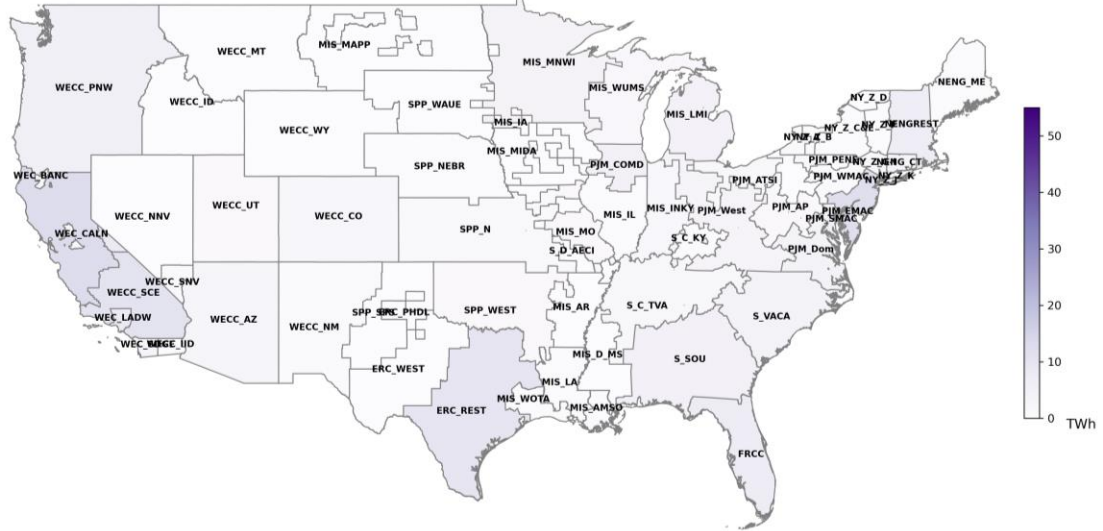
Following the PEV charging simulations, load profiles were aggregated from counties to IPM regions and converted from local time to Eastern Standard Time (EST) for IPM implementation. A final corrective step was taken to ensure that the annual energy consumption estimates supplied by OMEGA were reflected in the PEV load profiles. For a given OMEGA national PEV stock projection file, the modeling framework produces a typical weekday and weekend 24-hour (EST) load profile for all IPM regions and IPM analysis years (2028, 2030, 2035, 2040, 2045, 2050, 2055).<sup>7</sup> Load profiles were analyzed using OMEGA output for 2023 no-action case that included modeling of electric vehicle provisions from the IRA within the OMEGA compliance model and compliance with 2023 and later GHG standards (86 FR 74434 2021) with the addition of heavy-duty vehicle (Class 4-8) charge demand estimated for the California Advanced Clean Trucks (ACT) Program and compliant with HDP2 GHG standards (86 FR 73478 2016).

These analytical cases are described in more detail below. Figure 4 provides an example of how specific load profiles may be used to infer annual PEV charging demands for 2030 and 2050. The purple shading in Figure 4 represents the relative light- and medium-duty vehicle charging demand in each of the 67 IPM regions. In addition to the total hourly energy demands for PEV charging, energy demands were also broken out by the following charging types – home Level 1 (L1), home Level 2 (L2), depot L2 (applicable to medium-duty PEVs), work L2, public L2, and public DCFC (Figure 5). Note that these have been converted to EST and reflect an unmanaged charging scenario where drivers do not prioritize charging at certain times of the day (i.e., charging starts as soon as possible when vehicles are plugged in without consideration of electricity price or other factors). Note that the time-of-day charging does not include implementation of vehicle-to-grid technologies or other vehicle time-of-day charge demand shifting anticipated to be in use by 2030 (Wood, Borlaug, et al. 2023).

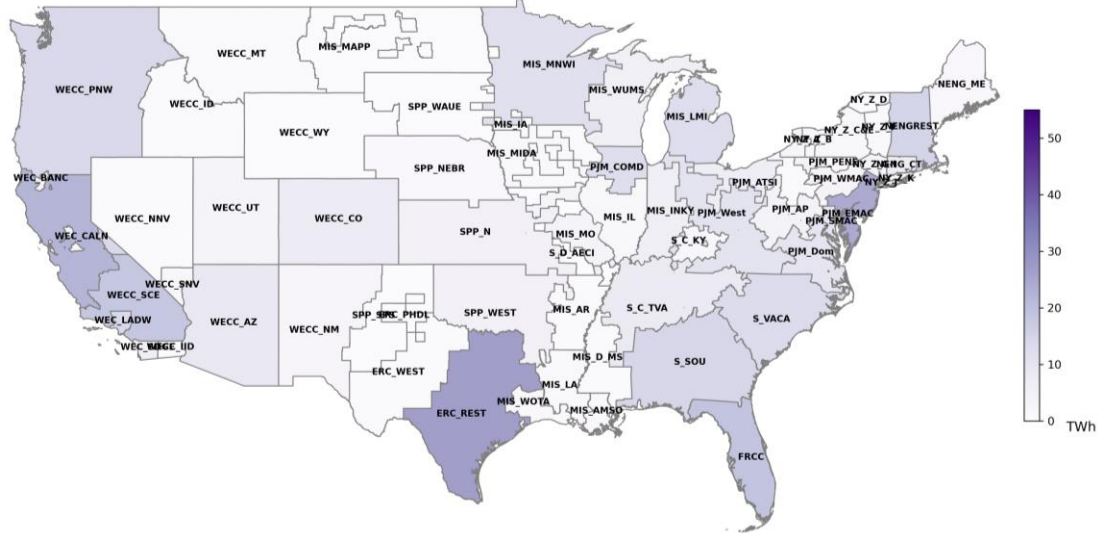
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<sup>7</sup> Output from OMEGA and EVI-X was also generated for Hawaii, Alaska, and Puerto Rico, however the IPM analysis only included IPM regions for the contiguous United States along with transmission dispatched across the U.S.-Canada border.

a) Annual light- and medium-duty PEV charging demand in 2030



b) Annual light- and medium-duty PEV charging demand in 2050

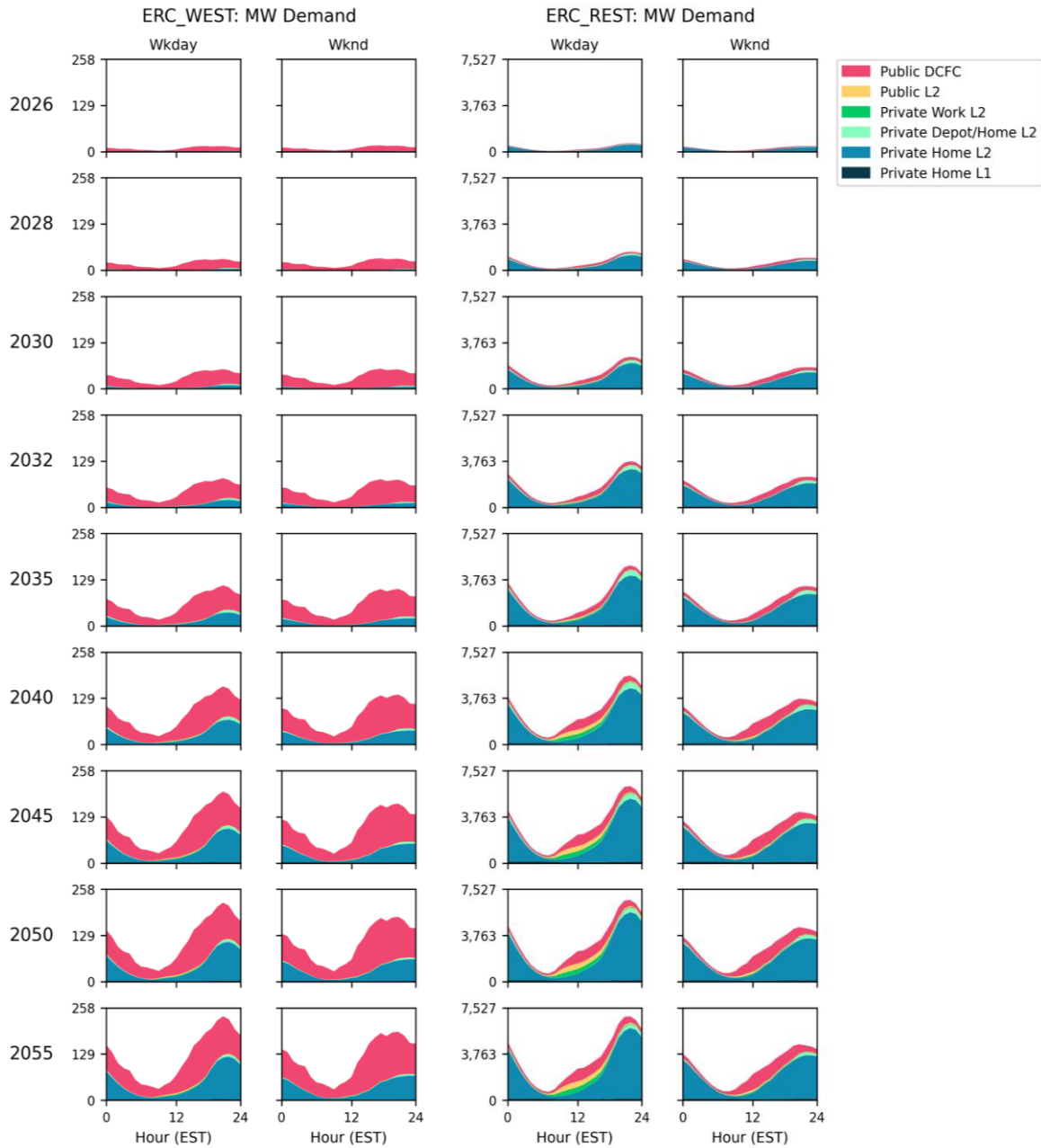


**Figure 4: Annual light- and medium-duty vehicle PEV charging loads (2030 and 2050 are shown) for each IPM region in the contiguous United States based on EVI-X regionalization of OMEGA PEV charge demand for EPA 2023.**

In Figure 5, there are clear differences in the magnitude, shape, and charger types between the West Texas (left—ERC\_WEST, containing mostly rural areas and small cities such as Midland and Odessa) and East Texas (right—ERC\_REST, including multiple major population centers such as Houston, San Antonio, Austin, and Dallas-Ft. Worth) regions. The EVI-X modeling framework conducts charging simulations that incorporate regional differences in EV adoption, vehicle type preferences, home ownership, weather conditions, and travel patterns. These demonstrative results reflect how in ERC\_WEST, EV adoption is projected to be low (due to limited population and revealed vehicle preferences) leading to a reduced demand for home-based charging while public DCFC demands for long-distance travel within the region (e.g., road trips) are amplified. This leads to a disproportionate share of public DCFC charging demand along highway corridors within the ERC\_WEST region. Alternatively, simulated charging demands in the

ERC\_REST are dominated by home and workplace charging due to the higher EV adoption and urban travel patterns more common to the region.

The OMEGA national PEV outputs and the resulting regionalized light- and medium-duty IPM inputs from EVI-X for both analyzed cases, for each IPM region and all analytical years (2026, 2028, 2030, 2032, 2035, 2040, 2045, 2050, 2055) are summarized within a separate PEV Regionalized Charge Demand Report (McDonald 2023).



**Figure 5: Yearly hourly (in EST) weekday and weekend load profiles for two IPM regions (ERC\_WEST, west Texas; and ERC\_REST, east Texas) broken out by charger type for OMEGA modeling conducted for EPA 2023 Reference Case.**



## **Calculation of Heavy-Duty Incremental Demand Input**

To calculate heavy-duty electricity demand, we performed state-by-state MOVES runs to account for state-specific HD ZEV adoption rates. IPM requires grid demand to be specified by day type (i.e., for an average weekday and weekend day), hour of the day, and by each of IPM's geographic regions. We first calculated total energy demand for a typical weekend day and weekday for both BEVs and FCEVs using MOVES output. Because MOVES energy consumption output for BEVs represents the total grid demand related to the running and charging of the vehicles, we used MOVES output for BEVs with no further processing.

However, MOVES does not capture upstream emissions due to the production of hydrogen for fuel cell electric vehicles (FCEVs). Hydrogen in the U.S. today is primarily produced via steam methane reforming (SMR), largely as part of petroleum refining and ammonia production. Given the BIL and IRA provisions that meaningfully incentivize reducing the emissions and carbon intensity of hydrogen production, as well as new transportation and other demand drivers and potential future regulation, we anticipate there will be a shift in how hydrogen is produced. Therefore, we made a simplifying assumption that the increased levels of hydrogen necessary to fuel FCEVs will be produced using grid electrolysis. Thus, all hydrogen production is represented as additional demand to EGUs and the emissions are modeled using IPM.<sup>8</sup>

We developed yearly scalar multipliers to apply to MOVES FCEV energy consumption to model emissions for hydrogen production coming from electrolysis. The resulting energy demand represents the total grid demand from the hydrogen production necessary to support the levels of FCEVs projected. First, we assumed hydrogen is produced by a series of decentralized, grid-powered polymer electrolyte membrane (PEM) electrolyzer systems, each with a hydrogen production capacity around 1,500 kilograms per day.<sup>9</sup> Next, we assumed the gaseous hydrogen is compressed and pre-cooled for delivery to vehicles using grid-powered electrical equipment. Finally, we assumed a linear improvement between our estimated current and future efficiency for hydrogen production. The linear interpolation is between current values that start in 2025 and future values represented for 2055, assuming a period of diffusion for more efficient electrolysis technology improvements to spread. The final scaling factors range from 1.748 in 2025 to 1.616 in 2055.

We allocated total daily demand of FCEVs and BEVs by the hour of day separately. FCEV energy demand is allocated uniformly across all hours of the day because hydrogen fuel can be produced and compressed at any time of day.

We developed charging load profiles to reflect the share of total daily demand from BEV charging that we expect to occur each hour for both weekdays and weekends. Because vehicle use and charging patterns vary by application, we developed individual charging profiles for each of MOVES heavy-duty source types based on soak or hotelling data in MOVES.<sup>10</sup>

Except for long-haul vehicle types, we used soak times of 12 or more hours as a proxy for when a vehicle may be parked at a depot, warehouse, or other off-shift location and can charge. We assume charging activity to be evenly distributed across the 12 hours of soak time before the vehicle starts. For long-haul vehicles, we instead calculate charging profiles using MOVES hotelling data in lieu of available soak data. Hotelling data accounts for the length of time that a vehicle is parked while en route and represents an opportunity for charging. Hotelling data is applied directly and does not assume the same 12-hour proxy as these vehicles may not regularly return to a depot for off-shift charging.

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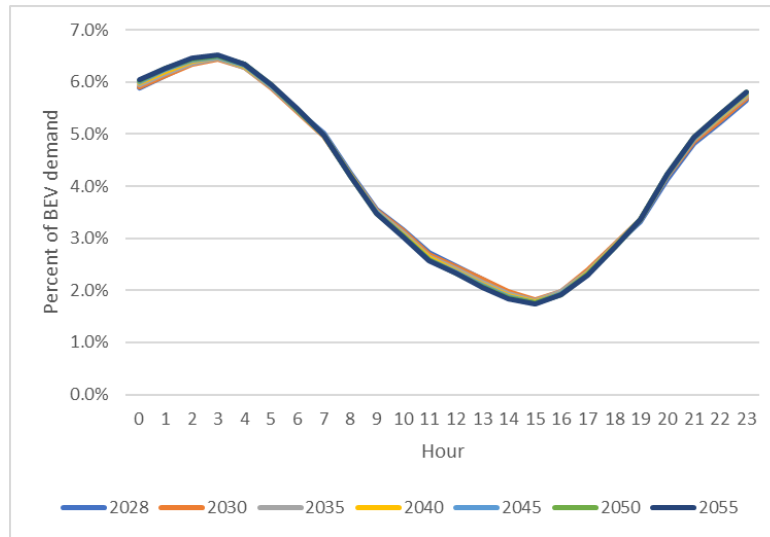
<sup>8</sup> The relative emissions impact of hydrogen production via SMR versus grid electrolysis depends on how electricity is produced, which varies significantly by region across the country. Electrolysis powered by electricity from the grid on average in the U.S. may overestimate the upstream emissions impacts that are attributable to HD FCEVs in our analysis. New electrolysis project announcements predominantly pair electrolyzers with zero-carbon energy sources. As the carbon intensity of the grid declines over time in response to the BIL and IRA and incentives, these impacts should be mitigated

<sup>9</sup> This is based on assumptions from the Hydrogen Analysis Production (H2A) Model from the National Renewable Energy Laboratory (NREL). National Renewable Energy Laboratory (NREL). "H2A: Hydrogen Analysis Production Model: Version 3.2018". Available online: <https://www.nrel.gov/hydrogen/h2a-production-archive.html>

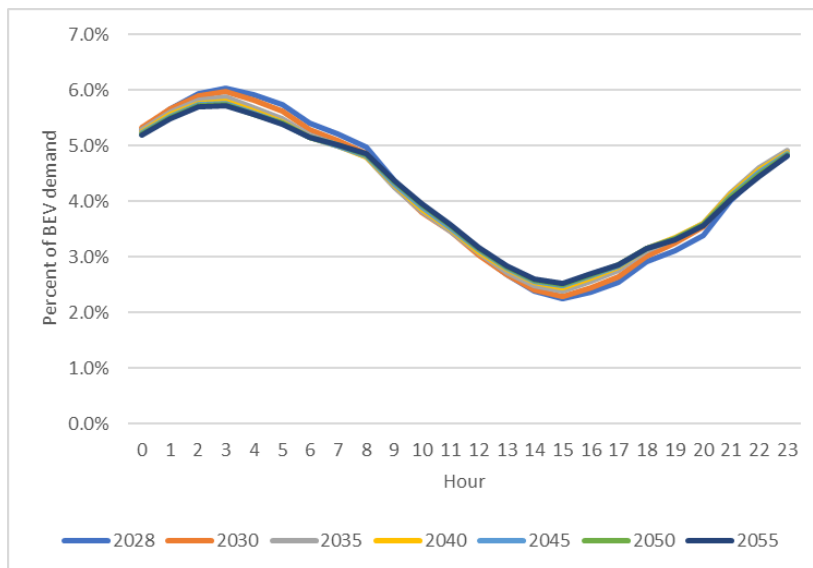
<sup>10</sup> Soaking is the time between when a vehicle is powered off and when it starts again, so it indicates when vehicles are not driving and may have an opportunity to charge. Hotelling is the hours spent by drivers of long-haul trucks with their trucks parked during mandatory rest periods.

We expect that the charging beginning time and duration will vary due to different energy consumption, charging equipment, and the charging preferences of BEV owners or operators. Finally, charging profiles for each source type were weighted by their share of electricity demand to calculate overall HD BEV national charging profiles for weekdays and weekends. We calculated separate HD BEV charging profiles for each calendar year run in IPM.

The HD BEV charging profiles used for allocating HD BEV electricity demand by time of day for the calendar years in which we ran IPM are shown in Figure 6 (weekdays) and Figure 7 (weekends). The small differences in the profiles for each year reflect the dependency that charging profiles have on the BEV fleet composition, as does the difference in the general profile shape between weekdays and weekends.



**Figure 6: Heavy-duty BEV charging profiles for weekdays for the interim reference case**



**Figure 7: Heavy-duty BEV charging profiles for weekends for the interim reference case**

Finally, IPM requires grid demand to be geographically allocated by IPM region. We developed regional allocation factors based on county-level CO<sub>2</sub> emissions in the 2016v2 emissions modeling platform.<sup>11</sup> We used CO<sub>2</sub> emissions as our basis for regional allocation because CO<sub>2</sub> scales well with VMT while capturing differing fleet characteristics in different counties. IPM includes a mapping of each county to an IPM region, which we used to aggregate county allocation factors by IPM region.

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<sup>11</sup> U.S. EPA. "2016v2 Platform". January 23, 2023. Available online: <https://www.epa.gov/air-emissions-modeling/2016v2-platform>

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