MODELING ELECTRIC VEHICLE IMPACTS ON AIR QUALITY

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16. Abstract

This study delves into the environmental impact of light-duty plug-in electric vehicle (PEV) adoption within Texas's metropolitan regions, with a primary focus on the mitigation of criteria pollutants associated with vehicular activities. The research endeavors encompass three main components. First, researchers developed future PEV adoption scenarios tailored to Texas metropolitan areas. Second, researchers quantified the emissions reductions attributable to PEV adoption in relation to vehicle activities. Third, researchers estimated the additional emissions stemming from electric-generating units in response to the demand for PEV charging. The specific analysis zeroed in on the potential emissions reductions linked to vehicle activities within the Dallas-Fort Worth metropolitan area using PEV adoption projections for 2026. Notably, the research revealed no significant overall change in emissions when comparing the increase associated with the operation of fossil fuel power plants for PEV charging and the maximum achievable reductions through PEV adoption. The most substantial prospective emissions reductions were observed in carbon dioxide emissions, contingent upon the average fuel economy of the displaced internal combustion engine vehicles and the fuel composition of power plants supplying the requisite additional generation for PEV charging. The outcomes of this investigation can potentially guide transportation and environmental agencies such as the Department of Transportation and Air Agency in addressing issues related to the environmental and public health implications of PEV adoption. Furthermore, these findings can serve as a cornerstone for shaping policies that steer the development of the PEV fleet in Texas.

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Executive Summary

This project investigated the environmental impact of plug-in electric vehicle (PEV) adoption in Texas metropolitan areas, specifically focusing on the reduction of criteria pollutants associated with vehicle activity.

The approach involved three primary components:

- **PEV adoption scenarios:** This study developed multiple future PEV adoption scenarios for Texas metropolitan areas by leveraging Texas vehicle registration data and PEV projections from the Energy Information Administration's (EIA's) Annual Energy Outlook (AEO).
- **Emission reduction estimation:** To gauge the potential emission reductions resulting from PEV adoption, this study assumed one-to-one replacement of internal combustion engine (ICE) vehicles with PEVs of the same model year. This study estimated the maximum potential emission reduction by comparing the total emissions produced by the replaced ICE vehicles.
- **Electric generating unit (EGU) emission impact:** This study assessed the additional emissions from EGUs due to PEV charging demand. A microscopic simulation model was created based on outputs from a traditional four-step travel demand model. This model simulated the movement of both PEVs and ICE vehicles, allowing us to estimate their energy consumption, PEV's charging demand and the spatiotemporal distribution of charging demand. Additional EGU emissions were determined by mapping the charging demand onto the grid network and solving an optimal power flow problem.

In this project, our specific evaluation centered on potential emission reductions linked to vehicle activity in the Dallas-Fort Worth metropolitan area using PEV adoption projections for 2026, considering three scenarios outlined in EIA's AEO. Key findings include:

- **Criteria pollutants:** For pollutants like nitrogen oxide and sulfur dioxide, we observed no significant change in total emissions between the increases associated with operating fossil fuel power plants to charge PEVs and the maximum achievable reductions through PEV adoption. This is mainly due to the low emission rates of modern ICE vehicles.
- **Carbon dioxide reduction:** The most significant potential emissions reductions were related to carbon dioxide, contingent on the average fuel economy of the displaced ICE vehicles and the fuel mix of power plants supplying the necessary additional generation for PEV charging.
- **Electricity sources:** Until zero-emission electricity sources (e.g., wind, solar, nuclear, and hydro) can fully meet grid demands, fossil fuel sources such as coal and natural gas will continue to play a significant role in providing the additional generation required for charging PEVs and other electricity-dependent activities.

Recommendations for future work are to:

- Expand the analysis to include medium-duty and heavy-duty PEVs as more data become available.
- Consider multiple scenarios for estimating the net increase in generation needed to charge PEVs, particularly during periods of low wind power generation when ozone levels are typically highest.
- Investigate changes in the spatiotemporal distribution of emissions because vehicle activity and EGU activity may exhibit different activity patterns.

The outcomes of this research can inform the Texas Department of Transportation in addressing issues related to the environmental and public health implications of PEV adoption. Furthermore, these findings can serve as a foundation for shaping policies that guide the development of the PEV fleet in Texas.

Acknowledgments

The project team would like to acknowledge the collaboration with Dr. Farnaz Safdarian, Dr. Thomas Overbye, and their research team members at the Texas A&M Engineering Experiment Station, who generously shared their work, expertise, and data, which were instrumental in advancing our research. The project team would also like to acknowledge generous support from the North Central Texas Council of Governments.

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Background and Introduction

Electric vehicles (EVs) are anticipated to bring about the greatest upcoming change in the transportation infrastructure.

The four major categories of EVs are:

- **Battery EV (BEV):**
  - BEVs are solely powered by an electric propulsion system that does not rely on an internal combustion engine (ICE).
  - Since BEVs burn no fuel, they do not produce any emissions at their tailpipes.
- **Hybrid EV (HEV):**
  - HEVs operate using both an ICE and an electric motor, where the electric motor assists the ICE during certain operations, such as during the vehicle starts when fuel consumption is highest.
  - The HEV battery is recharged by the ICE during driving.
- **Plug-in Hybrid EV (PHEV):**
  - PHEVs have both an ICE and an electric engine.
  - A PHEV's battery needs to be charged by plugging into a power source. Compared with BEVs, PHEVs have a shorter operation range on electric motors. PHEVs switch over to the ICE after the battery is exhausted.
- **Fuel Cell EV (FCEV):**
  - FCEVs generate their electric power using hydrogen and oxygen.
  - The adoption of FCEVs has been slow, and they are not yet widely available in the United States.

CARTEEH QUICK FACTS

CARTEEH is a Tier 1 University Transportation Center, funded by the U.S. Department of Transportation's Office of the Secretary for Research and Technology.

According to the definition in the California Air Resources Board's (CARB's) Advance Clean Cars II regulation, BEVs, PHEVs, and FCEVs are classified under zero-emission vehicles (ZEVs) [1].

By the mid-2030s, the number of new PEVs is anticipated to surpass those of conventional automobiles. Between 2011 and 2018, EV sales in the United States climbed from 17,763 to 326,643. In 2019, the Tesla Model 3, introduced in 2017, represented 47 percent of the United States EV market [2]. As Figure 1 shows, the Dallas-Fort Worth (DFW) metropolitan area accounts for the state's highest EV adoption rate compared to other Texas cities [3]. This accelerated growth can be attributed to several factors, including advancements in battery and EV technology, an increase in the number of available EV models, an improvement in the charging infrastructure, and the development of regulations, policies, and incentive programs for both the purchase and use of EVs. With EV sales expanding at an ever-increasing rate, it is crucial to comprehend the potential effects of greater electrification on air quality.

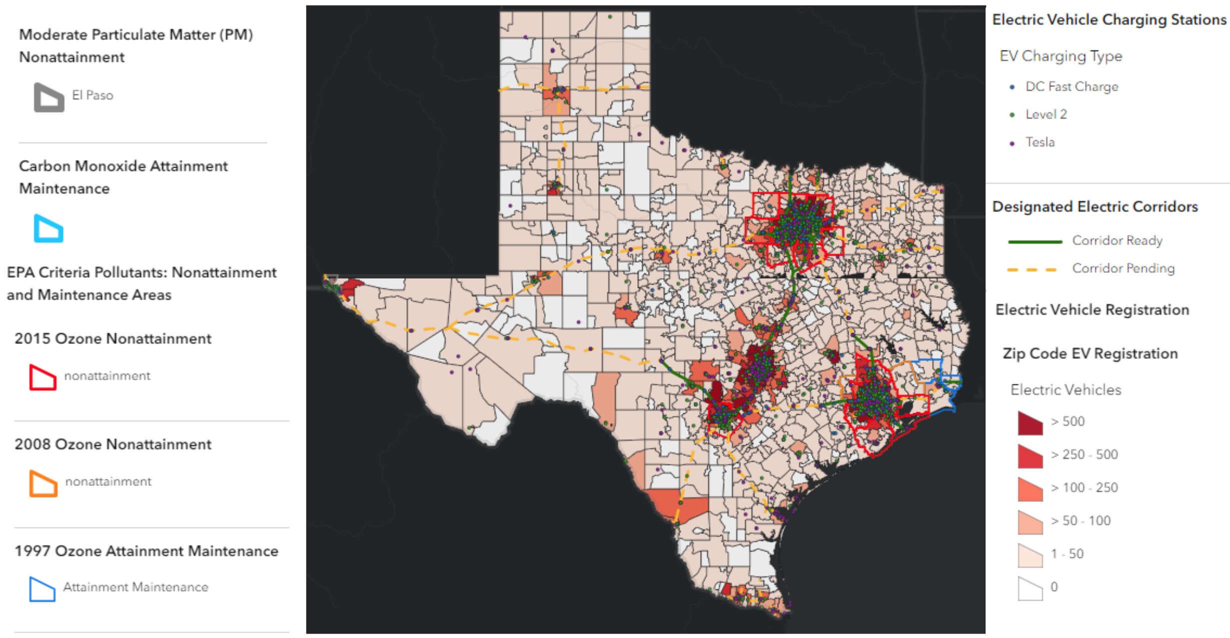


Figure 1. Current state of EVs in Texas, showing the EV registrations by zip codes, EV charging stations, ozone and particulate matter non-attainment areas, and designated EV corridors.

Greenhouse gas (GHG) and criteria pollutant emissions, such as ground-level ozone (O_3), nitrogen dioxide (NO_2), particulate matter (PM), sulfur dioxide (SO_2), and carbon monoxide (CO), are anticipated to be reduced significantly by the increasing adoption of PEVs by American consumers. While PEVs have significantly lower exhaust emissions, their widespread adoption will inevitably increase the demand for electric power generation, transmission, and distribution. The improvement in GHG emissions is also heavily dependent on the percentage of the fossil-fuel component of the EV mix [4]. The increased demand for electricity may cause a rise in power plant emissions, a scenario known as moving tailpipe emissions to power plants. This shifting in emission patterns also raises environmental justice issues as tailpipe emissions, which are more prevalent in urban areas, migrate to power plant emissions that are more commonly located in rural areas. PEV technology, PEV activity, energy sources for electricity generation, the location and time of electricity generation, electricity consumption, and charging behavior are important determinants of the interaction between PEVs and the global implications for air quality. The nature and volume of emissions vary and depend on the type of EV. While HEVs are largely driven by gasoline, with modest batteries supporting the ICE engine, PHEVs are powered by both gasoline and electricity, and BEVs are powered by electricity alone. If the power is sourced from nonrenewable sources (e.g., coal or natural gas), the energy generation produces air pollutants and GHG emissions that negatively impact human health, quality of life, and climate change. Consequently, analyzing the true consequences of PEV adoption on the total air quality would necessitate a study that goes beyond the tailpipe emissions; we propose adopting a more holistic approach by studying the interconnectivity between important factors affecting both tailpipe and electric generating unit (EGU) emissions. This study aims to characterize the complicated relationships between the PEV population, activities, charging profiles, electricity-generating mix, energy consumption and emissions, and ozone levels.

Four regions within Texas are in non-attainment (NA) for the 2015 Ozone National Ambient Air Quality Standards (NAAQS): the Houston-Galveston-Brazoria (HGB), DFW, San Antonio (SAN), and El Paso (ELP) metropolitan regions. ELP is also in NA for the 1987 particulate matter with a diameter of 10 micrometers or less (PM_{10}) NAAQS [5]. It is crucial for state agencies and metropolitan planning organizations (MPOs) to accurately understand how various elements in the expanded PEV adoption would affect ground-level ozone because these agencies are responsible for developing and executing transportation network plans. We believe the results of this study can assist these organizations in evaluating the anticipated implications of various PEV scenarios on tailpipe and EGU emissions and, consequently, on regional ozone. In addition, the built framework, which includes the model setup, data sources, and procedures, will serve as templates for evaluating future scenarios. Given the extraordinary expansion within the PEV sector, we believe that this study's results will aid decision-makers in identifying and establishing the appropriate policies and tactics that would maximize the advantages while minimizing the disadvantages of operating PEVs in Texas's metropolitan areas.

Project Goals

The goal of this study was to evaluate the impact of future PEV scenarios on the emissions of criteria pollutants in Texas metropolitan areas, especially those that are currently in NA. The study focused on characterizing the complex interactions between the PEV population, vehicle activities, charging behavior, electricity generation mix, energy consumption, and emission reduction from the switching of ICE vehicles to EVs.

Research Plan

The study consisted of five tasks, which are shown and described in Figure 2. Task 1 was project management and research coordination to ensure progress and quality control for the entire course of the project, which was followed by Task 2, a comprehensive review of existing research and a state-of-the-practice assessment of PHEV's air quality impact. Task 3 related to developing scenarios based on key factors identified as part of Task 2. Task 4 focused on estimating emissions from PEVs resulting from both on-road and EGU sources. Final project documentation, including research reports, and a visualization dashboard, were prepared as part of Task 5.

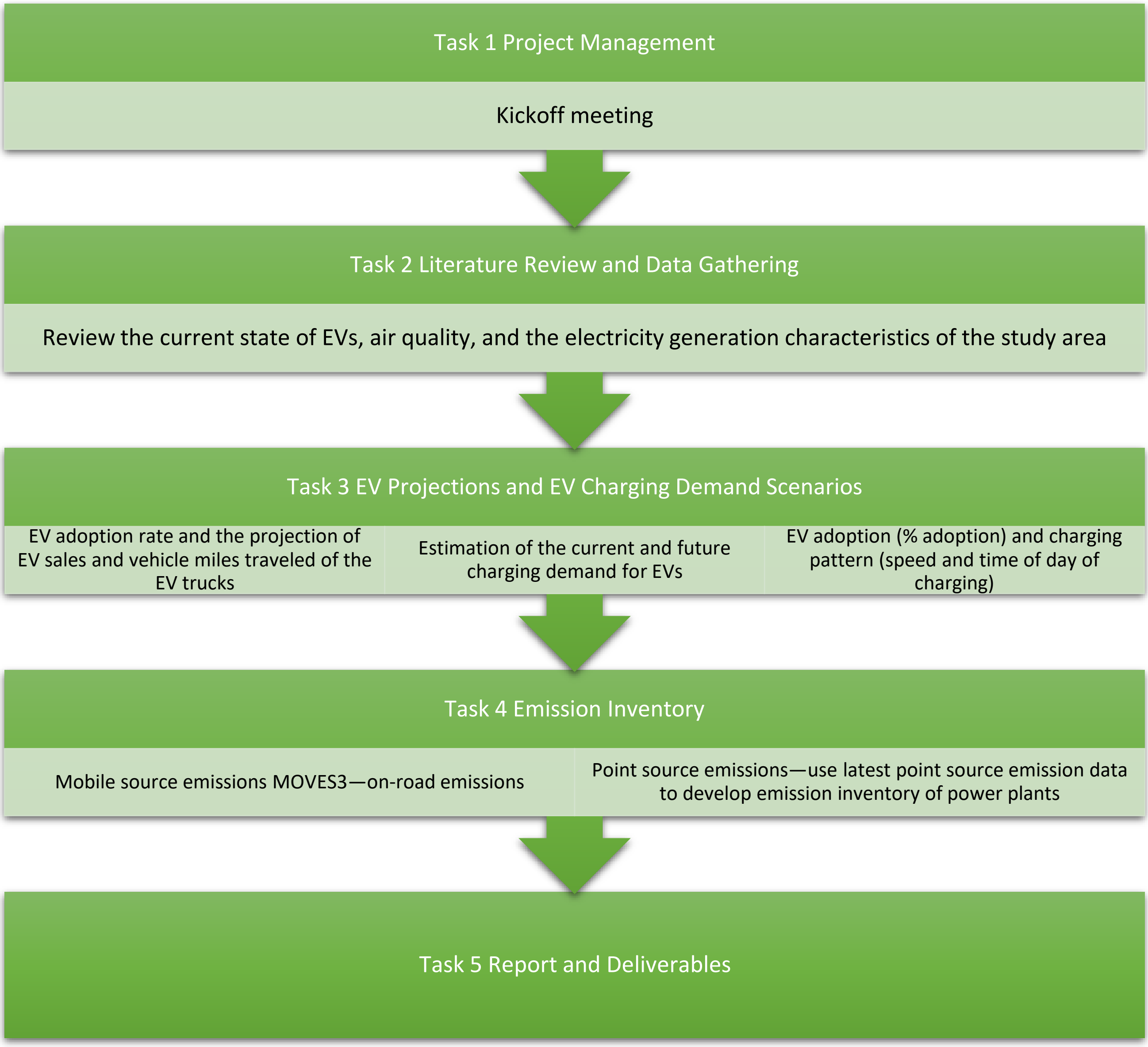


Figure 2. Work plan of the study.

The details of the tasks are as follows:

- **Task 1: Project management:** This task aimed to complete the required contractual processes and kick off the project.
- **Task 2: Literature review and data gathering:** This task identified existing research and data that could be used to inform the other project tasks and identify any information gaps. This task built on the understanding of the problem statement, evaluated the current gaps in the literature, and identified existing research and information that could be leveraged as part of the following tasks in this project. The task resulted in a comprehensive assessment of the state of the practice and state of research on PEVs and their impact on air quality.
- **Task 3: EV projections and EV charging demand scenarios:** This step characterized the population, activity, and energy consumption characteristics of PEVs (PHEVs and BEVs), charging profiles associated with these vehicles, electricity generation mix and emissions, and existing ozone studies and data for the

selected study areas. ElectroTempo or similar utilities were used to estimate the energy demand in urban areas. This information was used to identify potential EV adoption scenarios for emissions and ozone impact evaluation.

- **Task 4: Emission inventory:** This task characterized emissions corresponding to each of the scenarios developed in Task 3. The emission characterization included on-road mobile sources and EGUs. On-road emissions were estimated using the latest available version of the Environmental Protection Agency's (EPA's) Motor Vehicle Emission Simulator (MOVES) emission model and regional travel demand model. EGU emissions were calculated using the emission rates from EPA's Continuous Emission Monitoring System (CEMS), where CEMS data included hourly EGU emissions and gross power output. CEMS emission data were sorted by region and power plant. We used the CEMS data to calculate the change in energy generation and the change in emissions between one hour and the next.
- **Task 5: Report and deliverables:** After the data analysis activities, a final report documenting the work performed, methodologies, outcomes, and next steps was developed. The deliverables included a final study report, briefing materials (e.g., presentations), and a dashboard.

Literature Review and Data Gathering

This chapter summarizes the literature review that the research team performed to identify existing research and data that could be used to inform the project tasks and identify any information gaps. The chapter also provides a comprehensive assessment of the state of the practice and state of research on PEVs and their impact on air quality.

Literature Review

This section discusses the findings from the literature review we performed.

EV Market Penetration

National EV Market Penetration Trend

There has been a significant increase in the sale of EVs, especially HEVs, in the past decade, which was the result of advancements in EV technology. As the information gathered by the International Energy Agency in Figure 3 shows, the market shares of EVs have grown from 1 percent of total car sales in 2016 to 5 percent in 2021 [6]. The findings also show a 436 percent increase in BEV and 126 percent in PHEV sales from 2016 to 2021 (87,000 and 73,000 in 2016 to 446,000 and 165,000 in 2021 for BEVs and PHEVs, respectively) [6].

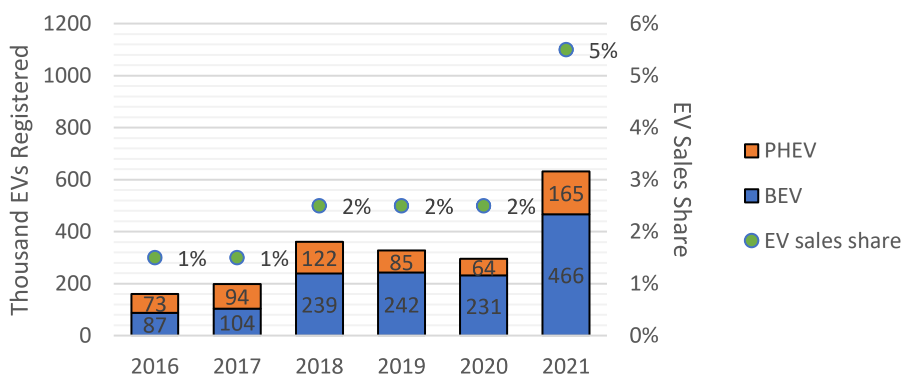


Figure 3. EV registration in the United States (2016–2021) [6].

In the past decade, PEV technology and market share have advanced significantly. Bloomberg New Energy Finance (BNEF) attributed this increase in market share to advances in battery technology and a decrease in battery cost (in U.S. dollars per kilowatt hour [kWh]) [7]. The Alliance for Automotive Innovation compiled new registration retail and fleet data for 2021 and summarized that HEVs were 6.47 percent of the new light-duty vehicles (LDVs) registered in 2011 across the United States, whereas ZEV-class vehicles have a combined share of 4.35 percent (BEVs at 3.17 percent, PHEVs at 1.16 percent, and FCEVs at 0.02 percent) [8]. Figure 4 shows the U.S. Department of Energy's (DOE's) Alternative Fuels Data Center's (AFDC's) summary of the number of EVs registered in each state as of December 31, 2021. According to AFDC's summary, California has the greatest number of EVs (approximately 563,070), which is approximately 39 percent of EVs nationwide, followed by Florida (approximately 95,640) and Texas (approximately 80,900) [9].

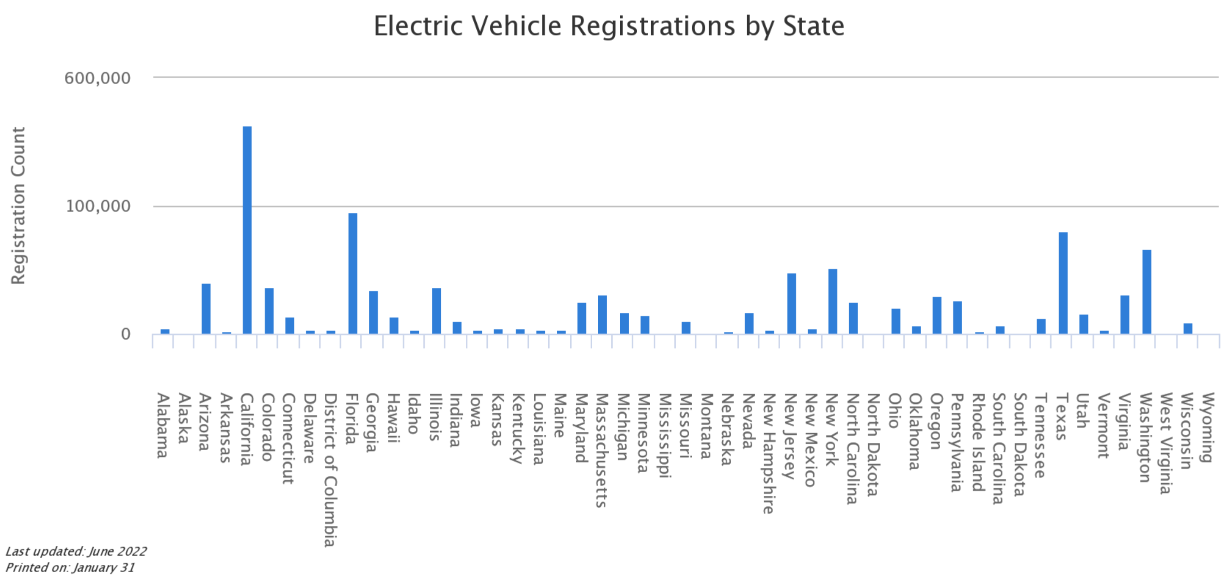
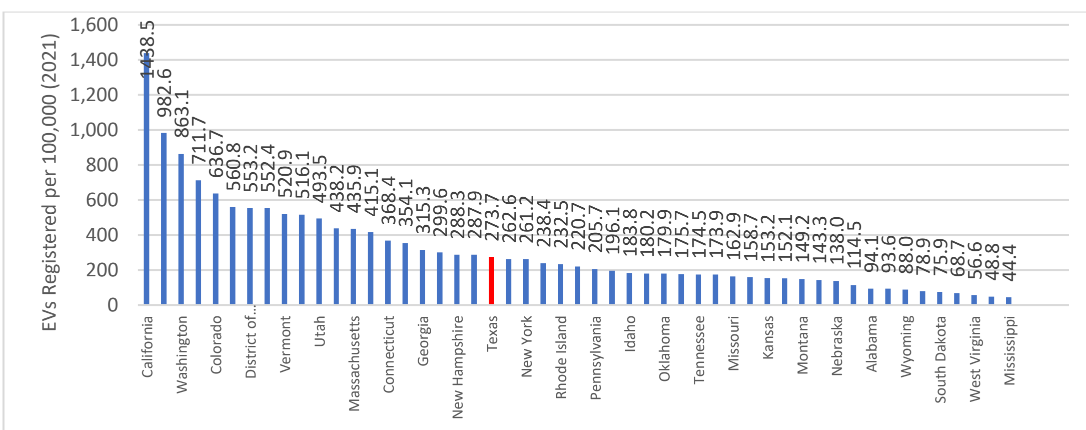


Figure 4. EV registration by state as of December 31, 2022 [9].

Texas EV Market Penetration Trend

Texas is the second most populous state in the United States. If we look at the AFDC data on the number of EVs registered by state and factor in the state population, Texas ranks significantly lower in terms of EVs registered per 100,000 people. As Figure 5 shows, Texas ranks 22nd out of 50 states for EVs registered per 100,000 people. As of 2021, 80,900 EVs were registered in Texas, and the state population total was 29,558,864; therefore, for every 100,000 people in Texas, 273.7 EVs were registered. Texas ranked significantly lower than California's 1,428.5 (ranked first) and Florida's 438.2 (ranked 13th). However, the Texas Department of Transportation (TxDOT) noted that the total number of EVs nearly tripled between 2020 and July 2022 due to more people adopting the technology [10]. As of January 31, 2023, the total number of EVs registered in Texas totals 170,389, with Harris (23,729 EVs) and Travis (23,728 EVs) Counties leading the state [3]. TxDOT also predicted that EV adoption rates in Texas will grow rapidly. Using the current Texas Department of Motor Vehicles (TxDMV) growth trends for EVs, TxDOT estimated that the number of EVs will reach 1 million by 2031 and that it will be necessary to ensure the infrastructure in Texas is ready to meet the demands of these new EVs on the road [10].



Note: 2021 EV registration data were used because 2021 is the latest year with a full year of data available from AFDC [9]. Population data for 2021 are from the U.S. Census Bureau's State Population Totals: 2020–2022 estimates, available at https://www.census.gov/data/tables/time-series/demo/popest/2020s-state-total.html.

Figure 5. EVs registered per 100,000 people by state in 2021.

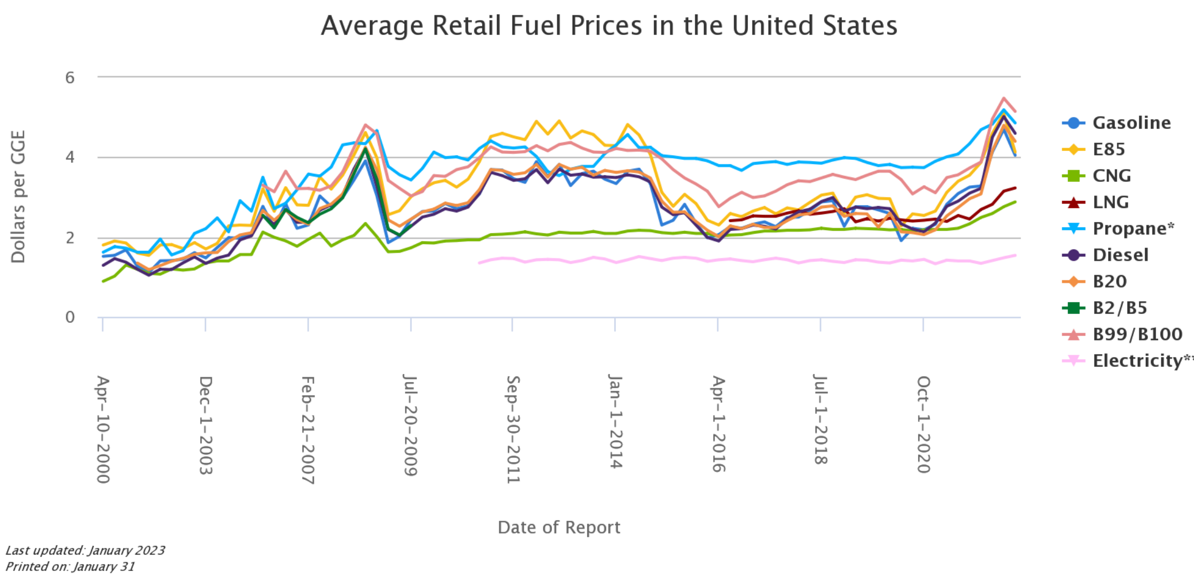
Factors Impacting EV Market Penetration

In their 2014 report, Farzaneh et al. list the cost of conventional fuel, battery cost, vehicle range, and infrastructure as several factors that affect the market penetration rate of EVs [11]. This section discusses the impacts of these four factors on EV market penetration and the outlook of these factors.

Conventional Fuel Cost and Future Outlook

One factor in the increased adoption of EVs is the increase in the price of gasoline since EVs become more economical as gasoline prices rise. BEVs have no ICE and therefore never need gasoline. HEVs and PHEVs also have lower average fuel usage compared to conventional vehicles.

Figure 6 shows average monthly retail fuel prices in the United States from 2000 to 2022, with the prices for electricity starting in 2011 when the availability of commercial vehicles and charging stations became significant in the market [12]. According to AFDC, petroleum fuel (gasoline and diesel fuel) prices are the primary driver of alternative fuel prices because the demand for alternative fuel in non-dedicated alternative fuel vehicles (AFVs) fluctuates according to petroleum fuel prices. However, since transportation only constitutes a tiny portion of the natural gas and electricity market, prices have been buffered by this driver [12].



Notes:
Fuel volumes are measured in gasoline gallon equivalents (GGEs).

* Propane prices reflect the weighted average of primary and secondary stations. Primary stations have dedicated vehicle services and tend to be less expensive. Secondary stations are priced for the tank and bottle market and tend to be more expensive.

** Electricity prices are reduced by a factor of 3.54 because electric motors are 3.54 times more efficient than ICE (per AFDC based on AFLEET 2019) and converted to GGEs at a rate of 33.7 kWh per GGE (per AFDC). Electricity prices are based on residential rates for LDVs because most of the vehicle charging happens at home. These prices are lower than at most public or commercial medium/heavy-duty fleet charging stations because they do not include costs for infrastructure development, maintenance, operation, electric demand charges, network/host fees and profits, and highway motor fuel taxes or other fees collected in some states to replace those taxes.

Figure 6. Average retail fuel prices in the United States from 2000 to 2022 [12].

As one of the major oil and gas producing states in the country, Texas oil and gas prices are usually among the lowest in the country, as Table 1 shows.

Table 1. Annual Retail Gasoline (All Grade) Prices from 2017 to 2022 by State (Dollars)

State	2017	2018	2019	2020	2021	2022
California	$3.080	$3.551	$3.677	$3.132	$4.100	$5.406
Colorado	$2.429	$2.748	$2.660	$2.335	$3.265	$3.891
Florida	$2.485	$2.704	$2.513	$2.148	$2.956	$3.809
Massachusetts	$2.511	$2.823	$2.665	$2.234	$3.013	$4.099
Minnesota	$2.387	$2.649	$2.504	$2.051	$2.871	$3.819
New York	$2.619	$2.895	$2.730	$2.324	$3.105	$4.105
Ohio	$2.384	$2.615	$2.544	$2.081	$2.932	$3.829
Texas	$2.294	$2.527	$2.357	$1.899	$2.729	$3.553
Washington	$2.911	$3.269	$3.186	$2.733	$3.520	$4.659

Note: Data were retrieved from the U.S. Energy Information Administration's (EIA's) weekly retail gasoline and diesel prices (dollars per gallon, including taxes) for the product "Gasoline—All Grade" and period "Annual," available at https://www.eia.gov/dnav/pet/pet_pri_gnd_a_epm0_pte_dpgal_a.htm .

Battery Cost and Future Outlook

The cost of battery technologies also impacts the market penetration of EVs. Batteries make up a very large part of an EV's cost, and $100/kWh is often cited by industry analysts as the threshold that will enable electric cars to become truly cost-competitive with traditional gasoline-powered vehicles.

The cost to replace a lithium-ion battery pack for a BEV can be very high and is a detractor to the adoption of EVs. On average, a lithium-ion EV battery pack costs between $10,000 and $12,000. However, recent advancements in BEV and PHEV battery technology have started to lower this concern. The previous decade saw a significant decrease in the average market cost of battery packs. BNEF reported that lithium-ion battery pack prices continue to drop and dropped by 89 percent from $1,200/kWh in 2010 to $132/kWh in 2021 [13]. With advancements in technology and increasing adoption of EVs, it has been predicted that battery packs will continue to drop and will cost approximately $104/kWh in 2025 and $72/kWh in 2030 [14]. Some researchers also predict that by 2030, due to the high fuel savings from EVs, an owner will be able to reach the parity point of purchasing a more expensive EV than conventional vehicles by one or two years sooner [14].

In the *Texas Electric Vehicle Infrastructure Plan* [10], TxDOT predicts a significant growth in the EV population in Texas, and the Electric Reliability Council of Texas (ERCOT) and TxDMV predict the state will reach 1 million EVs on the road by 2028 and 2031, respectively. TxDOT also notes that the planned production of EV batteries is increasing throughout the country. As Table 2 shows, at least 15 owners/operators are setting up battery factories across the country; notably, for Texas, the Tesla factory in Austin has the largest annual capacity among this list.

Table 2. Existing and Planned Battery Factories in North America [10].

Owner/Operator	Location	Annual Capacity*	Planned Year
Tesla/Panasonic	Sparks, NV	38 GWH	2022
Tesla	Fremont, CA	10 GWH	2022
Tesla	Austin, TX	100 GWH	2022+
GM/LG	Lordstown, OH	30–35 GWH	2022
GM/LG	Spring Hill, TN	30–35 GWH	2023
GM/LG	Lansing, MI	5 GWH	2022/2023
Ford	Memphis, TN	43 GWH	2025
Ford/SK Innovation	Kentucky	86 GWH	2025
Stellantis/LG	Windsor, Ontario	45 GWH	2025
Stellantis/Samsung SDI	Kokomo, IN	33 GWH	2025+
SK Innovation	Atlanta, GA	21.5 GWH	2023
Toyota	Greensboro, NC	200,000 vehicles	2025
Volkswagen	Chattanooga, TN	TBD	TBD
Mercedes/Envision	Bibb County, AL	TBD	2024
Various manufacturers	Virginia	90 GWH	2022+

Note:

**Annual capacity* refers to the yearly output of battery capacity produced at each factory. 1 gigawatt hour (GWH) = 13,000 EVs with a battery pack capacity of 77 kWH.

Vehicle Range

Range anxiety is another concern that impacts the penetration of EVs for some users, but as with battery life, as the single charge range of EVs increases, the barriers to additional penetration decrease. When the first BEV became available in the United States in 2011, its average range was 80 miles [15], but by the end of 2022, the average BEV increased to 277 miles per charge [16, 17]. PHEVs have a much smaller battery range, with an average battery range of approximately 24 miles and an average total range (combining battery and gasoline) of 439 miles [17]. According to the Office of Energy Efficiency and Renewable Energy, more than half of all daily trips in 2021 were less than 3 miles, and 93 percent of all daily trips were under 25 miles [18]. Thus, the range of a 2022 EV would comfortably cover the daily trips of an average driver.

EVs, when on battery, are also significantly more energy efficient than ICEs. According to the Renault Group, the efficiency of an electric motor refers to the ratio between useful energy and the total energy consumed, expressed as a percentage. For example, an EV motor with energy efficiency estimated at 90 percent wastes 10 percent of the electricity consumed by the electric motor, and the remaining 90 percent is used in the propulsion of the vehicle. Figure 7 shows AFDC's estimations of the efficiency of EVs on the road in the United States as of 2020, which used the data from the National Renewable Energy Laboratory (NREL) and the Greenhouse Gas, Regulated Emissions, and Energy Use in Transportation (GREET) model from Argonne National Laboratory. AFDC estimated the average EV range to be 240 miles, corresponding to an efficiency factor of 3.54 (with the assumption that the relationship between 100 miles and 300 miles was linear). This indicated that on average an EV is 3.54 times more efficient than its conventional fuel counterpart [19].

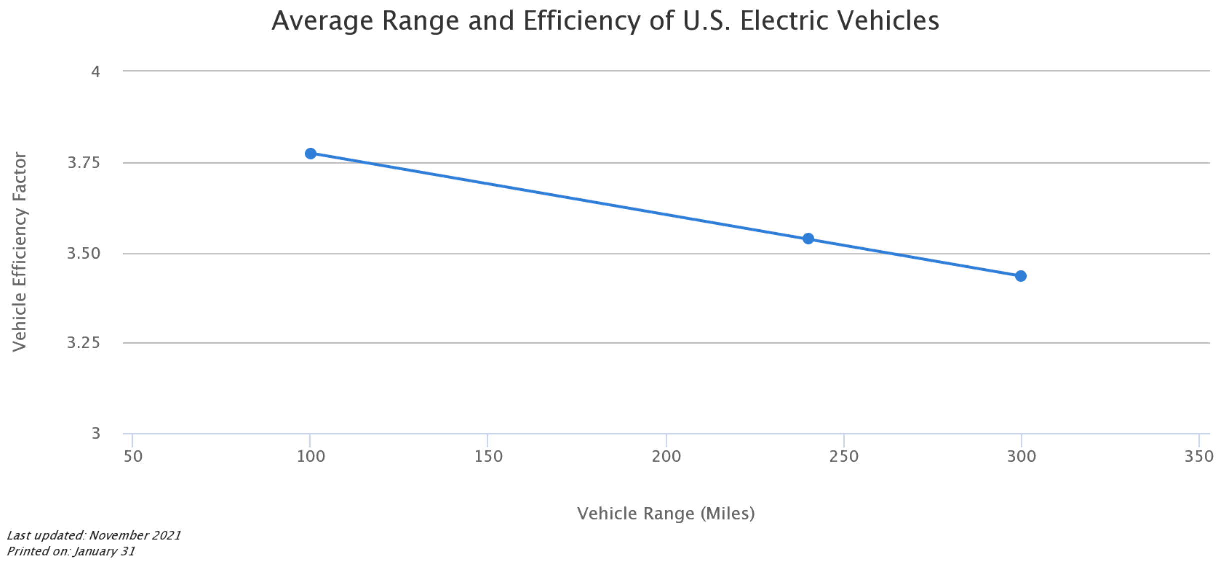


Figure 7. Average range and efficiency of U.S. EVs as of 2020 [19].

Infrastructure and Future Outlook

While most EV owners tend to charge their vehicles at home, mass adoption of EVs would involve installing more publicly available charging stations. Adding these stations would support those who cannot charge at home or work (i.e., no chargers are available at home or workplace) and lower public anxiety about not having readily available EV charging stations when their vehicles require a charge.

The Federal Highway Administration (FHWA) anticipates most states will contract with private entities for the installation, operation, and maintenance of EV charging infrastructure. The federal Infrastructure Investment and Jobs Act (IIJA), signed into law on November 15, 2021, established a $5 billion National EV Infrastructure (NEVI) Formula Program and a $2.5 billion Discretionary Grant Program to establish a nationwide network of 500,000 EV chargers by 2030. NEVI funds, which are available for up to 80 percent of eligible project costs, must first go toward designated alternative fuel corridors along public roads. The goal of the NEVI program is to ensure a convenient, reliable, affordable, and accessible charging experience for all users. In addition, the Justice40 Initiative, a federal program outlining that 40 percent of federal climate investments go directly to frontline communities most affected by poverty and pollution, is also a key piece of legislation in this effort. With TxDOT as a passthrough entity, Texas will receive $407.8 million in FY 2022–2026 from the IIJA funding to expand on its existing EV infrastructure to support future EV demands.

In the *Texas Electric Vehicle Infrastructure Plan* [10], TxDOT envisions a multi-year plan to meet current and future EV charging demands in Texas by building the Electric Alternative Fuel Corridor (EAFC). The EAFC needs to meet requirements set by FHWA, which are a 50-mile spacing for direct current (DC) Fast Chargers, 1 mile from the interstate exit, rated at 150 kW or greater. TxDOT notes that the spacing of the corridors could be slightly greater (70 miles) in rural counties, and a combination of DC and Level II charging will be used across large urban areas. The EAFC must support 1 million EVs when built out where each charging station must be adequately spaced (50 miles apart on the EAFC and 70 miles apart anywhere else) and deliver at least 150 kW of power to the vehicles (with at least four ports on each station, thus requiring at least 600 kW per station). Each charger on the EAFC or near the county seat must have at least one pull-through space for LDVs pulling trailers or recreational vehicles.

Figure 8 shows the planned infrastructure and timeline of the EAFC expansion. The 27 existing locations are represented as orange dots, the 26 locations funded through Texas Volkswagen Environmental Mitigation Program are represented as grey dots, and locations that will be focused on each year are represented as blue dots. Year 1 focuses on the EAFC, as required under the IIJA. Year 2 focuses on rural counties, small urban areas, and MPOs. Each county seat will have a DC Fast Charger on site or nearby. County seats are usually centrally located in the county (all roads lead to the county courthouse) and provide good spacing between urban clusters in rural areas. Vehicle miles traveled (VMT) were used to create a priority list of the most traveled non-interstate routes through rural areas. Installing DC Fast Charge stations at county seats with a power rating of 150 kW and a minimum of four ports will fill gaps across rural Texas for off-interstate travelers and enable local farm and work trucks to access the charging network. By the third year, the network will progress into more rural areas of the state. As the charging network spreads to more rural areas, the equipment installed may adjust to accommodate varying power supplies in the region. A combination of solar/battery equipment may be placed between the charging equipment and the power grid to minimize demand charges and ensure adequate power for four ports rated at 150 kW per connector.

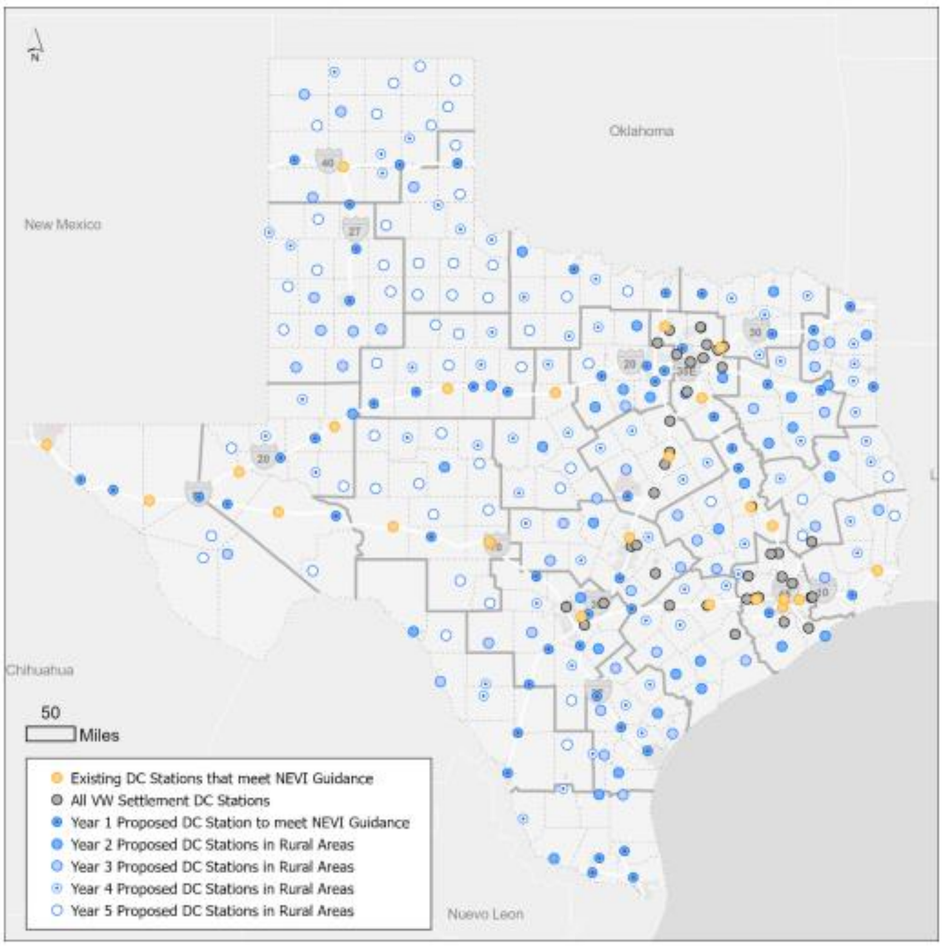


Figure 8. Timeline and infrastructure planned for year 3 and beyond of the Electric Alternative Fuel Corridor [10].

TxDOT will partner with the private sector to develop the EV charging network to support the EV charging infrastructure on and beyond the EAFC. The following are the typical specifications for the chargers on the corridor and rural county seat locations listed in the report [10]:

- Combined Charging System (CCS) connector (industry standard).
- 150–350 kW maximum power (higher power is acceptable assuming costs are not prohibitive):
  - 400–800 volts.
  - 150–600 amps.

    - Three phases.
- Any shared circuits providing 150 kW or more per connector. For example, one port powering two connectors should be capable of providing 150 kW or more to each connector at the same time.
- Idle fee after charging complete.
- A minimum of four DC Fast Charge connectors per location.
- A maximum of eight DC Fast Charge connectors per location (due to funding, not technical limits).
- At least one pull-through space for LDVs with trailers when the host location supports it.
- Open 24/7 and publicly available (without requirements to purchase goods or services from businesses hosting the EV stations).
- Adequate lighting, restrooms, and Americans with Disabilities Act compliance.
- A plug to charge preferred payments (payments handled by the vehicle when plugging in) by phone/app/card.
- Spaces marked EV only.
- Signs recommending charging to 80 percent.
- Station location, operational status, and cost/fees published online.
- Requirement that the vendor make usage data per plug available to TxDOT quarterly.
- Signage directing users to charge locations.

TxDOT also plans to balance the rollout of the network between urban and rural areas after the corridors are built by splitting funds per year on a 50/50 basis [10].

EV Emission Impact

This section briefly summarizes the literature that we reviewed regarding the emissions impact of EV adoption.

Analysis of Air Quality Regarding EV Promotion Coupled with Power Plant Emissions

Lin et al. simulated the impacts that power plant location has on the overall reduction in emissions for the hypothetical scenario where all conventional vehicles in Taiwan were electrified [20]. The authors developed different scenarios where coal-fired power plants in a region of Taiwan (i.e., northern, southern, etc.) absorbed all the increased electricity demands. Unsurprisingly, their model showed spatial and temporal variation and the summer-winter patterns vary significantly in all regions.

The key takeaway from this study was that the increased adoption of EVs could lead to worsening air quality in the local region surrounding power plants that have increased generation to accommodate charging needs. In addition, Lin et al. employed Equation 1 to estimate the additional electricity demand in relation to phasing out and replacing conventional vehicles with EVs.

$$ED = \sum_i \frac{VP_i \times VU_i \times VKT_i \times BE_i}{TE \times CE_i} \tag{1}$$

Where:

- ED = the power demand.
- i = different types of vehicles.
- VP = the number of a specific type of vehicle i.
- VU = the utilization rate of a specific type of vehicle i.
- VKT = the average driving mileage of a specific type of vehicle i.
- BE = the battery efficiency of a specific type of vehicle i.
- TE = the power transmission efficiency.

- CE = the charger efficiency of a specific type of vehicle i.

Assessment of Ozone Impacts on EV Adoption in Texas

Prozzi et al. [21] concluded that the rate at which PEVs are adopted is the most important variable for assessing the impact PEVs will have on emissions and air quality. For this study, the authors focused on ozone impacts and the emissions of ozone precursors of volatile organic compounds (VOCs) and nitrogen oxides (NO_X). Prozzi et al. also indicate that the spatial and temporal distributions of VOC and NO_X sources are critical for developing accurate ozone forecasts because this assessment involved both stationary (i.e., power plant EGU emissions) and mobile sources.

Essentially, this study defined emission reductions from PEV adoption as the sum between the increased emissions from EGUs from PEV charging demands and the reduction in on-road emissions from switching over from ICEs to PEVs. To acquire these estimations, the authors had to first predict/project the PEV population at a given year, from which they could then estimate the charging demand and population of ICEs that were replaced. The authors showed that the annual compound growth rate G of PEVs, using 2022 as the base year, for each study location and each year, could be calculated using Equation 2.

$$G = (\frac{P_t}{P_b})^{\frac{1}{t-b}} - 1 \quad (2)$$

Where:

- P_t = the population at the year t.
- P_b = the population at the base year b (2022).

Then, the projected growth rates were converted to future-year forecast population F_t using Equation 3.

$$F_t = P_b \times (G+1)^{t-b} \quad (3)$$

The overall emission impact/reduction from PEV adoption covers both the increased emissions from EGUs and the reduction from the on-road sources (switching from ICE to PEV). For EGUs, the authors first projected the total power generation P_t, which is the sum of the baseline power generation EP and PEV charging demand P_a. Charging profiles were developed using the EV Infrastructure Projection Tool Lite (EVI-Pro Lite) by NREL and were used to develop the PEV charging demand P_a. For NO_X generation, the authors listed Equation 4 and Equation 5 and used modeling parameters as listed in Table 3. Equation 6 yields the additional NO_X emission E_a from EGUs that resulted from PEV adoption, which deducts the emissions from the baseline (*EP*) from the total emissions P_t.

$$EE = \begin{matrix} \alpha_1 P^2 + \alpha_2 P + \alpha_0 : P \geq P_{min} \\ EE_{min} : Otherwise \end{matrix} \quad (4)$$

$$EP = \begin{matrix} \beta_1 \sqrt{\beta_2 E - 1} + \beta_0 : E \geq E_{min} \\ \beta_1 \sqrt{\beta_2 EE_{min} - 1} + \beta_0 : Otherwise \end{matrix} \quad (5)$$

$$E_a = f(P_t) - f(EP);\ where\ f()\ referes\ to\ Equation\ 5 \quad (6)$$

Where:

- EP = the estimated power generation (megawatt hour [MWh]).
- E = the NO_X emission (lb/hr).

- E_{min} = the minimum NO_X emission (lb/hr).
- EP_{min} = the minimum estimated power (MWh).
- EE = the estimated NO_X emission (lb/hr).
- P = power generation (MWh).
- EE_{min} = the minimum estimated NO_X emission (lb/hr).

Table 3. EGU Power Generation and NO_X Emission Estimation Model Parameters [21].

Area	Month Group	α_0	α_1	α_2	β_0	β_1	β_2	EE_{min}	EP_{min}
NCTCOG	May, Jun, Sep	2,930.0	0.00006	−0.53800	4,562.5	5,374.0	0.00059	1,702.7	4,566.8
	Jul, Aug	2,062.0	0.00004	−0.35523	4,003.9	5,518.3	0.00074	1,350.9	4,019.0
H-GAC	May	6,335.4	0.00007	−0.99652	7,556.1	6,243.5	0.00039	2,570.5	7,556.4
	Jun, Sep	9,488.7	0.00007	−1.28400	9,482.0	7,087.7	0.00029	3,401.3	9,493.7
	Jul, Aug	11,883.0	0.00007	−1.54972	10,526.6	7,115.0	0.00027	3,726.3	10,535.0

Note: NCTCOG = North Central Texas Council of Governments; H-GAC = Houston-Galveston Area Council.

To calculate the emission reduction from converting ICEs to PEVs, Prozzi et al. first calculated the activity data, both in running (in terms of VMT) and the vehicle starts. The authors stated that on-road running emissions were calculated using the daily average VMT and MOVES emission rates. Using the projected PEV population and Wejo data (third-party probe-based data), which were aggregated into six-digit geohash zones that cover the entire study area, the authors predicted the total PEV VMT activity for the target, using Equation 7 through Equation 9.

$$VMT = F_t \times M \tag{7}$$

$$PD_{i,j} = \frac{D_{i,j}}{\sum_{i,j} D_{i,j}} \tag{8}$$

$$T_{i,j} = VMT \times PD_{i,j} \tag{9}$$

Where:

- M = the daily mileage driven by each scenario.
- $PD_{i,j}$ = the percentage of total daily VMT for the study area from vehicle telematics data by time-of-day i and geohash j, where the sum of $PD_{i,j}$ at each day is 1.
- $D_{i,j}$ = the VMT at time-of-day i and geohash j.
- $T_{i,j}$ = the gridded hourly VMT in time-of-day i at geohash j.

Similarly, Prozzi et al. also predicted the activities for the vehicle starts using Equation 10 through Equation 12.

$$TS = F_t \times E \tag{10}$$

$$PS_{i,j,k} = \frac{S_{i,j,k}}{\sum_{i,j,k} S_{i,j,k}} \tag{11}$$

$$GS_{i,j,k} = TS \times PS_{i,j,k} \tag{12}$$

Where:

- TS = the total number of starts.

- E = the average number of starts per day, by day type.
- $PS_{i,j,k}$ = the percentage of total daily start for the study area from vehicle telematics data by time-of-day i, geohash j, and soak time k.
- $S_{i,j,k}$ = the start at time-of-day i, geohash j, and soak time k.
- $GS_{i,j,k}$ = the gridded hourly start in time-of-day i, geohash j, and soak time k.

For the reduction in running emissions, Prozzi et al. listed Equation 13 through Equation 16.

$$V_{r,b} = F_{r,b,BEV} + C_{PHEV} \times F_{r,b,PHEV} \tag{13}$$

$$I_{b,f} = V_{r,b} \times \frac{H_{b,f}}{\sum_f H_{b,f}} \tag{14}$$

$$ED_{b,f} = \sum\nolimits_{i,j} I_{b,f} \times VMT \times EDR_{b,f,i,j} \tag{15}$$

$$EDG_{b,f,i,j} = ED_{b,f} \times PD_{i,j} \tag{16}$$

Where:

- $F_{r,b,p}$ = the number of PEVs by range r, body type b, and battery type p; r = (LR/SR), b = (sedan/sport utility vehicle), and p = (BEV/PHEV).
- $H_{b,f}$ = the number of ICE vehicles by body type b and fuel type f; b = (passenger truck/passenger truck), and f = (gasoline/diesel).
- $V_{r,b}$ = the equivalent number of PEVs by range r and body type b.
- C_{PHEV} = the PHEV emission reduction factor (0 in this study).
- $I_{b,f}$ = the equivalent number of ICE vehicles by body type b and fuel type f.
- $ED_{b,f}$ = the total NO_X running emissions by body type b and fuel type f.
- $EDR_{b,f,i,j}$ = the running emission rate from MOVES by body type b, fuel type f, and day i at geohash j.
- $EDG_{b,f,i,j}$ = the NO_X running emission by body type b, fuel type f, and day i at geohash j.

Similarly, Prozzi et al. calculated the start emissions using Equation 17 and Equation 18.

$$ES_{b,f,k} = \sum\nolimits_{i,j} I_{b,f} \times E \times ESR_{b,f,i,j,k} \tag{17}$$

$$ESG_{b,f,i,j,k} = ES_{b,f,k} \times PS_{i,j,k} \tag{18}$$

Where:

- $ES_{b,f,k}$ = the total NO_X start emissions by body type b, fuel type f, and soak time k.
- $ESR_{b,f,i,j,k}$ = the start emission rate from MOVES by body type b, fuel type f, day i at geohash j, and soak time k.
- $ESG_{b,f,i,j,k}$ = the NO_X start emissions by body type b, fuel type f, day i at geohash j, and soak time k.

Finally, Prozzi et al. calculated the emissions impact/reduction from PEV adoption from the difference between the emissions reduced from on-road sources (the sum of start and running emissions, $ESG_{b,f,i,j,k}$ + $EDG_{b,f,i,j}$) and the additional EGU emissions E_a to meet PEV demands. In their study, all scenarios led to more reduction of on-road NO_X compared to the additional NO_X from EGUs, thus reducing the overall NO_X emissions.

Policies and Regulations for EV Adoption

Policies and regulations are the most important factors impacting EV adoption in the United States today. Federal and state policy instruments, like direct subsidies and tax credits, are critical in stimulating EV market penetration. The clean vehicle tax credit of up to $7,500 per vehicle incentivized by the federal government, along with additional state-specific tax credits, has greatly promoted EV sales. In addition, the tax incentive programs introduced in the 2022 Inflation Reduction Act (IRA) will continue to accelerate the growth of EV sales in the coming years. Furthermore, the current trend of EV policies shifts from providing direct subsidies to a greater reliance on regulations, such as ZEV mandates and fuel economy standards. This shift in policy trends aims to set explicit long-term goals for the auto industry and its consumers to support the government's transition to decarbonization in a more economically sustainable manner. Dedicated federal funds for EV charging infrastructure also incentivize EV adoption by alleviating user concerns related to range anxiety [22] [23] [24].

This section first provides an overview of the policies and regulations in the United States and compares them at the federal and state levels with a focus on Texas and California. This section then briefly summarizes the incentive policies and lists the most widely used ones from the federal and state levels, particularly those from Texas and California.

Policies and Regulations

Various government regulations from different jurisdictional levels influence EV adoption. From the auto manufacturers' perspective, government regulations often affect original equipment manufacturers, dealerships, and fuel/battery supplies via mechanisms such as EV sales tax credits, GHG emission and fuel economy standards, low-carbon fuel/battery standards, ZEV mandates, domestic and free-trade component sourcing and building requirements, and funding for pilot projects. The public sector is affected not only by the costs and revenues associated with companies and people transitioning to EVs, but also by direct regulation that governs building codes for public charging infrastructure, right-to-charge requirements, and public parking implications. From the consumers' perspective, regulations that impact EVs via incentives, fees, taxes, registration and licensing, vehicle fueling and operation, and access priority (e.g., high-occupancy vehicle [HOV] lane access) greatly affect their willingness to purchase EVs. Furthermore, EV adoption initiatives or programs can affect the public's attitude toward EVs and their overall prevalence in society [25].

According to data collected by AFDC, there are currently 1,115 clean transportation laws and regulations that were passed and adopted by federal and state legislation, most of which are related to BEVs and PHEVs [26]. Figure 9 shows the number of clean transportation laws and regulations for each state. Among them, California ranks first with a total of 92 clean transportation laws and regulations, whereas Texas (highlighted in red) ranks 35th nationwide with only 14 clean transportation laws and regulations. At the federal level (highlighted in green), there are 37 clean transportation laws and regulations.

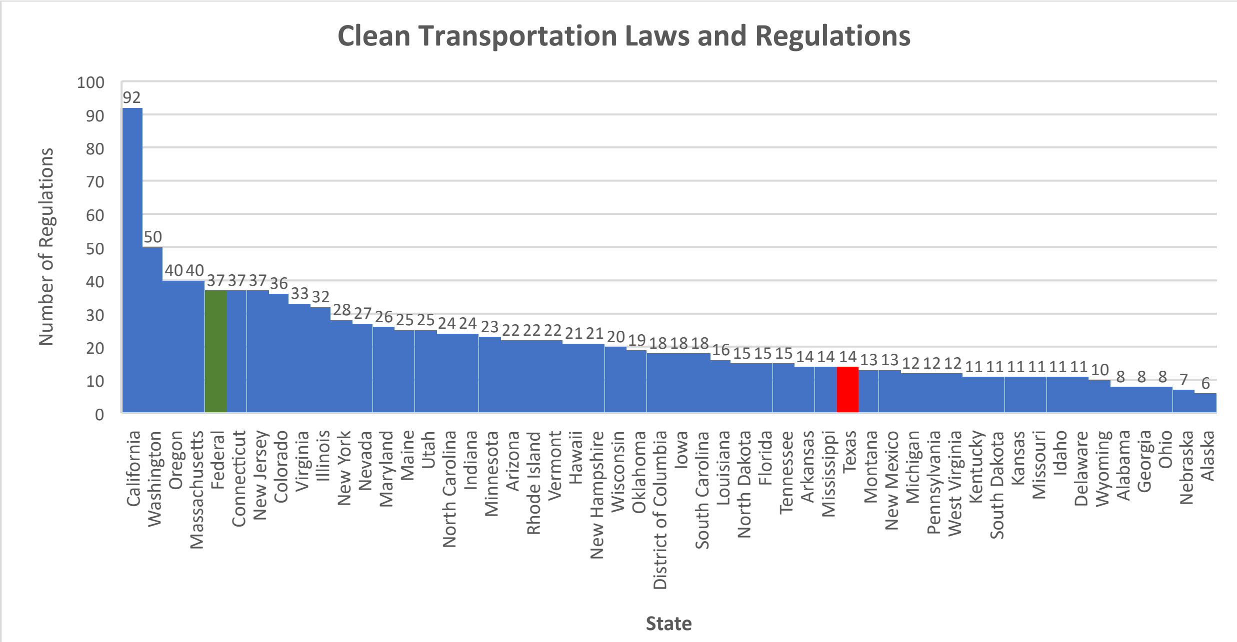


Figure 9. Clean Transportation Laws and Regulations by State.

Table 4 lists examples of the most widely adopted laws and regulations conducted for EVs from the federal, Texas, and California governments.

Table 4. Examples of Notable Clean Transportation Laws and Regulations in the Federal Jurisdiction, Texas, and California

Jurisdiction	Laws and Regulations	Description
Federal	Transportation decarbonization support	DOE, the U.S. Department of Transportation (USDOT), Department of Housing and Urban Development, and EPA (signatory agencies) joined in signing a memorandum of understanding to accelerate the development and adoption of affordable and equitable clean transportation. The signatory agencies must work to reduce GHG emissions from the transportation sector and ensure resilient and accessible mobility options for all Americans. By December 15, 2022, the signatory agencies must publish a draft decarbonization strategy for the transportation sector to guide future policy, research, development, demonstration, and deployment in the public and private sectors.
	Vehicle acquisition and fuel use requirements for federal fleets	Under the Energy Policy Act (EPAct) of 1992, 75 percent of the new LDVs acquired for the federal fleet must be AFVs. As amended in January 2008, Section 301 of EPAct 1992 expands the definition of AFVs to include HEVs, FCEVs, and advanced lean-burn vehicles. Fleets that use fuel blends containing at least B20 may earn credits toward their annual requirements. The federal fleets are also required to use alternative fuels in dual-fuel vehicles unless DOE approves waivers for agency vehicles; grounds for the issuance of a waiver include a lack of alternative fuel availability and unreasonable cost (per EPAct 2005, Section 701). Additional requirements for federal fleets were included in the Energy Independence and Security Act of 2007. These requirements include fleet management plans and petroleum reduction from 2005 levels (Section 142), low-GHG-emitting vehicle acquisition requirements (Section 141), and

Jurisdiction	Laws and Regulations	Description
		renewable fuel infrastructure installation requirements (Section 246). For more information, refer to the Fleet Sustainability Dashboard website.
	Utility EV promotion measures	The Federal Energy Regulatory Commission requires each state to consider measures to promote greater transportation electrification, by amending rates to: • Promote affordable and equitable EV charging. • Improve customer experience with EV charging. • Accelerate third-party investment in EV supply equipment (EVSE). • Recover marginal costs of electricity delivery to EVSE. Each state regulatory authority and each nonregulated utility must commence consideration or set a hearing date for consideration no later than November 15, 2022. They must also complete the consideration and decide no later than November 15, 2024. States with existing EV rate standards are exempted from this requirement. (Public Law 117-58)
	HOV lane exemption	States are allowed to exempt certified AFVs and EVs from HOV lane requirements within the state. Eligible AFVs are vehicles operating solely on methanol, denatured ethanol, or other alcohols; a mixture containing at least 85 percent methanol, denatured ethanol, or other alcohols; natural gas, propane, hydrogen, or coal-derived liquid fuels; or fuels derived from biological materials. EVs are vehicles that are rechargeable from an external source of electricity and have a battery capacity of at least 4 kWh. States are also allowed to establish programs allowing low-emission and energy-efficient vehicles to pay a toll to access HOV lanes. Vehicles must be certified by EPA and appropriately labeled to be allowed onto the HOV lanes. USDOT is responsible for planning and implementing the HOV programs, including the low-emission and energy-efficient vehicle criteria that EPA established. States that choose to adopt these requirements will be responsible for the enforcement and labeling of the vehicles. The HOV exemption for AFVs and EVs expires on September 30, 2025, and low-emission and energy-efficient vehicle toll access to HOV lanes expires on September 30, 2019. (Public Law 114-94 and 23 U.S. Code 166)
	EV charging on federal property	The U.S. General Services Administration (GSA) or any federal agency may install EVSE at federal facilities so employees and others authorized to park can charge their privately owned vehicles. However, employees and other users must pay to reimburse the federal agencies for the procurement, installation, and use of the EVSE. The federal agencies may provide EVSE through a contract with a vendor. GSA must submit a report to Congress by December 2018, and annually thereafter for 10 years, on the number of EVSE installed by GSA, the number of EVSE installation requests from other federal agencies, and the status of requests for EVSE from other federal agencies. (Public Law 114-94)
Texas	Alternative fuel Use and vehicle acquisition requirements	State agency fleets with more than 15 vehicles, excluding emergency and law enforcement vehicles, may not purchase or lease a motor vehicle unless the vehicle uses natural gas, propane, ethanol, or E85; methanol or fuel blends of at least 85 percent methanol; biodiesel or fuel blends of at least B20; or electricity (including PHEVs). Waivers may be granted for fleets if the fleet will operate primarily in areas where neither the state agency nor a supplier can reasonably be expected to establish adequate fueling infrastructure for these fuels or the agency is unable to obtain equipment or fueling facilities necessary

Jurisdiction	Laws and Regulations	Description
		to operate AFVs at a cost that is no greater than the net costs of using conventional fuels. Covered state agency fleets must consist of at least 50 percent of vehicles that can operate on alternative fuels and use these fuels at least 80 percent of the time the vehicles are driven. Covered state agencies may meet these requirements through the purchase of new vehicles or the conversion of existing ones. State agencies that purchase passenger vehicles or other ground vehicles for general use must ensure that at least 25 percent of the vehicles purchased during any state fiscal biennium, other than exempted vehicles, meet or exceed the Federal Tier II, Bin 3 emissions standards. (Texas Statutes, Government Code 2158.004–2158.009)
	AFV registration tracking program	TxDMV collects data on the number of AFVs registered in the state. TxDMV must submit an annual report to the Texas Legislature detailing the results of each data collection year. For this program only, AFVs include PEVs, HEVs, and natural gas vehicles. (Texas Statutes, Transportation Code 502.001 and 502.004)
	Authorization of governmental alternative fuel fleet grant program	The Texas Commission on Environmental Quality (TCEQ) must administer a grant program for governmental alternative fuel fleets to provide grants for the purchase or lease of a new vehicle and the purchase, lease, or installation of alternative fueling equipment. Eligible alternative fuels include natural gas, propane, hydrogen, and electricity. State agencies and political subdivisions are eligible to apply for grants under the program if the entity operates a fleet of more than 15 vehicles. Mass transit and school transportation providers are also eligible for the grants. TCEQ must establish standardized vehicle grant amounts based on the incremental costs associated with the purchase or lease of different categories of motor vehicles, including the fuel type, vehicle class, and other categories TCEQ considers appropriate. TCEQ will also establish standardized fueling equipment grant amounts. (Texas Statutes, Health and Safety Code 386.153)
	Public utility definition	EV charging service providers are not regulated as a public utility in areas of customer choice, where utility customers have the option to choose an alternate electricity supplier if desired. The Texas Public Utilities Commission is authorized to exempt EVSE from being regulated as a public utility. (Texas Statutes, Utilities Code 37.001)
California	Light-duty ZEV sales requirement	Also known as the Advanced Clean Cars II rule. All sales of new light-duty passenger vehicles in California must be ZEVs by 2035. ZEVs include BEVs and FCEVs. CARB will develop regulations related to in-state sales of new light-duty cars and trucks. CARB developed the *California Zero-Emission Vehicle Market Development Strategy* to support these regulations and assess statewide ZEV infrastructure. This strategy will be updated triennially. (Executive Order N-79-20)
	Medium- and heavy-duty ZEV requirement	Also known as the Advanced Clean Trucks program. The CARB program requires all new medium- and heavy-duty vehicles (HDVs) sold in California to be ZEVs by 2045. Zero-emission (ZE) technologies include all-electric and FCEVs. Beginning in 2024, manufacturers seeking CARB certification for Class 2b through Class 8 chassis or complete vehicles with ICEs will be required to sell ZE trucks as an increasing percentage of their annual California sales. Additionally, entities with annual gross revenues greater than $50 million, fleet owners with 50 or more medium- and HDVs, and any California government or

Jurisdiction	Laws and Regulations	Description
		federal agency with one or more vehicles over 8,500 pounds must report their existing fleet operations to ensure fleets are purchasing and placing ZE trucks in the correct service locations. (California Code of Regulations Title 13, Sections 1963-1963.5 and 2012-2012.2)
	Utility transportation electrification cost recovery regulations	The California Public Utilities Commission (PUC) must approve or modify utility transportation electrification programs, including those that deploy EV charging stations, through a reasonable cost recovery mechanism that does not unfairly compete with nonutility enterprises. At least 35 percent of the investments must be in underserved communities. This bill mandates that each electrical corporation must submit an advice letter by February 28, 2021. Additionally, the bill requires PUC to approve a new tariff by June 30, 2021, that grants authorization to electrical corporations to plan and implement all electrical distribution infrastructure on the utility side of the customer meter for customers installing separately metered infrastructure to support charging stations. The bill also specifies provisions for cost recovery in this process. (Assembly Bill 841, 2020)
	EV charging station location Assessment	The California Energy Resources Conservation and Development Commission (CEC), in partnership with CARB, must assess whether EV charging stations in California are located proportionately by geographical area, population density, or income level. If CEC and CARB determine that the EV charging stations have been disproportionately installed, CEC must use funding from the Clean Transportation Program, as well as other funding sources, to proportionately install new EV charging stations, unless the current locations of EV charging stations are deemed reasonable and further California's energy or environmental policy goals. (California Public Resources Code 25231)
	ZE transit bus requirement	By 2040, all public transit agencies must transition to 100 percent ZE bus fleets. ZE bus technologies include BEVs or FCEVs. (California Code of Regulations Title 13, Section 2023.1)

Incentive Policies

The substantial fiscal incentives provided by both federal and state governments have been instrumental in driving the adoption of EVs and supporting the expansion of EV manufacturing and battery industries within the private sector. The two main types of incentive policies are:

- Purchase based.
- Use based.

The purchase-based incentive policies include direct subsidies for EV purchases, exemptions from registration, emission, and tax fees, as well as grants, loans, tax rebates, and exemptions for EV manufacturers. These policies are most widely used by governments to narrow the price gap between EVs and conventional vehicles, thereby promoting the adoption of EVs.

The use-based incentive policies are designed to enhance the convenience of EV users and can vary across states. Examples of these policies include free parking, toll tax exemption, access to HOV lanes, and higher taxes on gasoline and diesel. It is essential to design and implement appropriate local incentive policies based on regional EV scenarios to effectively promote the adoption of EVs [25].

According to data collected by AFDC, there are currently 971 clean transportation incentive policies enacted by federal and state legislation. Most of these incentive policies are for BEVs and PHEVs [26]. Figure 10 shows a ranking of the number of clean transportation incentive policies conducted by states. Among them, California ranked first with 116 laws and regulations, whereas Texas (in red) ranked 13th with 21 incentive policies. At the federal level (in green), there are 73 incentive policies for clean transportation.

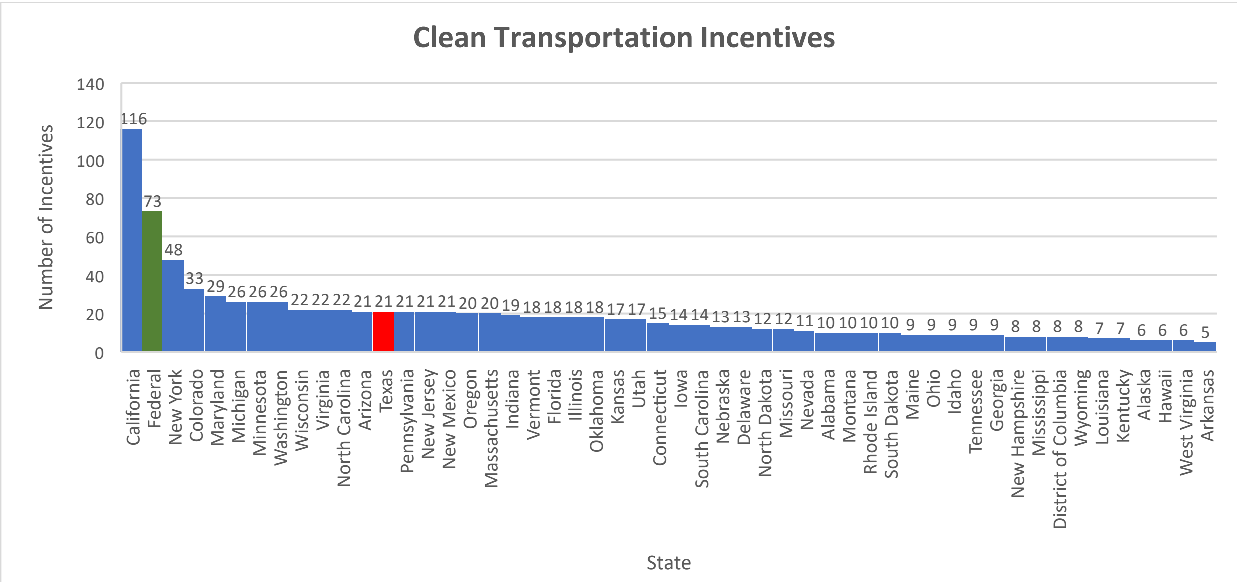


Figure 10. Clean transportation incentive policies by state.

Table 5 lists examples of EV incentive policies most adopted by the federal, Texas, and California governments.

Table 5. Examples of Notable EV Incentive Policies in Federal Jurisdiction, Texas, and California

Jurisdiction	Laws and Regulations	Description
Federal	EV and FCEV tax credit	The 2022 IRA (Public Law 117-169) amended the Qualified Plug-in Electric Drive Motor Vehicle Credit (IRC 30D), also known as the Clean Vehicle Credit. The 2022 IRA added a new requirement for the final assembly of the vehicle in North America that took effect on August 17, 2022, with additional requirements taking place beginning January 1, 2023. For vehicles placed in service on or after January 1, 2023, the Clean Vehicle Credit provisions will be subject to updated guidance from the Internal Revenue Service (IRS) and the U.S. Department of the Treasury. Consumers may qualify for a credit of up to $7,500 under Internal Revenue Code Section 30D when buying a new, qualified PEV or FCEV. The 2022 IRA changed the rules for this credit for vehicles purchased between 2023 and 2032. See the IRS Plug-In Electric Drive Vehicle Credit for further details. More details are provided by date of purchase and on the list of EVs with Final Assembly in North America.
	Commercial EV and FCEV tax credit	Beginning January 1, 2023, a tax credit will be available to businesses for the purchase of new EVs and FCEVs. Vehicles with a gross vehicle weight rating (GVWR) below 14,000 pounds must have a battery capacity of at least 7 kWh, and vehicles with a GVWR above 14,000 pounds must have a battery capacity of at least 15 kWh. The tax credit amount is equal to the lesser of the following amounts: • 15 percent of the vehicle purchase price for PHEVs. • 30 percent of the vehicle purchase price for EVs and FCEVs.

Jurisdiction	Laws and Regulations	Description
		• The incremental cost of the vehicle compared to an equivalent ICE vehicle. Maximum tax credits may not exceed $7,500 for vehicles under 14,000 pounds and $40,000 for vehicles above 14,000 pounds. Businesses may not combine this tax credit with the Clean Vehicle Tax Credit. (Public Law 117-169)
	Clean School Bus Program	EPA's Clean School Bus program provides funding to eligible applicants for the replacement of existing school buses with clean, alternative fuel or ZE school buses. EPA may award up to 100 percent of the cost of the replacement bus, charging equipment, or fueling infrastructure. Alternative fuels include electricity, natural gas, hydrogen, or propane. Eligible applicants are school districts, government programs at the state and local level, federally recognized Native American Tribes, non-profit organizations, and eligible contractors. EPA will prioritize funding for high-need local education agencies income, rural, and tribal schools as well as applications that cost-share through public-private partnerships, grants, or school bonds. For more information, including funding availability, timeline, and application materials, see the EPA Clean School Bus Program website. (Public Law 117-58 and 42 U.S. Code 16091)
	NEVI grants	USDOT will establish the Charging and Fueling Infrastructure Grants program to fill in the gaps in publicly accessible EV charging and alternate fuel refueling infrastructure in community locations, such as parking facilities, public schools, public parks, or spaces along public roads. Funding of up to 80 percent of project costs will be available for both development-phase planning activities and the acquisition and installation of charging or alternative fuel refueling infrastructure. Five percent of the grant fund awarded may be used for educational and community engagement activities to develop and implement education programs through partnerships with schools, community organizations, and vehicle dealerships to support the use of ZE vehicles and associated infrastructure. USDOT must prioritize projects that expand access to charging and alternative fuel refueling infrastructure within rural areas, low- and moderate-income neighborhoods, and communities with limited parking space or with a high ratio of multi-unit dwellings in single-family homes. Eligible entities include states, MPOs, local governments, political subdivisions, and Tribal governments. Additional funding eligibility and considerations will apply. (Public Law 117-58 and 23 U.S. Code 151)
	EV and FCEV manufacturing tax credit	Qualified advanced energy projects are eligible for a 30 percent tax credit for project investments to reequip, expand, or establish certain manufacturing facilities. Credits cannot be allocated to projects located within census tracts where projects have been previously allocated. Qualifying advanced energy projects include but are not limited to projects that reequip, expand, or establish manufacturing or industrial facilities that produce or recycle light-, medium-, and heavy-duty EVs, FCEVs, EV charging stations, and hydrogen fueling stations. Additional terms may apply. (Public Law 117-169 and 26 U.S. Code 48C)

Jurisdiction	Laws and Regulations	Description
Texas	Light-duty AFV rebates	TCEQ administers the Light-Duty Motor Vehicle Purchase or Lease Incentive Program for the purchase or lease of a new LDV powered by CNG, propane, hydrogen, or electricity. CNG and propane vehicles, including bio-fuel vehicles, are eligible for a rebate of up to $5,000. Electric drive vehicles powered by a battery or hydrogen fuel cell, including PHEVs with a battery capacity of at least 4 kWh, are eligible for a rebate of up to $2,500. One rebate is available per eligible vehicle. Rebates are awarded on a first-come, first-served basis. For more information, including eligibility requirements and the application form, see TCEQ's Texas Emissions Reduction Plan (TERP) website. (Texas Statutes, Texas Health and Safety Code 386 and Texas Administrative Code 114.610-114.613)
	HDV and equipment grants	TCEQ administers the Rebate Grants Program as part of the TERP. The program provides grants to eligible entities to replace or repower existing heavy-duty, diesel-powered vehicles. Replacement vehicles and engines may not be more than three years older than the calendar year purchased and must reduce NO_X emissions by at least 25 percent compared to the vehicle or engine being replaced. Eligible replacement on- and off-road vehicles must be powered by diesel, natural gas, propane, or electricity. For more information, see TCEQ's TERP website. (Texas Statutes, Texas Health and Safety Code 386.104)
	Clean fleet grants	TCEQ administers the Texas Clean Fleet Program (TCFP) as part of the TERP. The TCFP provides grants to fleets to replace existing fleet vehicles with AFVs or HEVs. An entity that operates a fleet of at least 75 vehicles and commits to placing 20 or more qualifying vehicles in service for use in the Clean Transportation Zone may be eligible. Qualifying AFV or HEV replacements must reduce emissions of NO_X or other pollutants by at least 25 percent compared to baseline levels and must replace vehicles that meet operational and fuel usage requirements. Neighborhood EVs do not qualify. For more information, including current application periods, see TCEQ's TERP website. (Texas Statutes, Health and Safety Code 386 and 392, and Texas Administrative Code 114.650–114.657)
	Governmental fleet grants	TCEQ administers the Governmental Alternative Fuel Fleet Grant Program (GAFF) as part of the TERP for the purchase or lease of new vehicles powered by natural gas, propane, hydrogen, or electricity with grant amounts up to $70,000 per vehicle class. Up to 10 percent of awarded funds may be granted for the purchase, lease, or installation of refueling infrastructure or equipment, or refueling services in conjunction with an eligible vehicle purchase or lease. Special districts and government entities that operate a fleet greater than 15 vehicles are eligible. For more information, see the TCEQ GAFF website. (Texas Statutes, Water Code 5.124 and 5.229, and Health and Safety Code 386.153)

Jurisdiction	Laws and Regulations	Description
	Clean vehicle and infrastructure grants	TCEQ administers the Emissions Reduction Incentive Grants (ERIG) Program and the Rebate Grants Program as part of the TERP. The ERIG Program provides grants for various types of clean air projects to improve air quality in the state's nonattainment areas and other affected counties. Eligible projects include those that involve replacing, retrofitting, or repowering old HDVs; leasing or purchasing new HDVs; constructing alternative fuel dispensing, idle reduction, and electrification infrastructures; and promoting alternative fuel use. The Rebate Grants Program provides grants to upgrade or replace diesel HDVs and non-road equipment. Qualifying projects must reduce emissions of NO_X or other pollutants by at least 25 percent compared to baseline levels and must meet operational and fuel usage requirements. For more information, including eligibility and the application form, see the TCEQ TERP website. (Texas Statutes, Health and Safety Code 386 and Texas Administrative Code 114.620–114.629)
California	Plug-In hybrid and zero emission LDV rebates	The Clean Vehicle Rebate Project (CVRP) offers rebates for the purchase or lease of qualified vehicles, which includes light-duty EVs, FCEVs, and PHEVs that CARB has approved or certified. The rebate amounts are up to $4,500 for FCEVs, $2,000 for EVs, $1,000 for PHEVs, and $750 for zero-emission motorcycles. Rebates are available on a first-come, first-served basis to California residents who purchase or lease new eligible vehicles. Residents of San Diego County may be eligible for a preapproved rebate through the CVRP Rebate Now pilot. Manufacturers must first apply to CARB to have their vehicles included in the CVRP. For more information, including information on income verification, a list of eligible vehicles, and instructions on how to apply, see the CVRP website. (California Health and Safety Code 44274 and 44258)
	Bus replacement grant	CARB offers grants for the purchase of new ZE buses to replace old gasoline, diesel, CNG, or propane buses. The grants award up to $400,000 based on vehicle type. Non-compliant school buses are vehicles that are not compliant with the CARB Truck and Bus Regulation. Eligible applicants include owners of transit, school, and shuttle buses. Grants are awarded on a first-come, first-served basis. For more information, including funding availability, see the School Bus Replacement Program website.
	Heavy-duty low-emission vehicle replacement and repower grants	The South Coast Air Quality Management District offers grants for the replacement or repower of eligible Class 7 and 8 HDVs with low-NO_X vehicles. Grants may cover up to 50 percent of non-government project costs and up to 100 percent of government project costs, up to $3 million per entity. Eligible applicants include Class 7 and 8 freight trucks, drayage trucks, dump trucks, waste haulers, concrete mixers, and freight switcher locomotives. Grants are awarded on a first-come, first-served basis. The program is funded by California's portion of the Volkswagen Environmental Mitigation Trust. For more information, including program guidance and application, see the CARB's Volkswagen Settlement website.

Jurisdiction	Laws and Regulations	Description
	Plug-In hybrid and ZE light-duty public fleet vehicle fleet rebates	The CVRP offers rebates to eligible state and local public entities for the purchase of qualified light-duty fleet vehicles up to $4,500. Public fleets located in disadvantaged communities are eligible for increased incentives up to $7,000. Rebates are available on a first-come, first-served basis. Manufacturers must first apply to CARB to have their vehicles considered for rebate eligibility. Each entity may receive up to 30 rebates annually and may not receive CVRP incentives for the same vehicle. For more information, including a list of eligible vehicles, locations, and entities, see the CVRP for Fleets website. (California Health and Safety Code 44274 and 44258)
	EV charging station incentive program support	The California EV Infrastructure Project (CALeVIP), funded by the California Energy Commission, provides guidance and funding for property owners to develop and implement EV charging station incentive programs that help meet regional needs for Level 2 and DC fast charging stations. Level 2 EV charging stations must be Energy Star certified. CALeVIP evaluates proposed EV charging station incentive programs and solicits input from stakeholders to guide the development and implementation of the programs. CALeVIP also provides incentive funding for each program. For more information, see the CALeVIP website.

Data Gathering

This section lists the sources of data that the research team identified that could be potentially useful for building EV projections and EV charging demand scenarios. This section discusses the data collected for the study area, which is the counties within the jurisdiction of NCTCOG.

PEV Population

The EV population is arguably the single most critical information for evaluating its emission impact. A crucial step in creating plausible future scenarios for future analysis years is learning about the existing population in the selected study area. The sources of PEV population data frequently provide other data that may be used to map out where PEV charging occurs.

EV Registration Data

The primary source of information regarding the historical and current vehicle population in Texas comes from TxDMV registration statistics. The study group obtained TxDMV registration statistics from the Atlas EV Hub, an online platform with a large depository of information on the transportation electrification market [27]. The Atlas EV Hub can be accessed, with registration, at https://www.atlasevhub.com/. The Atlas EV Hub's Texas EV registration data are from the DFW Clean Cities (DFWCC), which was sourced from TxDMV and processed using the Atlas EV Hub's vehicle identification number decoder [28] The Atlas EV Hub provides a vehicle identification number decoder and car registration data, which the DFWCC Coalition and NCTCOG use regularly to create city-, county-, and regional-level estimates of the state's EV population.

The study group identified the following as the most important aspects of car registration data from the Atlas EV Hub:

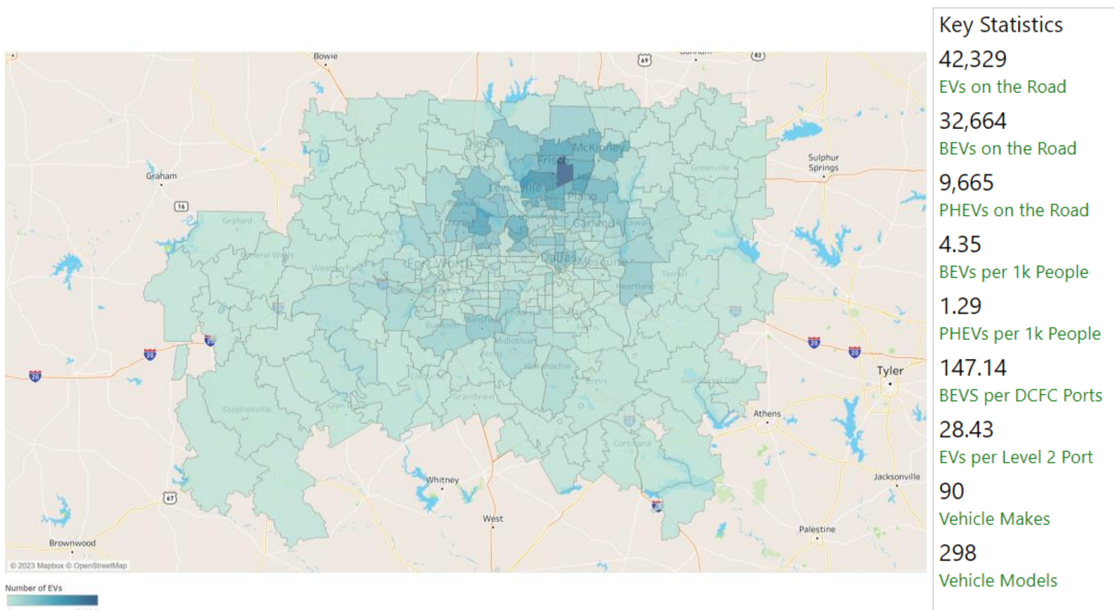
- Frequent updates (monthly or quarterly).
- Protection of individual privacy.
- Vehicle registration and expiration date.
- Local geography (zip code).

- Ability to determine vehicle make, model, and fuel type.

The latest state EV registration data for Texas from the Atlas EV Hub is available for download at https://www.atlasevhub.com/materials/state-ev-registration-data/#data.

Using the latest EV registration data from DFWCC (updated December 1, 2022), the study group filtered the data to only show information from the counties in the NCTCOG study area and visualized the data by zip code, as shown in Figure 11.

Figure 12 shows the trend of registrations in the NCTCOG area by technology type, and Figure 13 shows the market share of different automakers. Based on the most recent data available, there were 42,329 PEVs in the NCTCOG area, of which, 32,664 were BEVs and 9,665 were PHEVs. Also, over the years, the BEV population has increased exponentially, while the PHEV population has stagnated, as shown in Figure 14. The increase in the BEV population has mainly been attributed to the sales of Tesla vehicles, which account for 62 percent of all registered BEVs in the NCTCOG area, as shown in Figure 13. Most of the region's PEV population is concentrated in the central and northern counties of the region, which correspond to most of the urban and suburban population of the region.



DCFC: Direct-current fast charger

Figure 11. EVs on the road in the study area by zip code and key statistics of EVs.

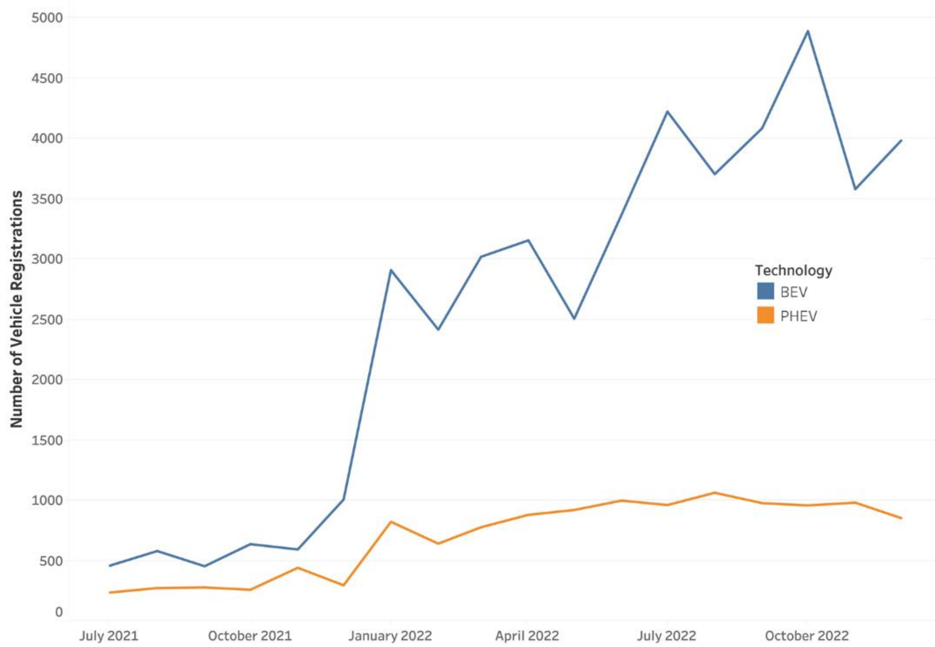


Figure 12. Trend of EV registrations in the study area.

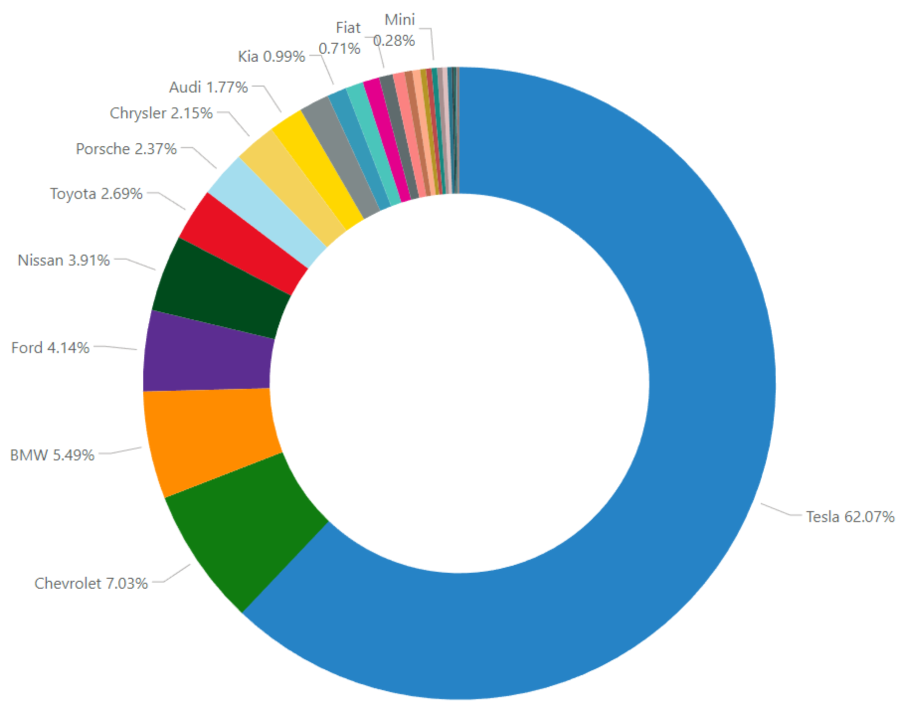


Figure 13. EV market share by vehicle make.

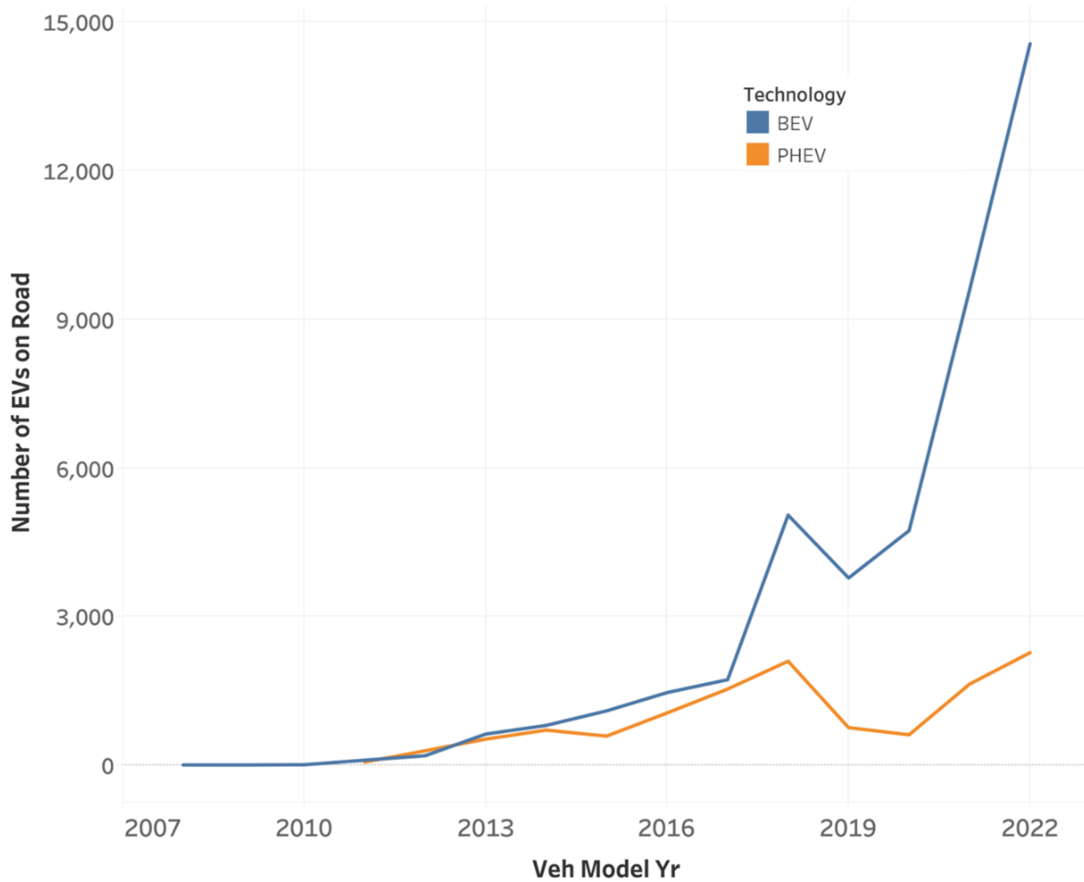


Figure 14. Trend of the number of BEVs and PHEVs on the road over different model years.

Annual Energy Outlook

The primary source of information regarding the future vehicle population in Texas comes from EIA's Annual Energy Outlook (AEO). The AEO presents a thorough examination of energy production and consumption by sector and activity type, including transportation. Based on an assessment of the various scenarios of EIA's AEO 2022, the most recent version of the AEO, the alternative future scenarios for the PEV operations were evaluated. EIA uses the National Energy Modeling System, an integrated model that includes connections between economic developments and energy supply, demand, and prices, to generate the AEO. Under DOE's Organization Act of 1977, which mandates that the EIA administrator create reports on trends and estimates for energy demand and supply, the AEO is released annually.

According to EIA, the AEO 2022 projections are modeled projections of what might occur given specific assumptions and a methodology rather than predictions of what will happen. Because it is impossible to predict with precision future advances in technologies, demography, and resources, as well as many of the events that drive the energy markets, these projections are inherently uncertain. As Figure 15 shows, AEO 2022 contains predictions for electric VMT (eVMT) from the present day to 2050 for several forecasting scenarios.

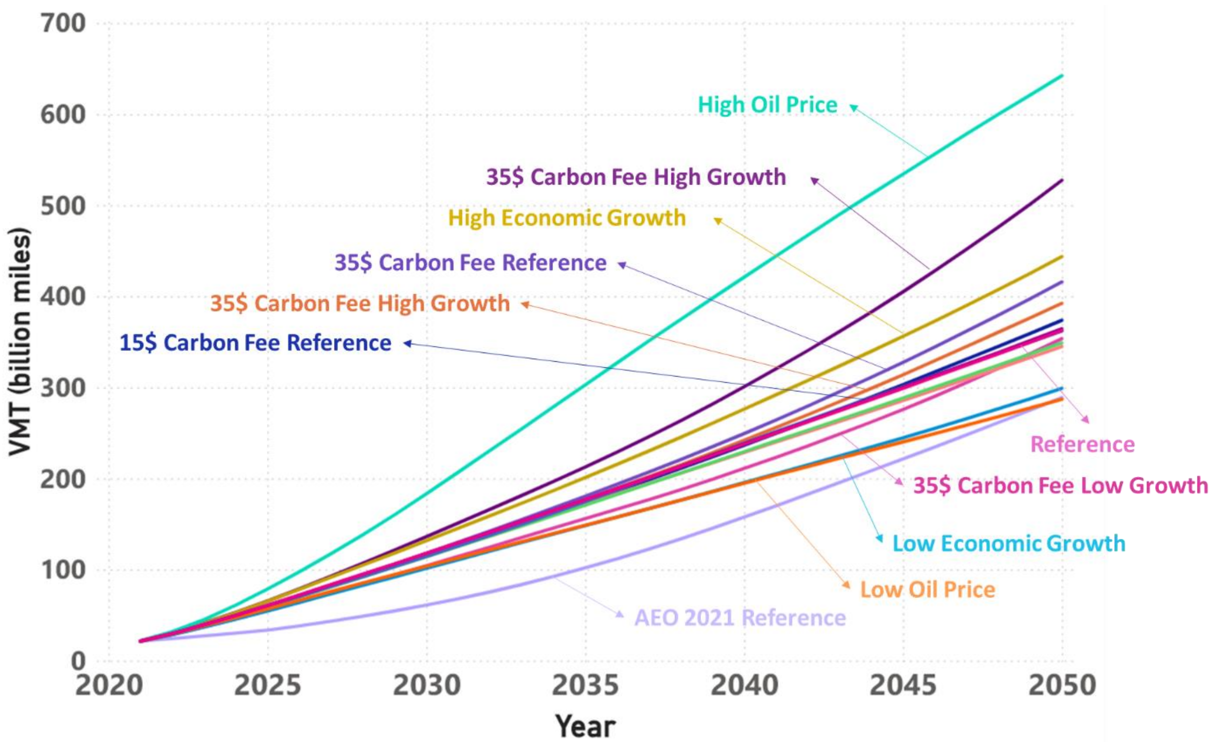


Figure 15. Comparison of eVMT projections for different scenarios of AEO 2022.

A main scenario (also known as the reference case) and alternate scenarios are frequently included in EIA estimates. In the alternative scenarios, some assumptions, such as the gross domestic product (GDP) growth, oil and gas output, or changes in policy or technology, were altered while others were left unchanged. These hypothetical situations shed light on the variety of potential future energy supply and demand conditions. These hypothetical situations show how susceptible the American energy system may be to changes in external variables like fuel costs. The following is a description of the various AEO 2022 scenarios:

- **Reference case:** The AEO 2022 reference scenario, which is based on basic assumptions meant to serve as a starting point for examining long-term trends, reflects EIA's best prediction of how the U.S. and global energy markets will function through 2050. The side cases, containing different assumptions, can be contrasted with the reference example as an acceptable baseline case. The reference case's economic and demographic trends are based on EIA's analysis of the most up-to-date predictions from top economists and demographers. The reference scenario generally presupposes that all currently in-effect laws and regulations, including those with expiration dates, will continue in place for the duration of the projection period.
- **High and low oil price:** Brent crude oil costs $173 per barrel in 2020 dollars in the AEO 2022 high-oil-price case by 2050, compared to $95 per barrel in the reference case and $48 per barrel in the low-oil-price case.
- **High and low oil and gas supply:** The high-oil-and-gas-supply case, compared to the reference case, considers lower costs and greater resource availability for oil and natural gas in the United States, allowing for increased production at lower costs. In the situation of limited oil and gas supply, fewer resources and greater expenses are presumptive.
- **High and low economic growth:** The implications of economic hypotheses on the energy consumption modeled in AEO 2022 are discussed in the high-economic-growth case and the low-economic-growth case. In contrast to the reference case's annual growth rate of 2.1 percent, the two examples assume

compound annual growth rates for the U.S. GDP of 2.6 and 1.6 percent, respectively, from 2020 through 2050.

- **High and low renewables cost:** The sensitivity of capital costs for renewable electric-power-generating technologies is examined in the high-renewables-cost case and the low-renewables-cost case. By 2050, costs will have decreased by around 40 percent from the reference case due to the low-renewables-cost case's assumption of higher learning rates for renewable technologies.
- **Alternate scenarios**: A set of alternative scenarios is included in AEO 2022 that evaluates the impact of a carbon fee of $25 or $35.

In comparison to the reference scenario for the previous iteration [29], the eVMT prediction for AEO 2022 is significantly higher. This variation can be explained by the fact that the AEO 2022 reference scenario had significantly more expected PEV sales for the following years than AEO 2021 did. Based on the anticipated PEV population and VMT, each of these potential outcomes is assessed. Equation 19 was used to determine the percent change of these parameters from the reference case.

$$\%\Delta A_{i,s} = \left(1 - \frac{A_{i,s}}{A_{i,s0}}\right) \times 100 \tag{19}$$

Where:

- $A_{i,s}$ = the total activity (population or VMT) for model year i and current scenario s.
- $A_{i,ref}$ = the total activity (population or VMT) for model year i and reference scenario s.

Figure 16 illustrates the percent change in the PEV population compared to the reference case for different AEO scenarios. As Figure 16 illustrates, the high-oil-price scenario has the maximum increase of PEV population for the year 2026 among all the scenarios. Figure 17 depicts a similar trend for VMT.

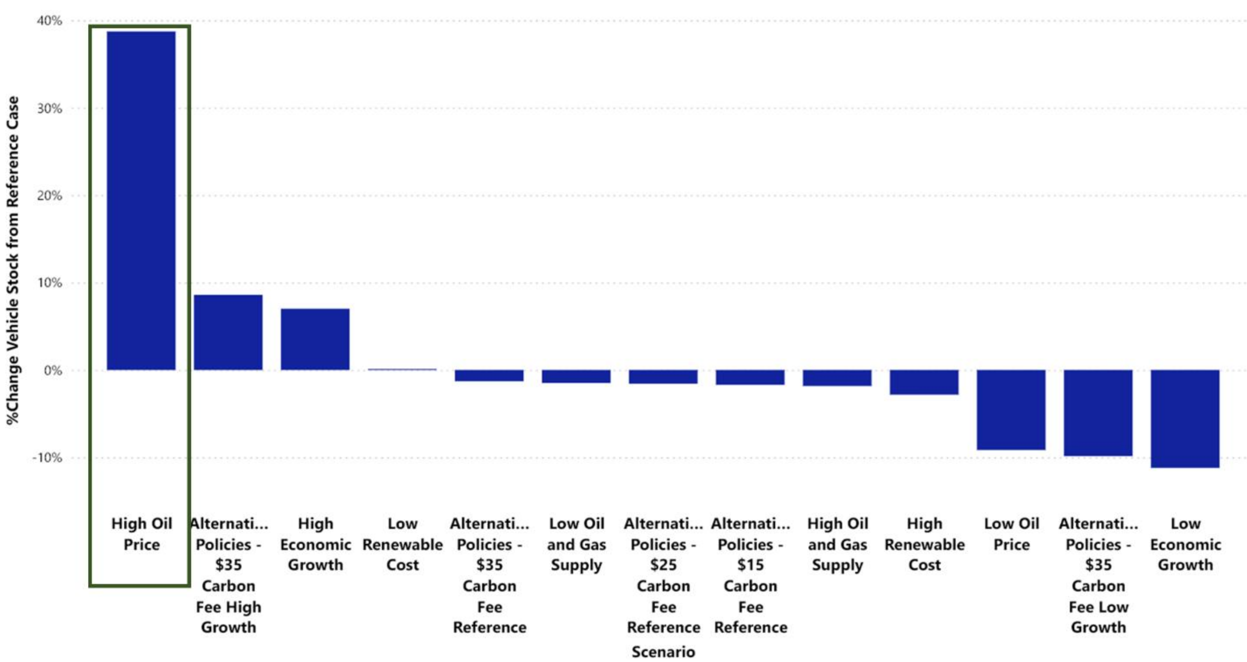


Figure 16. Percent change in vehicle stock (millions) compared to the reference case for the analysis year 2026.

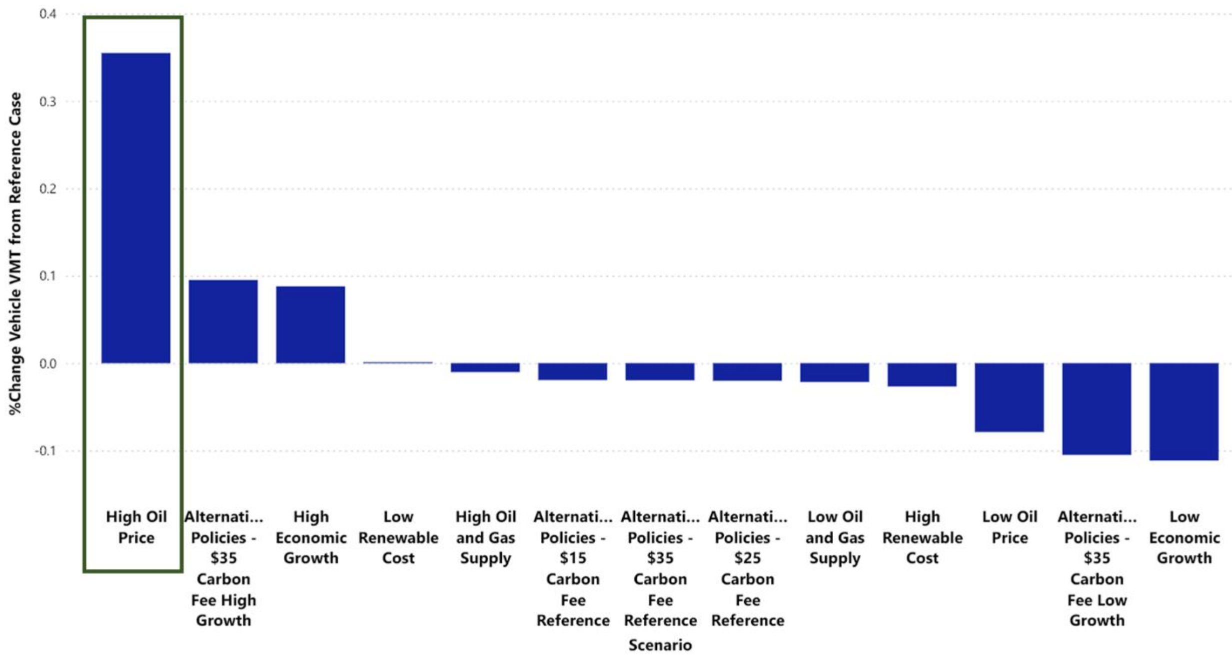
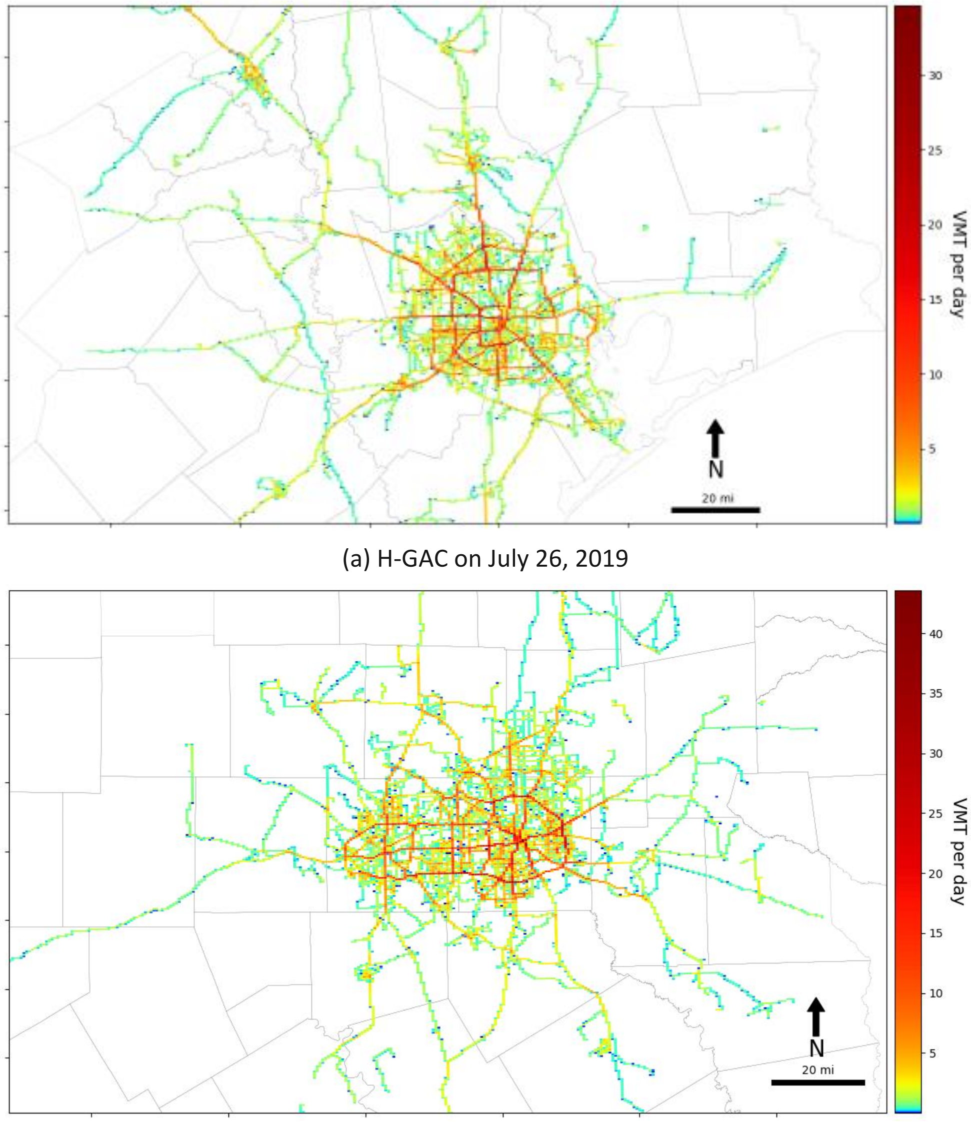


Figure 17. Percent change in VMT (in billion miles) compared to the reference case for the analysis year 2026.

Traffic Data from Wejo

Wejo is a data provider with over 13 million active vehicles in its database. Wejo uses this information to provide data analytic solutions to its customers regarding the real-time insights of EV data. More information on Wejo is available at https://www.wejo.com/.

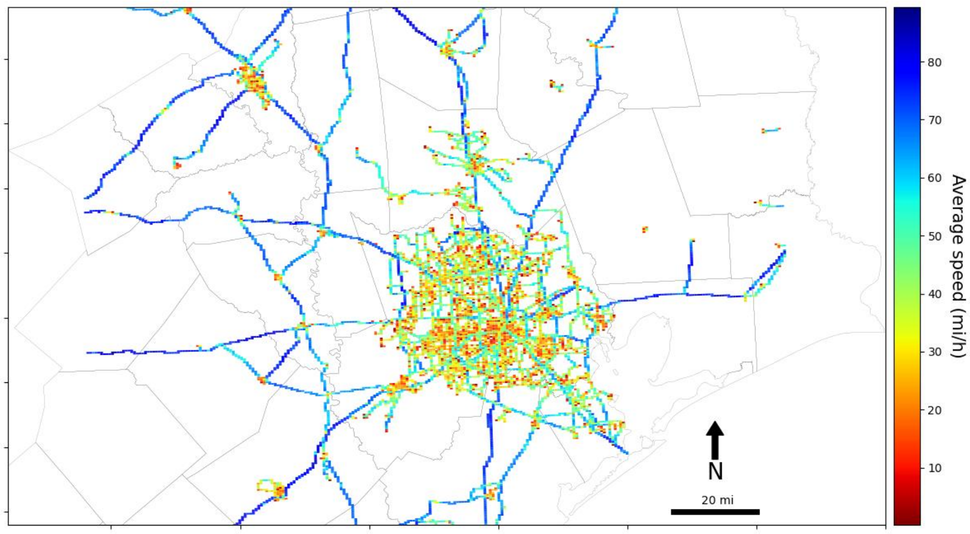
Wejo data were used in the Texas A&M Transportation Institute's previously developed *Assessing Ozone Impacts on Electric Vehicle Adoption in Texas* report [21], which was part of TxDOT's Routine Maintenance Contracts project (previously discussed in the section "EV Emission Impact"). The report uses Wejo data to study the then-current (July 2019) on-road vehicle activities in the H-GAC and NCTCOG study areas. The study areas in the Wejo data were aggregated in a six-digit geohash with a resolution of 0.75 miles by 0.38 miles. For each zone, the VMT (see Figure 18**Error! Reference source not found.**) by average speed (see Figure 19) and the number of starts by soak time for every hour of the day were calculated.



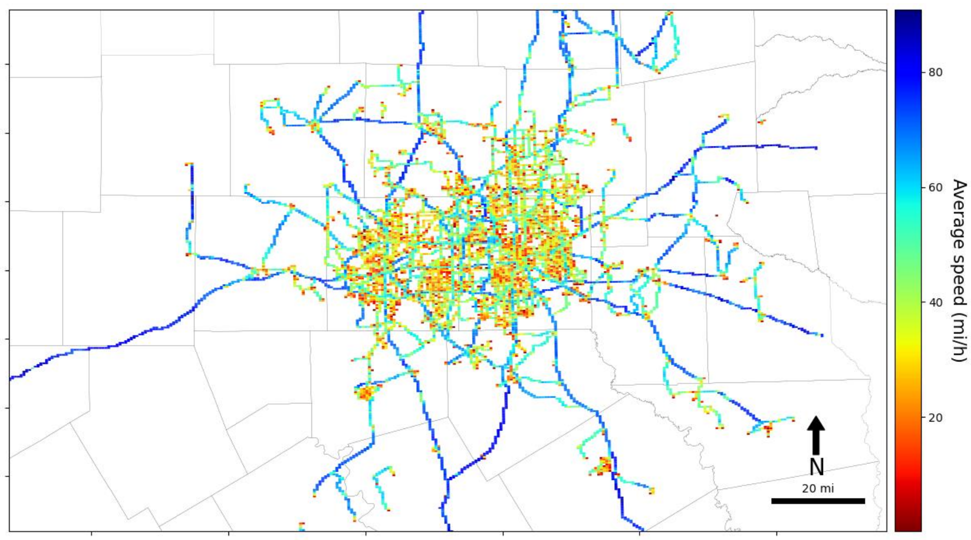
(a) H-GAC on July 26, 2019

(b) NCTCOG on July 26, 2019

Figure 18. Overview of Wejo VMT data.



(a) H-GAC on July 26, 2019



(b) NCTCOG on July 26, 2019

Figure 19. Overview of Wejo average speed data.

Charging Station Locations

Sources such as DOE's AFDC, which keeps a list of available charging outlets disaggregated by charging method and technology, provide data on the locations of public PEV charging stations.

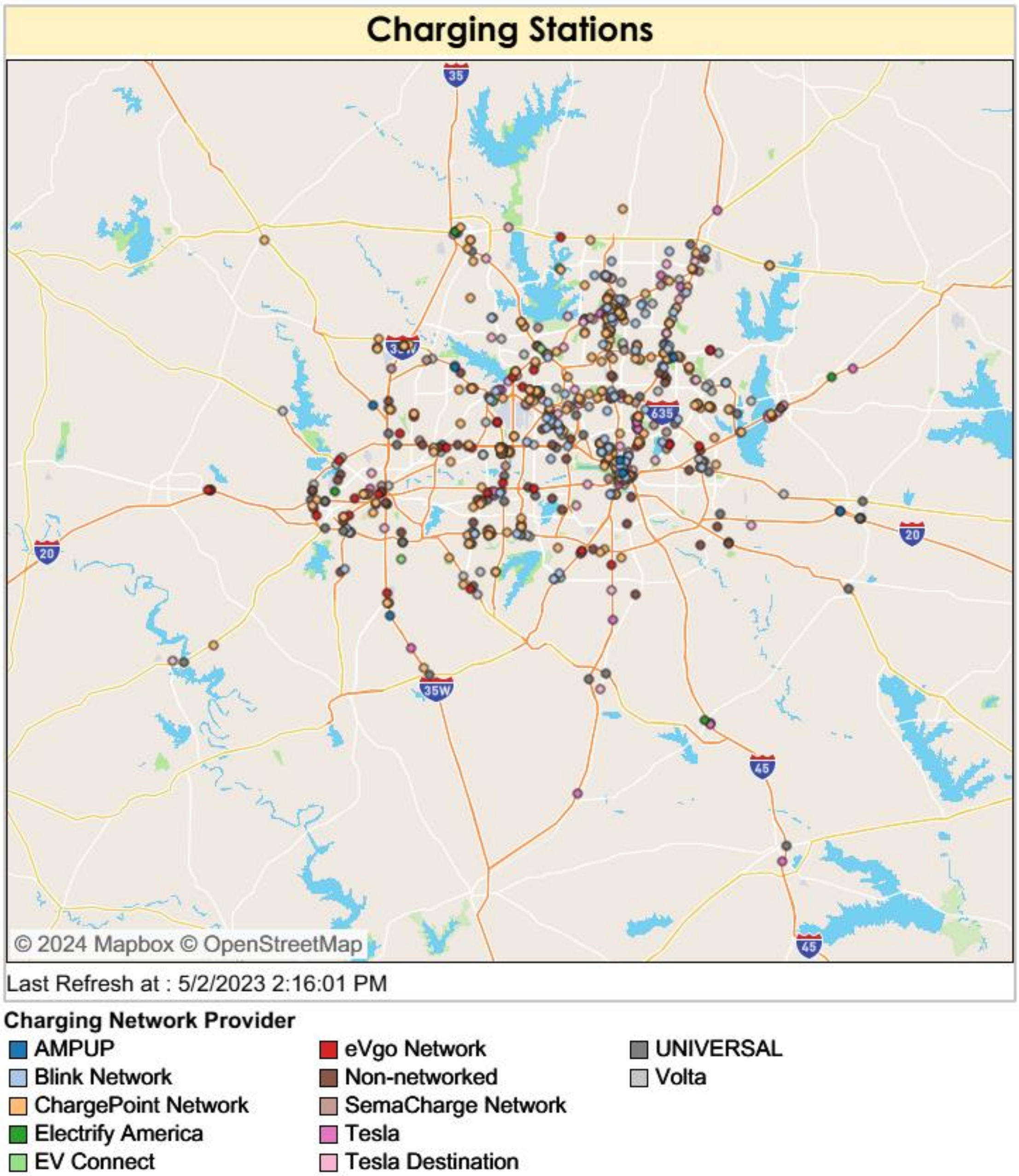


Figure 20 depicts the location of PEV charging stations in Texas in October 2020 based on data gathered from the AFDC website. Most public BEV chargers are in the main urban centers and along major corridors. Most of these BEV chargers are Level 2 alternating current (AC) outlets, followed by DC outlets as shown in Figure 21.

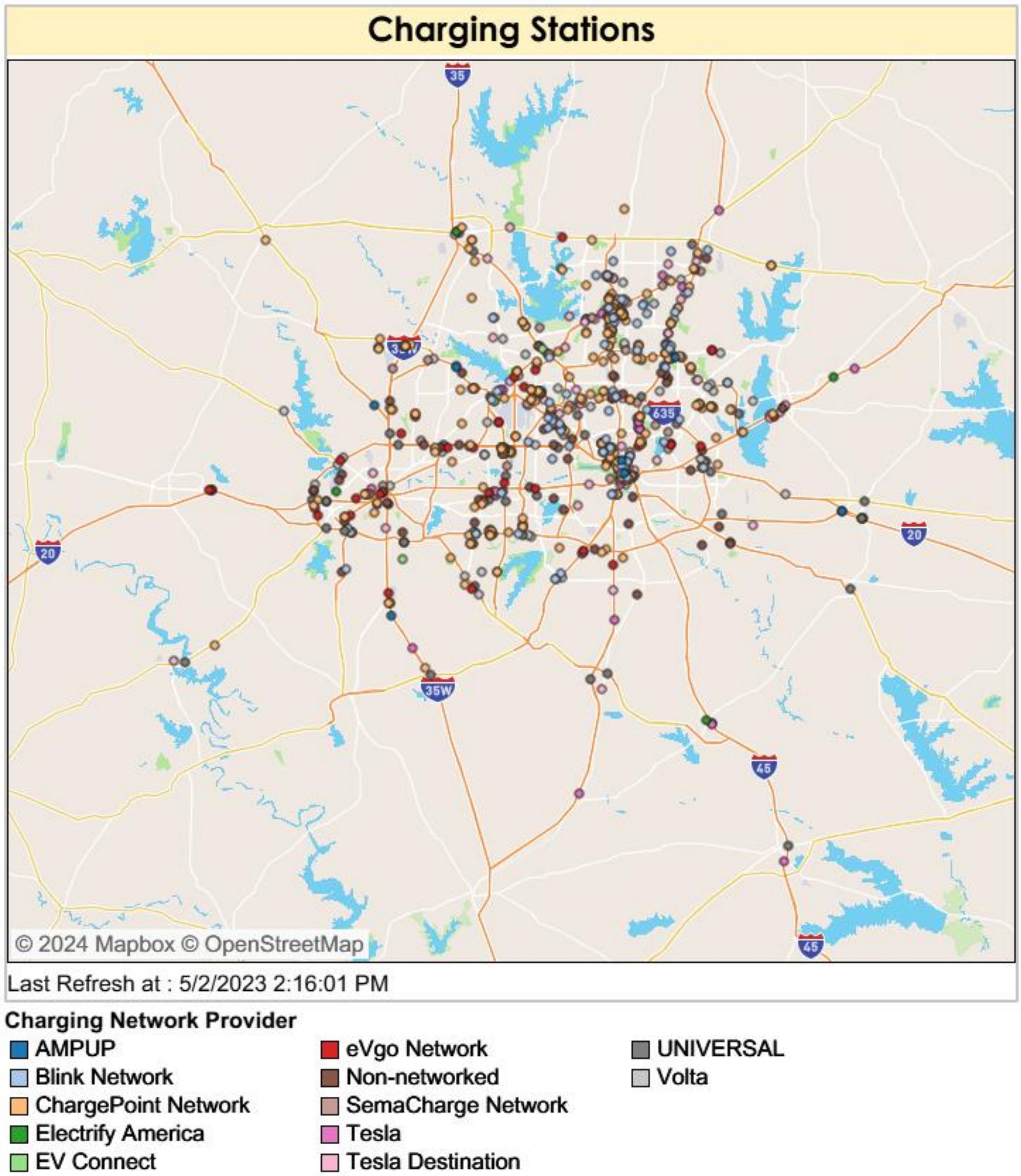


Figure 20. Public EV charging stations in the study area.

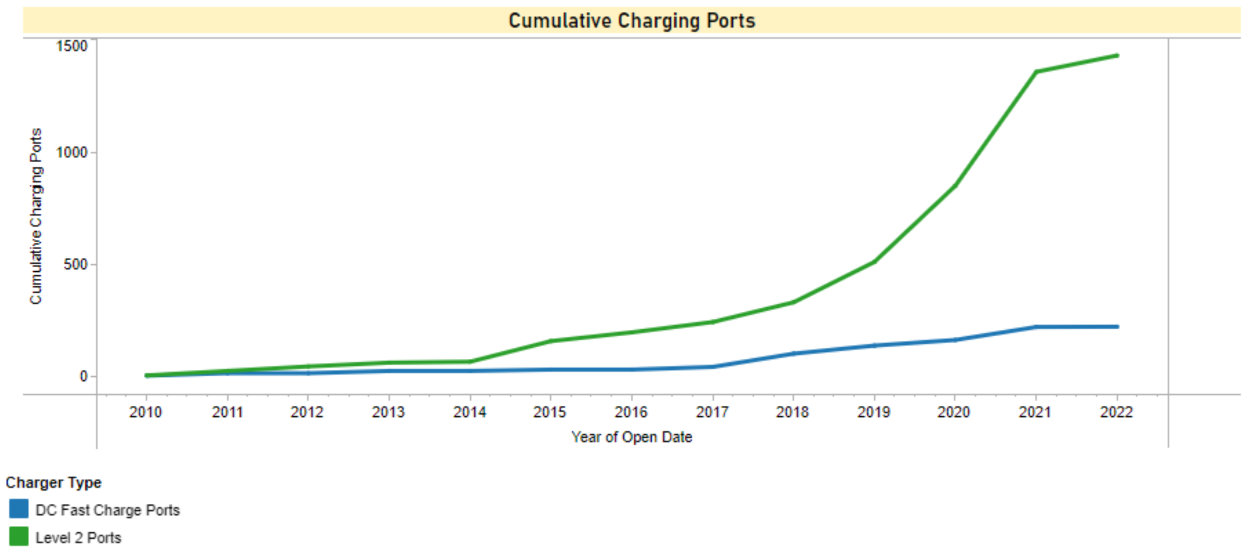


Figure 21. Trend in the number of charging ports available in the study area.

PEV Charging Profiles

The development of a realistic charging profile for PEVs is a crucial element of the analytical framework for evaluating the PEV's electricity demand on the grid in the study area and the emissions from EGUs that provide power to the area. A charging profile outlines PEV charging demand over time. The PEV charging profiles are used to assess the amount of increased power demand resulting from PEV charging and to estimate the changes in emissions from energy generation in the study regions. Researchers at NREL created the EV Infrastructure Projection Tool (EVI-Pro), which leverages precise data on personal vehicle travel patterns, PEV features, and charging station properties within a framework for bottom-up modeling. EVI-Pro calculates the amount and kind of charging infrastructure required to enable the adoption of PEVs.

NREL has also published EVI-Pro Lite, a reduced version of the EVI-Pro utility, available at https://afdc.energy.gov/evi-pro-lite. EVI-Pro predicts prospective home, office, and public charging criteria using PEV demand predictions and real-world trip data from mass market users. Objectives of the model include anticipating geographical and temporal charging demand and documenting variances concerning occupants of single-unit and multi-unit residences, weekday/weekend travel activity, and regional differences in travel behavior and vehicle adoption. EVI-Pro Lite needs the user to provide values for several essential criteria relating to the location and predicted PEV fleet population and consumption. The study team gathered and examined data pertinent to the NCTCOG region. When regional data were not accessible, equivalent values from state or national databases were used.

Table 6 presents the values of the selected critical parameters for the research region, also used in the Texas A&M Transportation Institute's previous report [21]. These data were entered into EVI-Pro Lite, which derived two charging behavior recommendations:

- Managed charging, which involves shifting the majority of PEV charging demand from peak energy demand hours to nighttime.
- Unmanaged charging, which involves beginning charging when a PEV arrives at its location.

Table 6. Input Variables in EVI-Pro Lite for the Analysis [21]

Variable	Input Values	Source
PEVs in the Fleet	10,000	Texas vehicle registration data[1]
Average Daily VMT per Vehicle	25 mi/35 mi/45 mi	Vehicle telematics data for the study regions
Average Ambient Temperature in Which the Fleet Drives	68°F/86°F	Historical temperature data for the study regions[2]
All-Electric Plug-In Vehicles	75%	Texas vehicle registration data[3]
Plug-In Vehicles That Are Sedans	80%	Texas vehicle registration data[3]
Mix of Workplace Charging	20% Level 1, 80% Level 2	Nationwide data[4]
Access to Home Charging	75%	—
Mix of Home Charging	20% Level 1, 80% Level 2	Nationwide data[4]
Preference for Home Charging	100%	—
Home Charging Strategy	Immediate—as fast as possible/ Delayed—start at midnight	Sacramento Municipal Utility District[5]
Workplace Charging Strategy	Immediate— as fast as possible	—

Notes:

1 North Central Texas Council of Governments (2020), *Air Quality Handbook.*

2 National Oceanic and Atmospheric Administration (2021), "NOWData—NOAA Online Weather Data, Monthly Summarized Data," https://w2.weather.gov/climate/xmacis.php?wfo=fwd.

3 U.S. Energy Information Administration (2021), *Annual Energy Outlook 2021*,.

4 FleetCarma (2020), "The Geography of EV Charging: Understanding How Regional Climate Impacts EV Charging and Driving Behavior," https://www.fleetcarma.com/geography-of-ev-charging/ Accessed Oct, 2023.

5 Sacramento Municipal Utility District (2019), *Resource Planning Report: IRP Filing Report for Submission to the California Energy Commission.*

EVI-Pro Lite generates charging profiles by charger type. The research team aggregated these charging profiles into an overall average per-PEV profile for the study areas. These average per-vehicle profiles can be used along with the estimated PEV population to determine the hourly PEV charging demand for a typical ozone season weekday and weekend. Figure 22 and Figure 23 depict the resulting managed and unmanaged charging profiles for weekdays; Figure 24 and Figure 25 illustrate the resulting charging profiles for weekends.

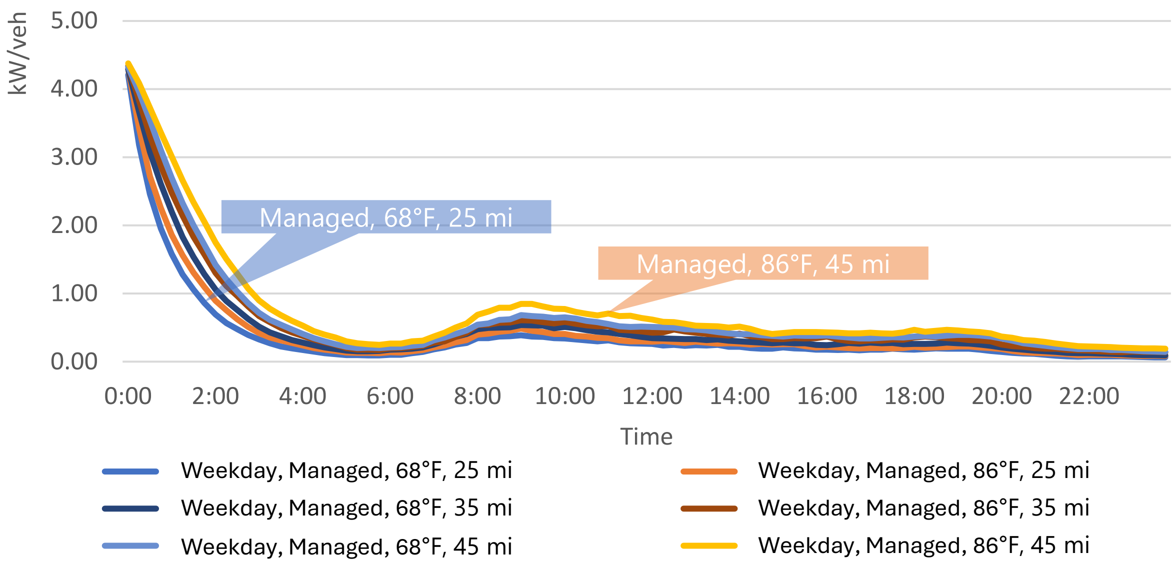


Figure 22. Weekday PEV managed charging profile.

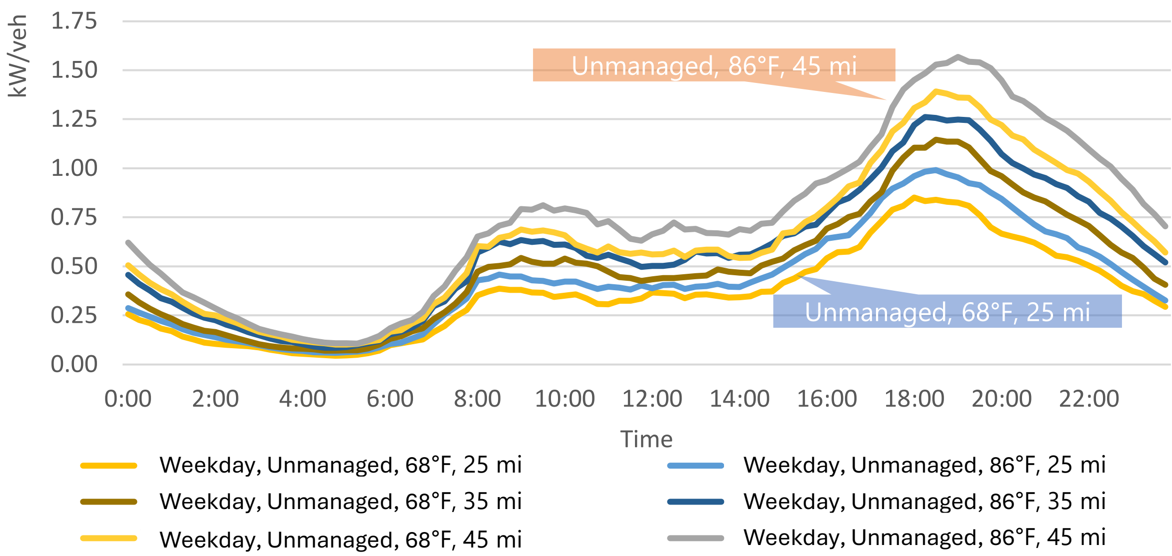


Figure 23. Weekday PEV unmanaged charging profile.

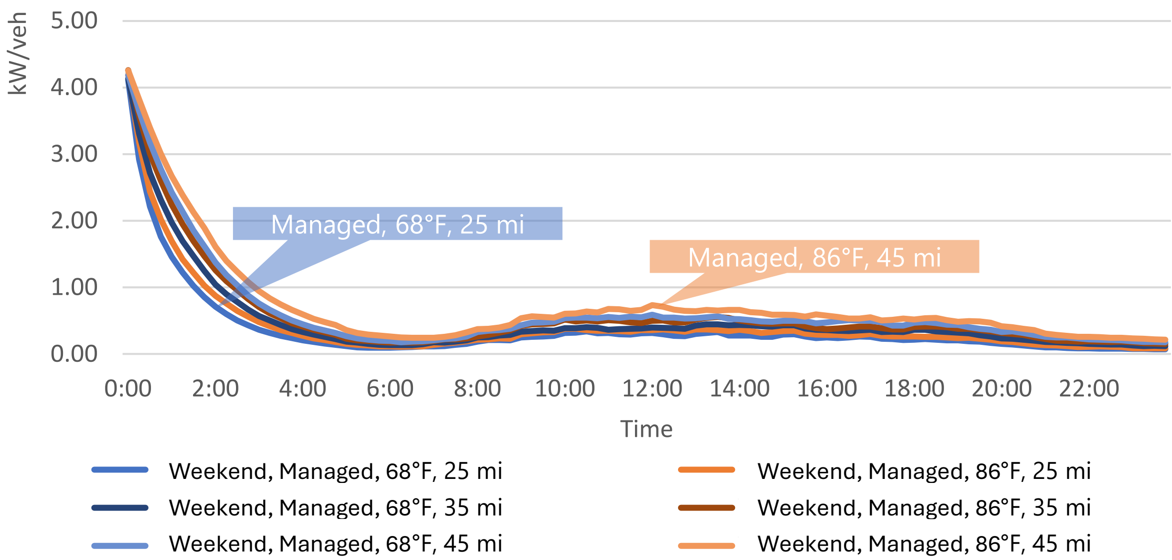


Figure 24. Weekend PEV managed charging profile.

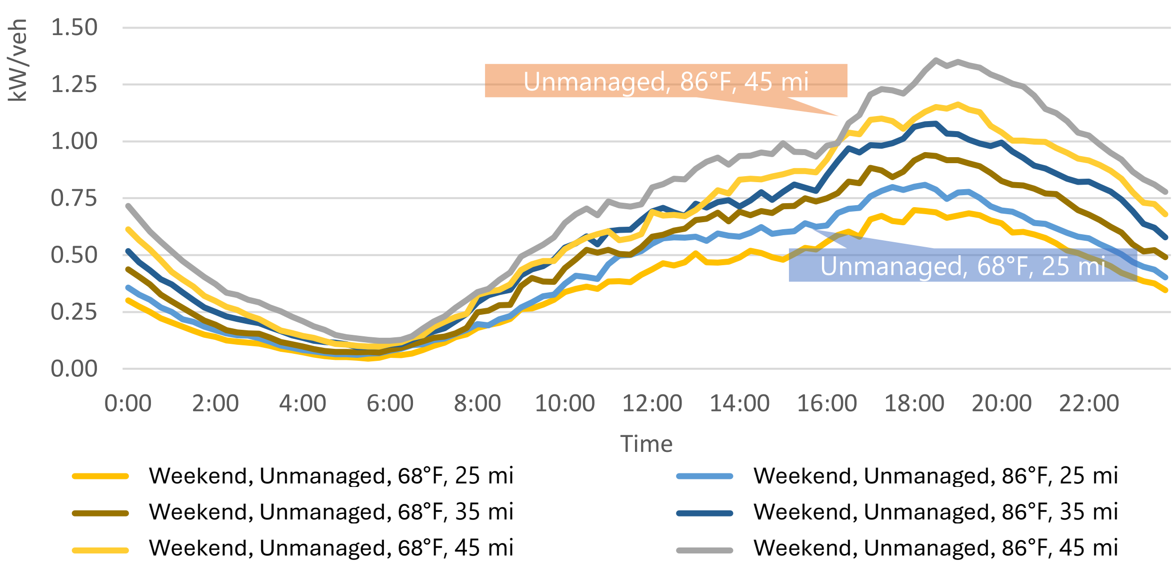


Figure 25. Weekend PEV unmanaged charging profile.

Scenario Building

This section presents projections of the EV adoption rate in the study area. The EV adoption rate in the United States has been growing steadily in recent years, driven by a combination of factors that are summarized by recent literature and reports, including:

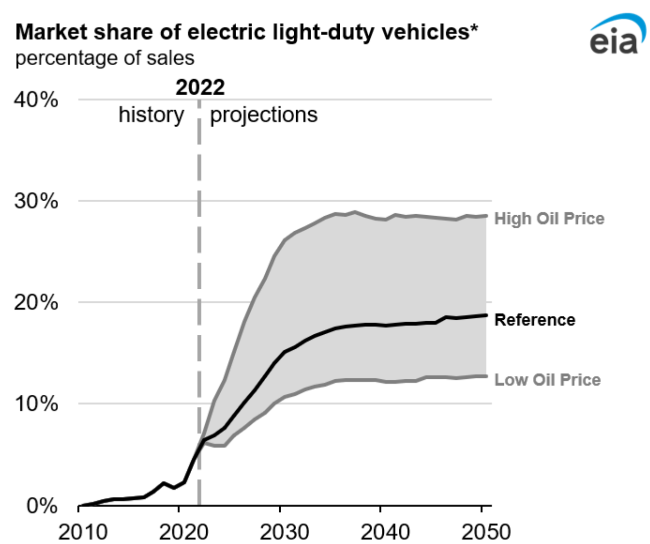
- Energy price and supply.
- Economic conditions.
- Government regulation and policy incentives.
- Technological advancements and cost cutting.
- Infrastructure development.
- Consumer preference

This section discusses driven factors for EV adoptions and several scenarios of EV adoption projections.

Driven Factors for EV Adoption

Energy Price and Supply, and Economic Conditions

Energy supply, demand, and price, as well as macroeconomic conditions, are important factors that impact EV adoption. Among them, the EIA AEO considers oil price the most determining factor. According to EIA's estimates, the market share of light-duty EVs, represented as a percentage of annual LDV sales, is projected to reach nearly 30 percent by the 2030 model year and maintain this level for an extended period, assuming oil prices remain high (see Figure 26) [30].



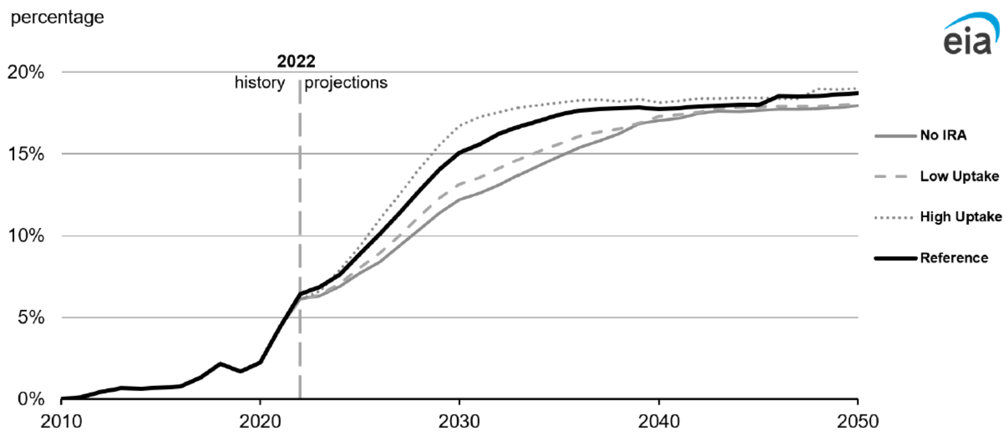
Note: Includes BEVs and PHEVs. Shaded regions represent maximum and minimum values for each projection year across the AEO 2023 reference case and side cases.
Data source: EIA, AEO 2023

Figure 26. Market share of light-duty EV projection.

Government Regulation and Policy Incentives

Both federal and state governments have introduced regulations and incentives to reduce GHG emissions. Among the introduced strategies, EVs have emerged as a viable solution to achieve GHG emission reduction targets. The government has been offering incentives, such as tax credits and rebates, to EV buyers. These measures play an important role in making EVs more affordable and therefore increase the adoption rate of EVs. A thorough discussion of government regulation and policy incentives on EVs is in the section "Policies and Regulations for EV Adoption" in this report.

Various federal and state-level incentives, such as the 2022 IRA, aim to accelerate EV adoption over the next few decades. As Figure 27 shows, AEO 2023 estimated that, in 2030, the share of EV sales will increase substantially from 12 percent in the "No IRA" case to 15 and 17 percent in the "Reference" and "High Uptake" cases, respectively. EVs will make up about 18 percent of total LDV sales by 2050 [30].



Note: Includes sales of both BEVs and PHEVs.
Data source: EIA, AEO 2023

Figure 27. EVs' share of light-duty vehicle sales.

Technological Advancements and Cost Cutting

Substantial technological advancements have been made in the field of EVs in the past decade. For example, the improvement in battery technology has led to increased driving range and reduced charging times for EVs. In addition, the cost of batteries has been steadily decreasing, leading to a reduction in the overall cost of EVs.

Infrastructure Development

The development of a robust charging network across the country has helped to alleviate concerns over EV range anxiety and to make EVs a more practical option for many consumers.

Consumer Preference

Consumer intentions for EV adoption refer to consumers' willingness or likelihood to purchase or adopt an EV as their primary mode of transportation. Factors affecting consumers' intention to adopt an EV include their attitudes, beliefs, and perceptions towards EVs, as well as other factors that may influence their decision-making process, such as government incentives, environmental concerns, infrastructure availability, and vehicle cost, performance, and reliability. Consumer intentions are hard to quantify and are usually measured through interviews and surveys.

Consumer intentions for EV adoption can be categorized into four types: adoption intention, purchase intention, behavioral intention, and usage intention. Each of these intentions is influenced by a different set of factors and can provide insights into the motivations and barriers to EV adoption. More information about consumer intentions on EV adoption is discussed in the next section of this report, "Literature Review Summary."

However, the factors influencing EV adoption rates vary across different regions. Forecasting these factors often involves significant uncertainty. When projecting the adoption rate, it is crucial to consider the unique characteristics and conditions of each local area, including geographical patterns, demographic changes, economic factors, and cultural influences.

Literature Review Summary

Table 7 summarizes sources that examined EV adoption based on the aforementioned factors. The literature review showed that no universally applicable methodology or dataset is currently available to create an accurate projection of EV adoption in the study area. Therefore, even though the approach taken by EIA in the AEO is conservative, it remains one of the best sources for developing projections of EV adoption. EIA assumes the growth in EV sales to be slow but steady, both in absolute terms and as a share of total LDV sales, which the EIA reference case estimates to stay relatively flat in the future.

Table 7. Literature Review of Scenarios Related to EV Adoption

Reference	Scenario	Findings	Additional Notes
Hidrue et al. (2011) [31]	Consumer preference	• Individuals were willing to pay between \$35 and \$75 for every mile added to the driving range. • For a 50-mile charge, individuals were willing to pay between \$425 and \$3,250 for every hour of reduced charging time. • The authors concluded that EV batteries must cost substantially less before EVs can find a mass market without government subsidies.	A stated preference study of EV choice using data from a national survey
Helveston et al. (2015) [32]	Consumer preference	• Gasoline vehicles continue to be the most attractive to consumers in both America and China. • The American respondents have a substantially lower willingness to pay for BEV technology than the Chinese respondents.	Consumer preferences for conventional gasoline vehicles, HEV, PHEV, and BEV in China and the United States are modeled using data from choice-based conjoint surveys fielded in 2012–2013.
Liao et al. (2017) [33]	Consumer preference and cost cutting	• A relatively shorter driving range compared to conventional gasoline vehicles is one of the biggest barriers to the widespread adoption of EVs. • Regarding one-time price-reducing policies, reducing the purchase tax has a significant impact on consumer preferences for EVs in all four cases whereas reducing purchase price is only significant in two of the four cases. • The density of charging stations has a positive impact on the utilities of EVs, which demonstrates the importance of charging infrastructure development when promoting EV adoption. • Free parking and toll reduction are not significant factors in any of the cases.	Estimates of consumer preferences for financial, technical, infrastructure, and policy attributes are reviewed in a comprehensive review of 26 studies.
Hardman et al. (2018) [34]	Infrastructure development	• The most important location for PEV charging is at the vehicle owner's residence, followed by work and public locations.	A comprehensive literature review

Reference	Scenario	Findings	Additional Notes
		• In the short term, PEV charging is not likely to cause an impact on electricity grid capacities. However, charging may need to be managed in the future when the EVs are being deployed in greater numbers. • The cost to charge a PEV should be lower than the refueling cost of conventional gasoline vehicles if PEVs are to retain the benefit of having a lower running cost.	
Kumar et al. (2020) [35]	Infrastructure deployment, incentives, and cost cutting	The authors provide some policy recommendations: • Policies should focus on reducing the total cost for a user to own an EV. • Policies should focus on fast-charging infrastructures. • Policies should facilitate home, residential, and workplace charging options. • Policies should optimize the charging network to minimize EV range anxiety in the public. • Policies should focus on functional attributes of the EV, such as range, top speed, and acceleration. • Policies should target high-income earners and individuals with advanced degrees.	A systematic review of 239 articles
Lee et al. (2020) [36]	Infrastructure development	• Both BEV and PHEV owners relied heavily on home charging, with more than half of them only using home chargers. • The use of the home, work, and public charging infrastructure types is interconnected. Some EV owners display a more mixed use between the three charging infrastructure types compared to others. • This paper highlights the importance of having an integrated infrastructure investment plan that will account for different locational charging patterns among PEV owners.	An examination of the charging behavior of 7,979 PEV owners in California
Sun et al. (2020) [37]	Technological advancements	• Charging infrastructure is crucial for EV use. The organization of the charging network, the technical challenges of infrastructure, and the possibilities of fair payment for charging are involved in the charging infrastructure network. • Economic profits of vehicle-to-grid technologies have received increased attention from grid operators and EV owners, and are heavily related to the strategies of charging and vehicle aggregation.	A review of EV technology development in key fields, such as the battery, charging, electronic motor, charging infrastructure, and emerging technology
Sanguesa et al. (2021) [38]	Technological advancements and infrastructure development	• Batteries play a critical role because they directly influence the EV’s autonomy and range. • The development of batteries with higher capacities will facilitate the use of faster and more powerful charging modes, along with the improvement of wireless charging technologies.	Review paper

Reference	Scenario	Findings	Additional Notes
		• The creation of a universal connector that can be used globally can also benefit the deployment of EVs. • The EV will play a highly important role in the future smart cities, and having different charging strategies that can adapt to the users' needs will be of special relevance.	
Forsythe et al. (2023) [39]	Technological advancements, infrastructure development, and consumer preference	• In recent years, technology improvements have been a more influential factor in driving the increase in the market share of BEVs than changes in consumer preferences. • The likelihood of consumers purchasing BEVs has grown over time because of technological improvements that have increased range and, in many cases, reduced price premiums of BEV models relative to their gasoline counterparts. • Most EVs with a range of at least 300 miles were valued by consumers equivalently or more than their conventional gasoline vehicle counterparts. • Although BEVs have certain disadvantages, such as longer recharging times compared to refueling a gasoline vehicle, these drawbacks are balanced out, on average, by lower operating costs and fast-charging capability, provided that the EV's range is sufficiently long.	Analysis of nationally representative survey data

EV Adoption Projections (AEO Approach)

Factors, such as future oil prices, economic growth, energy resource availability and generation cost, technological advancement and cost reductions, the expansion of charging infrastructure, and consumer intentions, can have substantial impacts on the growth trajectory of EV adoption and usage. However, projecting these factors for future implications comes with high levels of uncertainty. To account for these uncertainties, EIA developed several alternative scenarios using different assumptions and forecasts of these factors. The alternative scenarios for the EV activities were selected based on an evaluation of the different scenarios from AEO 2023.

As stated by EIA, the projections presented in AEO 2023 are not definitive predictions of future outcomes. Rather, they are modeled projections based on certain assumptions and methodologies. These projections are inherently uncertain in nature because many of the events that shape the energy market, as well as future developments in technologies, demographics, and resources, cannot be foreseen with a high level of certainty. The EIA projections typically include a main reference case scenario and several alternative scenarios. These alternative scenarios involve altering certain assumptions in the reference case, such as GDP growth, oil and gas production, and changes in policy or technology while keeping other factors consistent. These scenarios offer insights into the possible range of future energy supply and demand conditions. The level of sensitivity in the U.S. energy system might be changed by certain factors, such as fuel prices [30].

Baseline Reference

The AEO 2023 reference case represents EIA's best assessment of how the U.S. and global energy markets are expected to operate through 2050. The reference case serves as a benchmark to be compared against the alternative assumptions. EIA based the economic and demographic trends reflected in the reference case on the current views of leading economic forecasters and demographers. The reference case generally assumes that current laws and regulations that affect the energy sector, including those that have end dates, remain unchanged throughout the projection period [30].

Macroeconomic Growth Scenario

The high- and low-economic-growth cases were developed to reflect the uncertainty in economic growth projections. These cases show the effects of alternative economic growth assumptions that are higher or lower than the reference case. The factors that were changed in these scenarios are the macroeconomic parameters, which included the assumptions for population growth, nonfarm labor productivity, nonfarm employment, real disposable income per capita, and real GDP. Table 8 shows the changes in the macroeconomic parameters for both high- and low-economic-growth cases in comparison to the reference case [30].

Table 8. AEO Macroeconomic Annual Growth Scenario Build

Model Parameters	Reference Case	Low-Economic-Growth Case	High-Economic-Growth Case
Population	0.4%	0.2%	0.6%
Nonfarm labor productivity	1.9%	1.0%	2.4%
Nonfarm employment	0.4%	0.2%	0.6%
Real disposable income per capita	2.0%	1.7%	2.1%
Real gross domestic product	1.9%	1.4%	2.3%

Data source: EIA, AEO 2023, National Energy Modeling System, runs ref2023.d020623a, highmacro.d020623a, and lowmacro.d020623a

Oil Price Scenario

AEO 2023 considers three oil price cases (reference, low oil price, and high oil price) to assess the potential range of impacts on future oil prices. The world crude oil price was set as the benchmark in AEO 2023, which is based on historical spot prices for North Sea Brent crude oil and the international standard for light, sweet crude oil prices. In the reference case, it was assumed that global oil supply and demand will continue to increase through the projection period and crude oil prices will also rise steadily starting in 2023. The global consumption of petroleum and other liquid fuels continues to increase steadily throughout 2050 in the reference case, in part due to an increase in the number of vehicles globally. The impacts on the global consumption of petroleum and other liquid fuels from the increase in vehicles are somewhat offset by improvements in LDV and HDV fuel economy in developing countries, and the increased consumption of natural gas for transportation in most regions. The industrial sector also uses some substitutes for liquid fuels. Economic growth is assumed to be steady during the projection period. More detail can be found in AEO 2023 [30].

Table 9 shows assumptions of the North Sea Brent crude oil benchmark price in the most recent historical year and in the first and last years of the projection period for both oil price scenarios and the reference case.

Table 9. Oil Price Scenario Build

Case Groups	2022	2023	2050
Reference case	$102.13	$91.54	$101.34
Low-oil-price case	$72.87	$43.28	$51.28
High-oil-price case	$116.80	$169.06	$190.06

Data source: EIA, AEO 2023, National Energy Modeling System, runs ref2023.d020623a, highprice.d020623a, and lowprice.d020623a

Oil and Gas Supply Scenario

The oil and gas supply scenarios consider the inherent uncertainty surrounding shale oil and natural gas resources, which change over time through drilling, production, and technology advancements. The scenarios take into account the technically recoverable tight or shale oil and natural gas resources because the availability of these resources typically expands with the increase in production from tight or shale oil formations. These increases in technically recoverable resources are based on various assumptions that may not hold in the long term or encompass the entirety of the tight or shale formation. More detail can be found in AEO 2023 [30].

Table 10 presents the AEO 2023 high- and low-oil-and-gas-supply scenarios along with the reference case. In the low-oil-and-gas-supply scenario, the estimated ultimate recovery per well is assumed to be 50 percent lower than in the reference case, and in the high-oil-and-gas-supply scenario, it is 50 percent higher than in the reference case.

Table 10. Oil-and-Gas-Supply Scenario Build

Case Groups	Oil (Billion Barrels)	Natural Gas (Trillion Cubic Feet)
Reference case	321	2,528
Low-oil-and-gas-supply case	180	1,393
High-oil-and-gas-supply case	463	3,663

Data source: EIA, AEO 2023, National Energy Modeling System, runs ref2023.d020623a, lowogs.d020623a, and highogs.d020623a

IRA Incentive Scenario

The IRA, which was signed into law on August 16, 2022, contains $369 billion to be used in clean energy investments. The IRA extends tax credits for producing and purchasing EVs. This study uses the AEO 2023 reference case and three IRA scenarios to assess the range of impact of the IRA on EV adoption rates. Table 11 summarizes each of the reference and IRA scenario cases [30].

Table 11. IRA Incentive Scenario Build

Case Groups	Description
Reference	This case includes energy-related provisions, as explained in the AEO 2023 narrative. For eligible technologies, we assume the base tax credit and certain bonus credits.
No IRA	This case excludes the energy-related IRA provisions, as explained in the AEO 2023 narrative.
IRA low uptake	For technologies that qualify for tax credits, it was assumed that the tax credit value is the same or lower than the value assumed in the reference case. Specifically, it was assumed that the most qualified projects only receive the base tax credit, without the prevailing wage, domestic content, or energy community bonuses. The number of EVs assumed to qualify for the clean vehicle credit is lower than the number assumed in the reference case.
IRA high uptake	For technologies that qualify for tax credits, it was assumed that the tax credit value is the same or higher than the value assumed in the reference case. Where applicable, qualified projects were modeled to receive the maximum credit bonus. The number of EVs assumed to qualify for the clean vehicle credit is higher than the number assumed in the reference case.

Power Generation Cost Scenario

To address the uncertainty in the future costs of ZE power generation technologies, AEO 2023 provides two alternative scenarios: one assuming that technology costs are higher than those in the reference case and the other assuming them to be lower. The cost assumptions are based on the following sectors and technologies:

- Power sector:
    - Conventional hydropower.
    - Hydroelectric pumped storage.
    - Geothermal.
    - Solar thermal.

    - Solar photovoltaic, standalone, and hybrid.
    - Onshore and offshore wind.
    - Energy storage.
    - Nuclear units.
    - Advanced and small modular reactors.
- End-use sector:
    - Solar photovoltaic.
    - Wind.

In the high-ZE-technology-cost scenario, the overnight capital cost is held constant at the 2022 level throughout the projection period for all the technologies listed as well as biomass. The low-ZE-technology-cost scenario assumes overnight capital costs and fixed operating and maintenance costs decline more rapidly than the reference case, that is, 40 percent below the reference case equivalents by 2050 for all the technologies. Other assumptions within these two scenarios remain the same as in the reference case [30].

AEO Scenarios and EV Adoption Rate Summary

The EV adoption rates were calculated based on the AEO 2023 scenarios and the published national dataset tables (2019–2023). The main tables from the national dataset that were used in this study are Table 39, "LDVs Stock by Technology Type," and Table 45, "Transportation Fleet Car and Truck Stock by Type and Technology." For all AEO scenarios and the reference baseline, the subtotal stocks of light-duty cars and trucks, which include passenger, fleet, and commercial vehicles, were calculated for BEVs and PHEVs, and the total stocks were calculated for all vehicle types. Then, the adoption rates were calculated for BEVs, PHEVs, and BEVs and PHEVs together, and for the total stock year-over-year ratio (i.e., projected multipliers).

Table 12 shows a snapshot of the 2026 and 2050 projected adoption rate for BEVs and PHEVs based on the reference case and each alternative AEO scenario. The projected EV adoption rates for the reference case in 2026 and 2050 are 2.69 and 14.79 percent, respectively. The scenario with the highest adoption rate is the high-oil-price scenario, with adoption rates of 3.85 percent in 2026 and 23.70 percent in 2050. The scenario with the lowest adoption rates is the low-oil-price scenario, with adoption rates of 2.33 percent in 2026 and 10.31 percent in 2050. As discussed previously, these projections assume that the current laws and regulations that affect the energy, emissions, and automotive manufacturing sectors remain unchanged throughout the projection period. For example, the potential impacts of the recently proposed *Multi-pollutant Emissions Standards for Model Years 2027 and Later Light-Duty and Medium-Duty Vehicles* [40] were not considered in these projections. Figure 28, Figure 29, and Figure 30 show the projected EV adoption rate trends from 2023 to 2050 for BEVs, PHEVs, and BEVs and PHEVs together, based on the reference case and alternative AEO scenarios.

Table 12. 2026 and 2050 Projected EV Adoption Rates (BEV and PHEV) Based on AEO Scenarios

Abbreviation	Full Name	2026	2050
	Reference case	2.69%	14.79%
HOP	High-oil-price case	3.85%	23.70%
LOP	Low-oil-price case	2.33%	10.31%

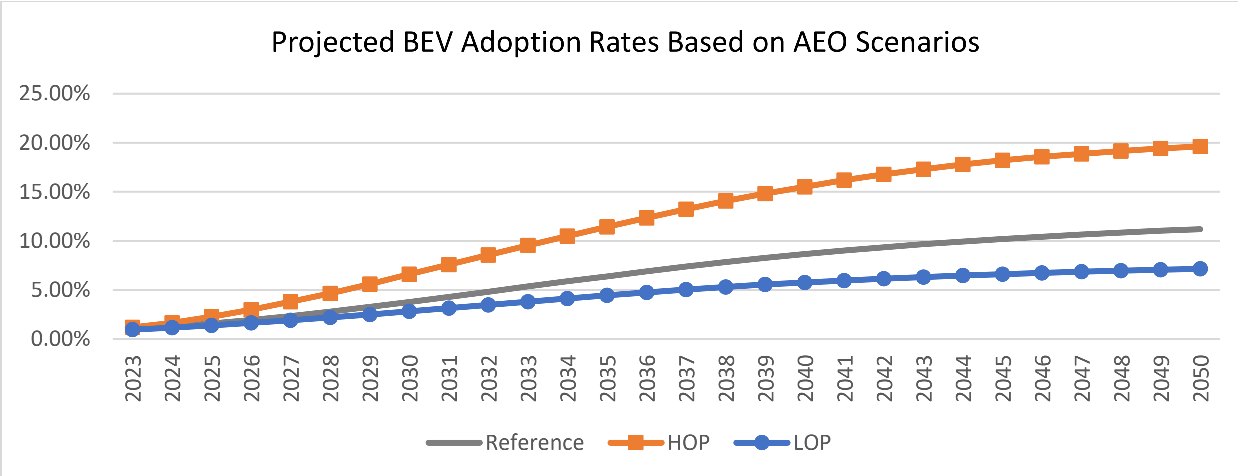


Figure 28. Projected BEV adoption rate based on AEO scenarios.

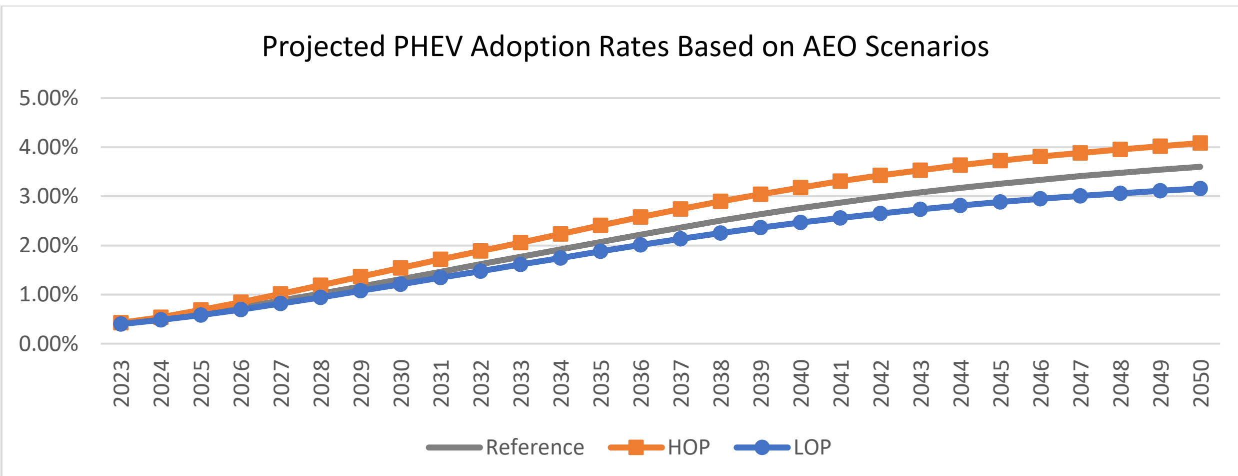


Figure 29. Projected PHEV adoption rate based on AEO scenarios.

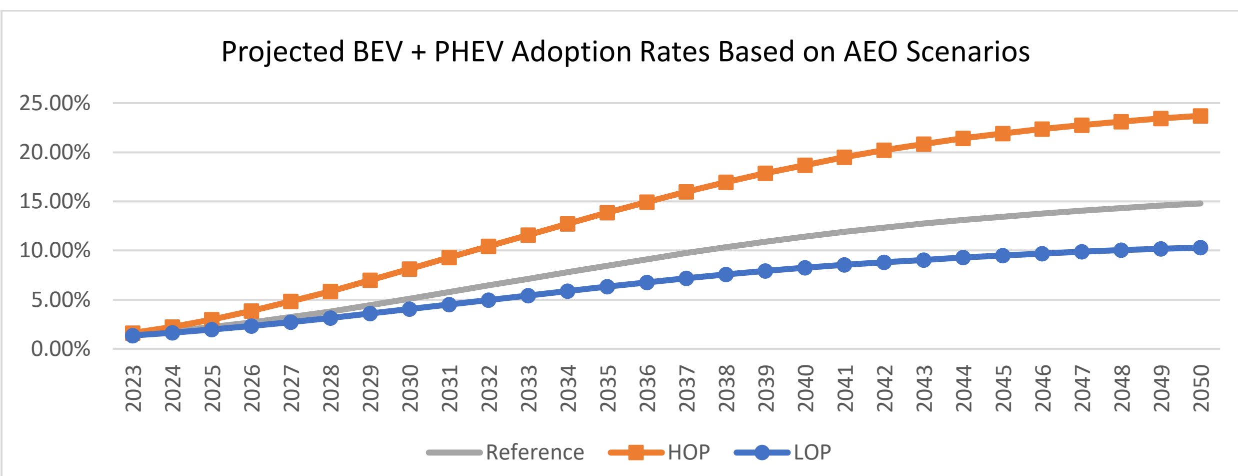


Figure 30. Projected BEV and PHEV adoption rate based on AEO scenarios.

NCTCOG EV Adoption

This section presents the regional variation of EV adoption within the areas that fall under the jurisdiction of NCTCOG. This section also describes the methodology employed to calibrate the national and state-level EV adoption data and apply them to the specific context of the NCTCOG jurisdiction area.

EV Adoption Overview within the NCTCOG Jurisdiction Area

According to ERCOT, an estimated 1 million EVs will be on the road in Texas by 2028. Similarly, based on current EV growth trends, TxDMV estimated that Texas will reach the milestone of 1 million EVs by 2031 [41]. As part of the network evaluation process, TxDOT will continue to monitor the adoption rate of EVs in the state and make necessary adjustments and developments to the network accordingly.

Based on the DFWCC data as of March 28, 2023, the current EV adoption rate (BEV and PHEV) within the NCTCOG jurisdiction area is approximately 0.98 percent [42]. However, there is a large variation among the 16 counties that comprise the NCTCOG jurisdiction area. As shown in Table 13, Collin, Denton, and Rockwall Counties have the highest EV adoption rates at 1.95, 1.57, and 0.97 percent, respectively, whereas Palo Pinto, Navarro, and Erath Counties have the lowest at 0.12, 0.14, and 0.17 percent, respectively. Figure 31 shows the density distribution of EV registrations at the census tract level within the jurisdiction area of NCTCOG. Collin, Dallas, Denton, and Tarrant Counties have the highest concentration of EV registrations within the area.

Table 13. Registered Vehicles by County within the NCTCOG Jurisdiction Area as of March 28, 2023.

County	All Vehicles	EV Count	EV Adoption Rate
Collin	901,621	17,563	1.95%
Denton	773,447	12,181	1.57%
Rockwall	104,377	1,010	0.97%
Dallas	2,186,473	18,902	0.86%
Tarrant	1,762,356	12,843	0.73%
Parker	155,455	753	0.48%
Kaufman	147,185	689	0.47%
Ellis	186,957	832	0.45%
Hood	66,754	277	0.43%
Johnson	176,757	597	0.34%
Hunt	99,612	239	0.24%
Somervell	9,933	23	0.23%
Wise	80,960	170	0.21%
Erath	36,847	62	0.17%
Navarro	49,312	68	0.14%
Palo Pinto	28,332	35	0.12%
NCTCOG	6,766,378	66,244	0.98%

Note: *All vehicles* include all registered vehicles; *EV count* includes both light-duty BEVs and PHEVs.

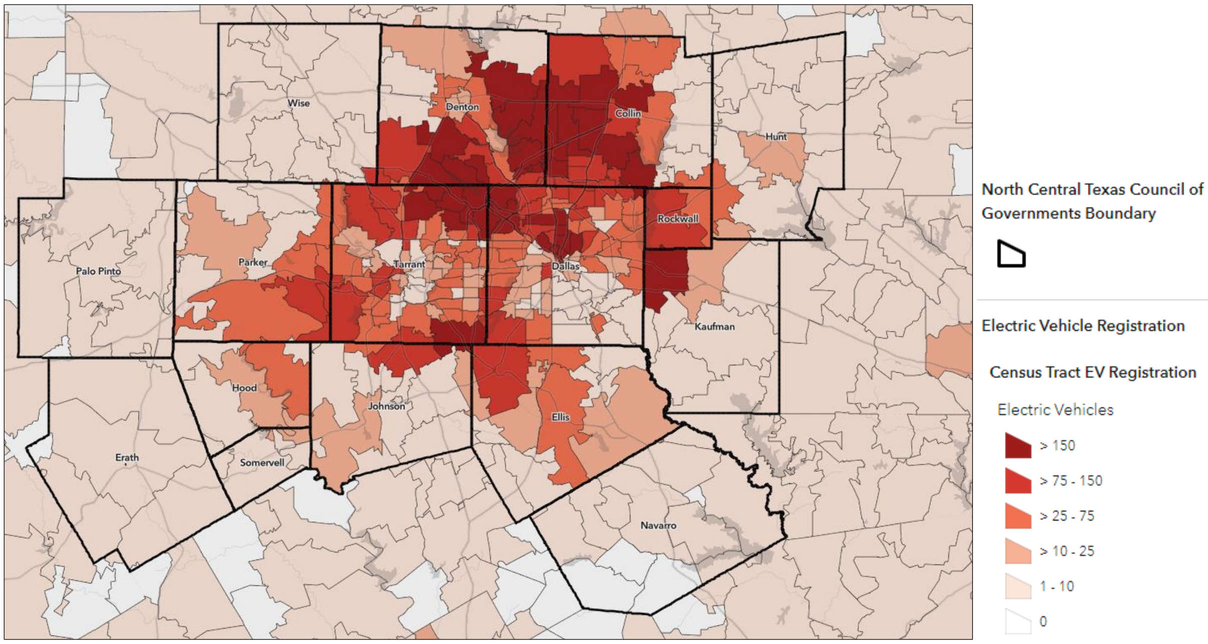


Figure 31. EV registration density at the census tract level within the NCTCOG jurisdiction area.

EV Adoption Rate Calibration

Due to restrictions in data availability, only 21 months of TxDMV EV registration data were available for the NCTCOG jurisdiction area. As discussed previously in the section "

Reference	Scenario	Findings	Additional Notes
Hidrue et al. (2011)	Consumer preference	• Individuals were willing to pay between \$35 and \$75 for every mile added to the driving range. • For a 50-mile charge, individuals were willing to pay between \$425 and \$3,250 for every hour of reduced charging time. • The authors concluded that EV batteries must cost substantially less before EVs can find a mass market without government subsidies.	A stated preference study of EV choice using data from a national survey
Helveston et al. (2015)	Consumer preference	• Gasoline vehicles continue to be the most attractive to consumers in both America and China. • The American respondents have a substantially lower willingness to pay for BEV technology than the Chinese respondents.	Consumer preferences for conventional gasoline vehicles, HEV, PHEV, and BEV in China and the United States are modeled using data from choice-based conjoint surveys fielded in 2012–2013.
Liao et al. (2017)	Consumer preference and cost cutting	• A relatively shorter driving range compared to conventional gasoline vehicles is one of the biggest barriers to the widespread adoption of EVs.	Estimates of consumer preferences for financial, technical, infrastructure, and policy attributes are reviewed in a comprehensive review of 26 studies.

Reference	Scenario	Findings	Additional Notes
		• Regarding one-time price-reducing policies, reducing the purchase tax has a significant impact on consumer preferences for EVs in all four cases whereas reducing purchase price is only significant in two of the four cases. • The density of charging stations has a positive impact on the utilities of EVs, which demonstrates the importance of charging infrastructure development when promoting EV adoption. • Free parking and toll reduction are not significant factors in any of the cases.	
Hardman et al. (2018)	Infrastructure development	• The most important location for PEV charging is at the vehicle owner's residence, followed by work and public locations. • In the short term, PEV charging is not likely to cause an impact on electricity grid capacities. However, charging may need to be managed in the future when the EVs are being deployed in greater numbers. • The cost to charge a PEV should be lower than the refueling cost of conventional gasoline vehicles if PEVs are to retain the benefit of having a lower running cost.	A comprehensive literature review
Kumar et al. (2020)	Infrastructure deployment, incentives, and cost cutting	The authors provide some policy recommendations: • Policies should focus on reducing the total cost for a user to own an EV. • Policies should focus on fast-charging infrastructures. • Policies should facilitate home, residential, and workplace charging options. • Policies should optimize the charging network to minimize EV range anxiety in the public. • Policies should focus on functional attributes of the EV, such as range, top speed, and acceleration. • Policies should target high-income earners and individuals with advanced degrees.	A systematic review of 239 articles
Lee et al. (2020)	Infrastructure development	• Both BEV and PHEV owners relied heavily on home charging, with more than half of them only using home chargers. • The use of the home, work, and public charging infrastructure types is interconnected. Some EV owners display a more mixed use between the three charging infrastructure types compared to others. • This paper highlights the importance of having an integrated infrastructure investment plan that will account for different locational charging patterns among PEV owners.	An examination of the charging behavior of 7,979 PEV owners in California

Reference	Scenario	Findings	Additional Notes
Sun et al. (2020)	Technological advancements	• Charging infrastructure is crucial for EV use. The organization of the charging network, the technical challenges of infrastructure, and the possibilities of fair payment for charging are involved in the charging infrastructure network. • Economic profits of vehicle-to-grid technologies have received increased attention from grid operators and EV owners, and are heavily related to the strategies of charging and vehicle aggregation.	A review of EV technology development in key fields, such as the battery, charging, electronic motor, charging infrastructure, and emerging technology
Sanguesa et al. (2021)	Technological advancements and infrastructure development	• Batteries play a critical role because they directly influence the EV's autonomy and range. • The development of batteries with higher capacities will facilitate the use of faster and more powerful charging modes, along with the improvement of wireless charging technologies. • The creation of a universal connector that can be used globally can also benefit the deployment of EVs. • The EV will play a highly important role in the future smart cities, and having different charging strategies that can adapt to the users' needs will be of special relevance.	Review paper
Forsythe et al. (2023)	Technological advancements, infrastructure development, and consumer preference	• In recent years, technology improvements have been a more influential factor in driving the increase in the market share of BEVs than changes in consumer preferences. • The likelihood of consumers purchasing BEVs has grown over time because of technological improvements that have increased range and, in many cases, reduced price premiums of BEV models relative to their gasoline counterparts. • Most EVs with a range of at least 300 miles were valued by consumers equivalently or more than their conventional gasoline vehicle counterparts. • Although BEVs have certain disadvantages, such as longer recharging times compared to refueling a gasoline vehicle, these drawbacks are balanced out, on average, by lower operating costs and fast-charging capability, provided that the EV's range is sufficiently long.	Analysis of nationally representative survey data

EV Adoption Projections (AEO Approach)," the AEO 2023–2050 national BEV and PHEV adoption rates and the 2017–2022 Texas EV registration data were compared against the NCTCOG jurisdiction area EV data from TxDMV. Then, the EV adoption rates were calibrated for the area.

Based on the 21 month-to-month data points, the BEV and PHEV adoption rates within the NCTCOG jurisdiction area were projected using both linear and exponential regression methods, as shown in Figure 32. However, the trends only fit well between 2020 and 2023. The linear regression trend saw negative values before 2020. The trend also underestimated the EV adoption rates after 2023. Conversely, the projection trend from the exponential regression experienced substantial acceleration after 2023, which resulted in an overestimation of the adoption rates. Overall, the trends projected using state-level data fit well with the AEO's national baseline adoption rate projection. Therefore, the EV adoption rates in the AEO's scenarios were adopted for the NCTCOG jurisdiction area.

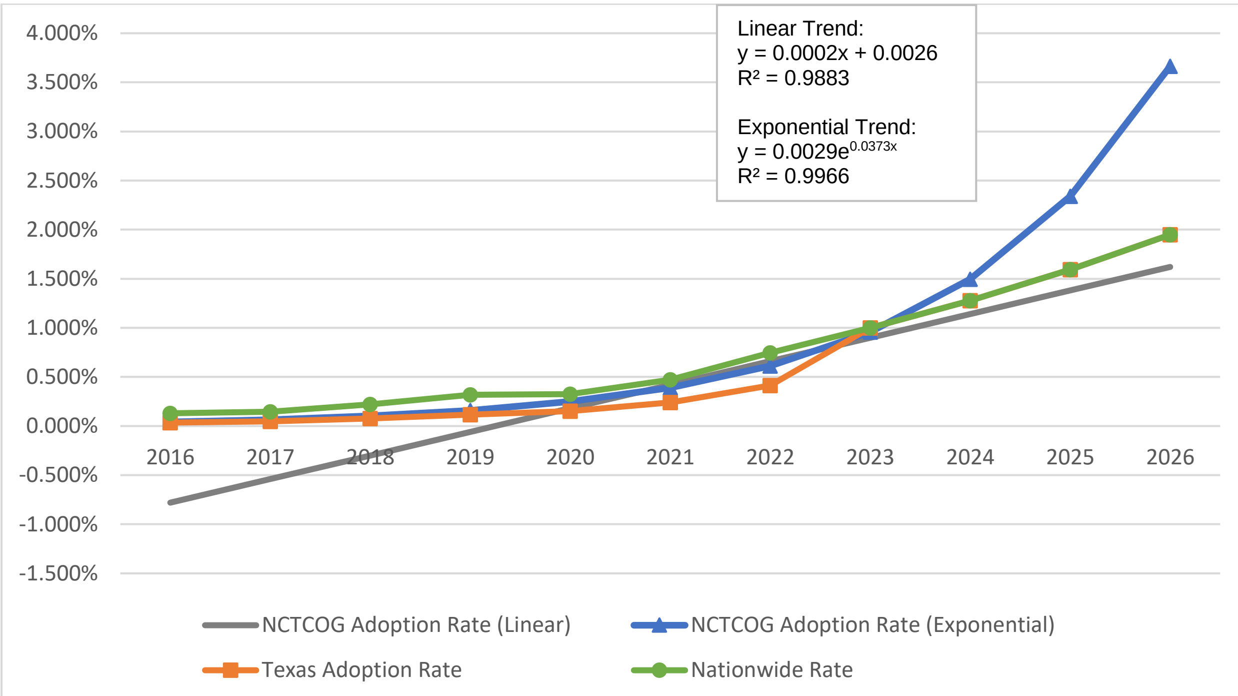


Figure 32. Comparison of the EV adoption rates of the different methodologies.

NCTCOG 2026 EV Adoption Rate

Based on the then-latest-available county-level EV registration data (Table 13) and the AEO's reference, high-oil-price, and low-oil-price scenarios (Figure 30), the BEV and PHEV adoption rates for 2026 were projected for the NCTCOG jurisdiction area counties. The two oil price scenarios assume that the promotion or impediment of EV adoption is primarily influenced by the fluctuations in high or low oil prices. Oil and gas supply, followed by economic growth and policy incentives, plays a subsequent role, while power generation cost (zero-carbon technology cost) has the least impact on EV adoption.

The projections assumed that the EV adoption trends among the NCTCOG jurisdiction area counties in 2026 remained consistent with the 2023 vehicle registration data. Table 14 lists the projected EV adoption rate for 2026 for each county that makes up the NCTCOG jurisdiction area. Based on the reference case, the EVs are estimated to be 2.69 percent of all registered vehicles in the area in 2026. Through the low- and high-oil-price scenarios, it was projected that the EV adoption rate in the area will be between 2.33 and 3.85 percent in 2026.

The results show that from 2023 to 2026, the projected EV adoption rate in the study area increases from 0.98 to 2.69 percent (baseline reference), 2.33 percent (low scenario), and 3.85 percent (high scenario), which represent notable increases of 174, 138, and 293 percent, respectively. In terms of regional variation, the projected EV adoption rates vary from 0.55 to 7.66 percent among counties in NCTCOG in 2026.

Table 14. Projected 2026 EV Adoption Rate (BEVs and PHEVs) in NCTCOG Counties

County	Baseline Reference Case			High-Oil-Price Scenario			Low-Oil-Price Scenario		
	All Vehicles	EV Count	EV Adoption Rate	All Vehicles	EV Count	EV Adoption Rate	All Vehicles	EV Count	EV Adoption Rate
Collin	911,404	44,266	4.86%	909,510	69,675	7.66%	915,912	42,464	4.64%
Dallas	2,210,196	52,174	2.36%	2,205,605	74,518	3.38%	2,221,129	45,415	2.04%
Denton	781,839	33,693	4.31%	780,215	48,123	6.17%	785,706	29,328	3.73%
Ellis	188,985	2,334	1.24%	188,593	3,334	1.77%	189,920	2,032	1.07%
Rockwall	105,509	2,809	2.66%	105,290	4,012	3.81%	106,031	2,445	2.31%
Tarrant	1,781,478	35,697	2.00%	1,777,777	50,984	2.87%	1,790,289	31,072	1.74%
Parker	157,142	2,070	1.32%	156,815	2,957	1.89%	157,919	1,802	1.14%
Kaufman	148,782	1,919	1.29%	148,473	2,741	1.85%	149,518	1,671	1.12%
Hood	67,478	796	1.18%	67,338	1,138	1.69%	67,812	693	1.02%
Johnson	178,675	1,668	0.93%	178,304	2,382	1.34%	179,559	1,451	0.81%
Hunt	100,693	663	0.66%	100,484	947	0.94%	101,191	577	0.57%
Somervell	10,041	63	0.63%	10,020	91	0.90%	10,090	55	0.55%
Wise	81,838	472	0.58%	81,668	674	0.83%	82,243	411	0.50%
Erath	37,247	174	0.47%	37,169	248	0.67%	37,431	151	0.40%
Navarro	49,847	192	0.38%	49,743	274	0.55%	50,094	167	0.33%
Palo Pinto	28,639	94	0.33%	28,580	135	0.47%	28,781	82	0.29%
NCTCOG	6,839,793	183,806	2.69%	6,825,584	262,521	3.85%	6,873,625	159,995	2.33%

Note: The 2026 baseline reference case, high-oil-price case, and low-oil-price case projected multipliers (growth ratio based on AEO data) for all vehicles are 1.01085, 1.00875, and 1.01585, respectively.

EV Projections and Charging Demands

To accommodate the widespread adoption of EVs, new requirements are demanded from the transportation and energy infrastructure, most importantly charging facilities and energy demands. To help us understand the potential broader impacts of widespread EV adoption on charging demands—and, consequently, the potential increase in pollutants emitted from power plants within Texas—we aimed to estimate the current and future EV charging demands based on the latest available EV adoption rates and projection of EV sales.

Overview of Electrical Generation for Texas

This section provides an overview of the key data sources that we identified to project EV charging demands.

Electric Reliability Council of Texas

ERCOT is the independent system operator for the region that manages the flow of electric power to more than 26 million Texans. More information on the organization is available on its website: https://www.ercot.com/about.

ERCOT oversees roughly 90 percent of electricity generated for consumption in the state, and the ERCOT grid covers 214 of the 254 counties in Texas, as shown in Figure 33. The portions of Texas excluded from the ERCOT grid are the 22 counties in eastern Texas along the borders of Louisiana and Arkansas, the 16 counties in portions of the Texas Panhandle, and 2 counties at the western tip of the state (El Paso and Hudspeth). ERCOT regularly provides fuel mix reports that contain the electrical generation by source type in 15-minute increments, available at https://www.ercot.com/gridinfo/generation [43].

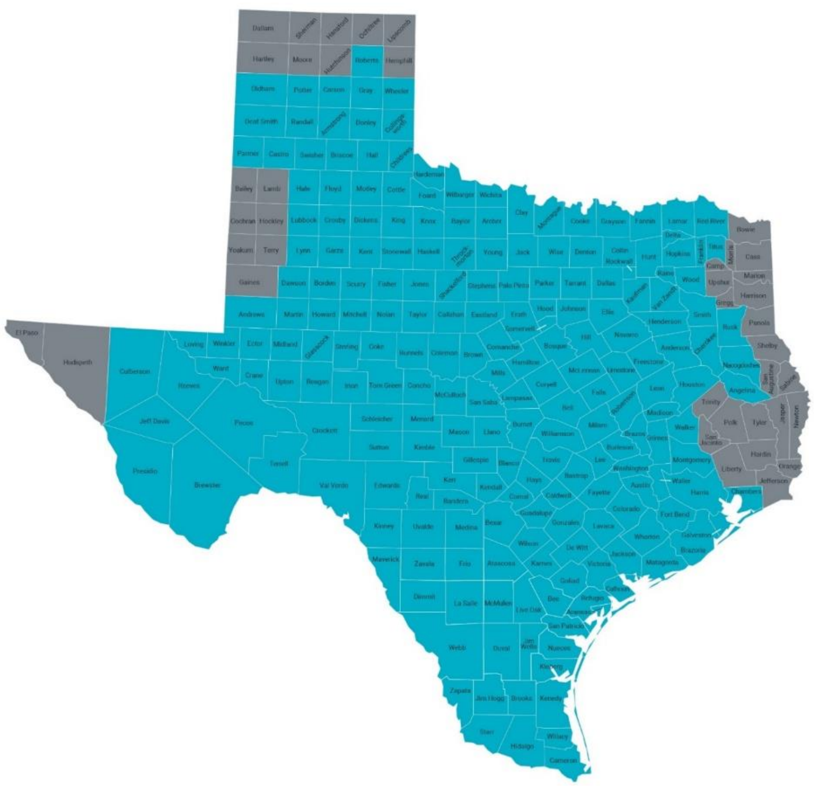
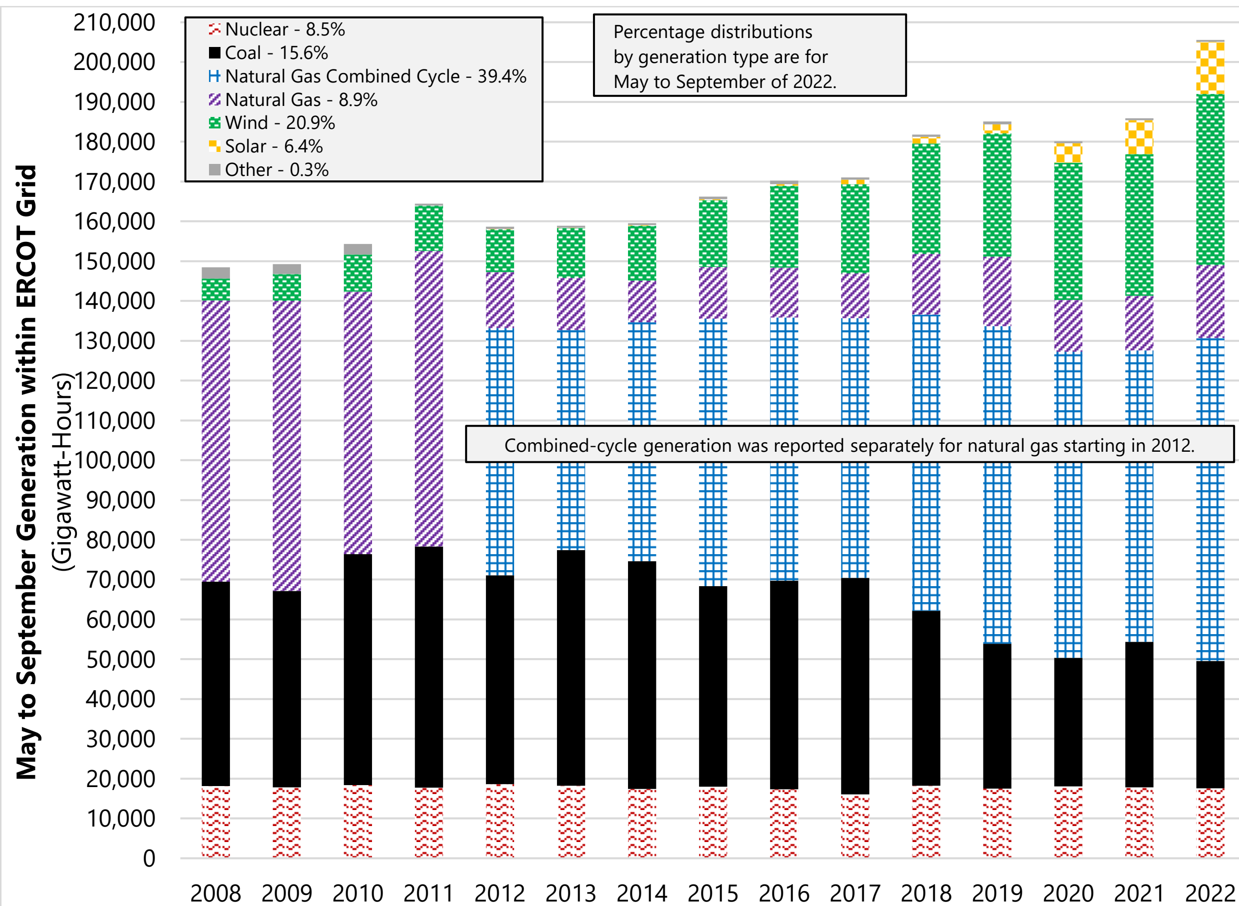


Figure 33. 214-county coverage of the ERCOT grid.

Overall Electricity Generation Trend in the ERCOT Grid

The peak ozone season in the Texas metropolitan areas typically occurs during the warmer months of May through September. We chose to focus on these five months because the highest eight-hour ozone concentrations are typically measured during this period. Figure 34 provides a summary of ERCOT electrical generation by fuel type for the five months of May to September from 2008 through 2022. On average, the total amount of electricity generated during these peak ozone season months has increased to meet the additional demands that come from population growth. The exceptionally hotter summers of 2011 and 2022 showed notable increases in electricity generation compared to adjacent years.

In addition to the overall electricity generation trend, we also looked at the individual electricity generation trend for each fuel source type. As shown in Figure 34, during the 15 years, the share of electricity generation from coal plants (shown in black) started declining after 2013. Electricity generation from the two nuclear plants in Texas (shown in red) has remained relatively constant, whereas the electricity generation from natural gas, wind, and solar plants has increased, more substantially for natural gas (shown in blue and purple) and in a steady pace for wind (shown in green) and solar (shown in yellow). Upon closer inspection, Figure 34 shows that the combined amount of electricity generated from natural gas and coal has hovered between 140,000 and 150,000 GWH across the 15 years. So, the decline in coal generation over the last 10 years has essentially been offset by an increase in natural gas generation. Since nuclear generation has remained constant, the net increase in total electricity demand over this period was essentially provided by steady growth in wind and solar sources.



Notes:
Solar generation was not reported separately in the ERCOT fuel mix reports until 2012.
Prior to 2012, all generation from natural gas was grouped for reporting. Starting in 2012, natural gas generation was broken out into “combined cycle” and “turbine-only” categories. The combined cycle is a two-step process that combusts the fuel to run a gas turbine and then uses the heat of the exhaust to boil water for running a steam turbine. The turbine-only process involves running just a gas turbine or just a steam turbine. For a given quantity of natural gas input, the combined cycle yields higher generation output and is suited for continuous base-load operation. The turbine-only process is less efficient per unit of natural gas input but is more suited to intermittent peaking operation that lasts for a limited number of hours and requires rapid start-up and shutdown.

Figure 34. Electrical generation by fuel type in the ERCOT grid, May to September 2008 to 2022.

Electricity Generation in the ERCOT Grid in 2022

A more in-depth analysis of the electricity generation by source type was performed for the most recent May-to-September period from the year 2022 by looking at the electricity generation by the hour (Figure 35) and by the day (Figure 36).

Figure 35 presents the average amount of electricity generated by the hour for each source type within the ERCOT grid during May to September 2022. As shown, the two nuclear plants (in red) continuously provide steady-state base-load power of roughly 5,000 MWh. The base-load coal plants (in black) and combined-cycle natural gas plants (in blue) have their minimum generation overnight and maximum in the afternoon but do not vary nearly as much as natural gas turbine plants (in purple) where generation differs significantly from overnight to afternoon. On average, wind power is higher during overnight hours than in the afternoon, but the total generated does not vary as much as natural gas turbine generation. Finally, solar generation peaks during midday hours and is nonexistent overnight.

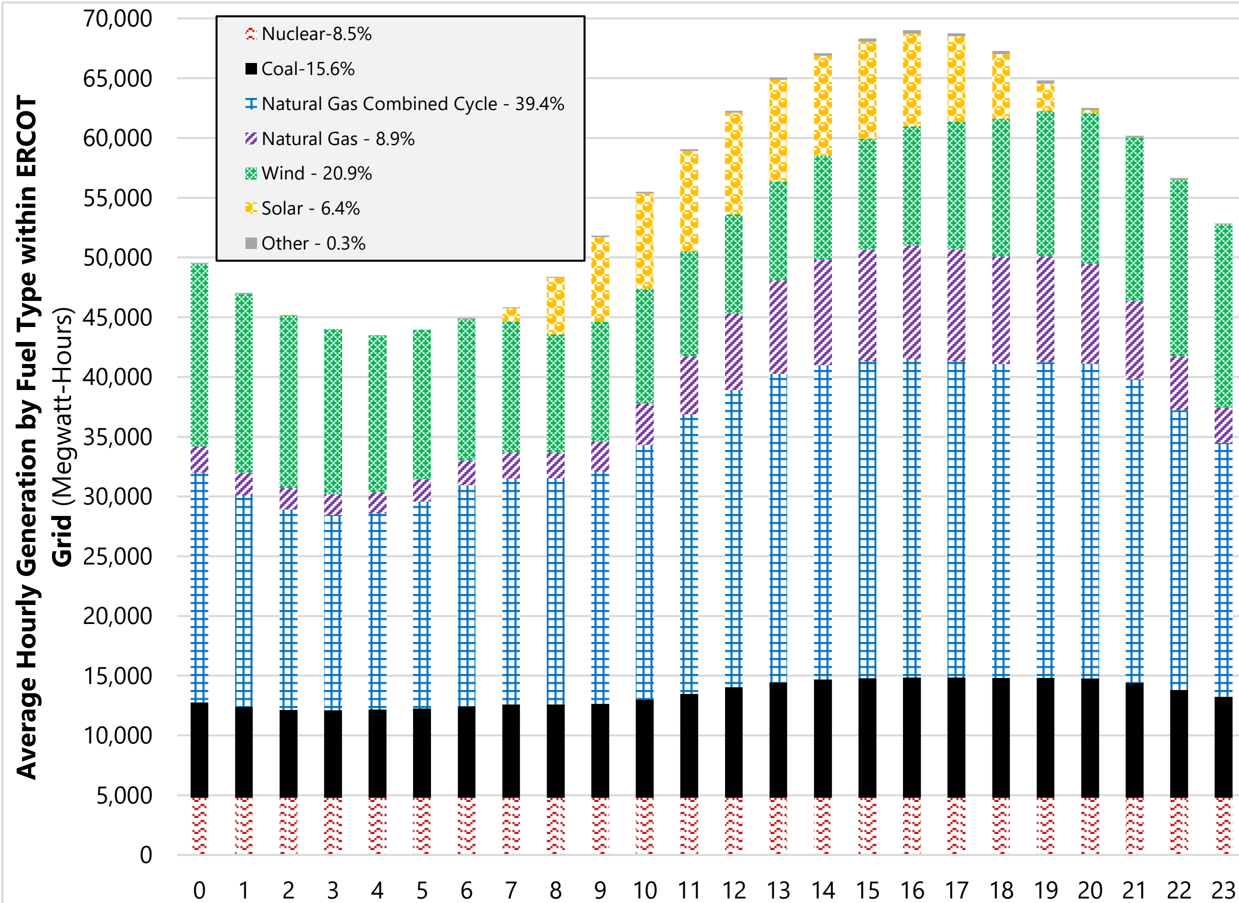


Figure 35. Average hourly electricity generated by fuel type in the ERCOT grid, May to September 2022.

On any given day, both the total demand for electricity and the mix of source types providing that electricity will vary. This is demonstrated in Figure 36 for the daily generation from the six primary source types contained within the ERCOT grid for May to September 2022. As shown, the peak demand days[1] in 2022 ranged from mid-June through mid-August 2022, with the highest demand days occurring in July due to the highest outdoor temperatures and demands for indoor cooling. During these peak demand days, nuclear (in red) generation remained relatively constant while the generation from other sources varied, particularly from wind (in green) and natural gas turbine (in purple) sources. The daily total generation from each source type for the 153 days from May to September 2022 is available in Appendix A.

[1] Peak demand refers to the period (day, season, or year) when electricity demand is at its highest. During summer months, the peak demand period is usually in the afternoon to account for cooling demands.

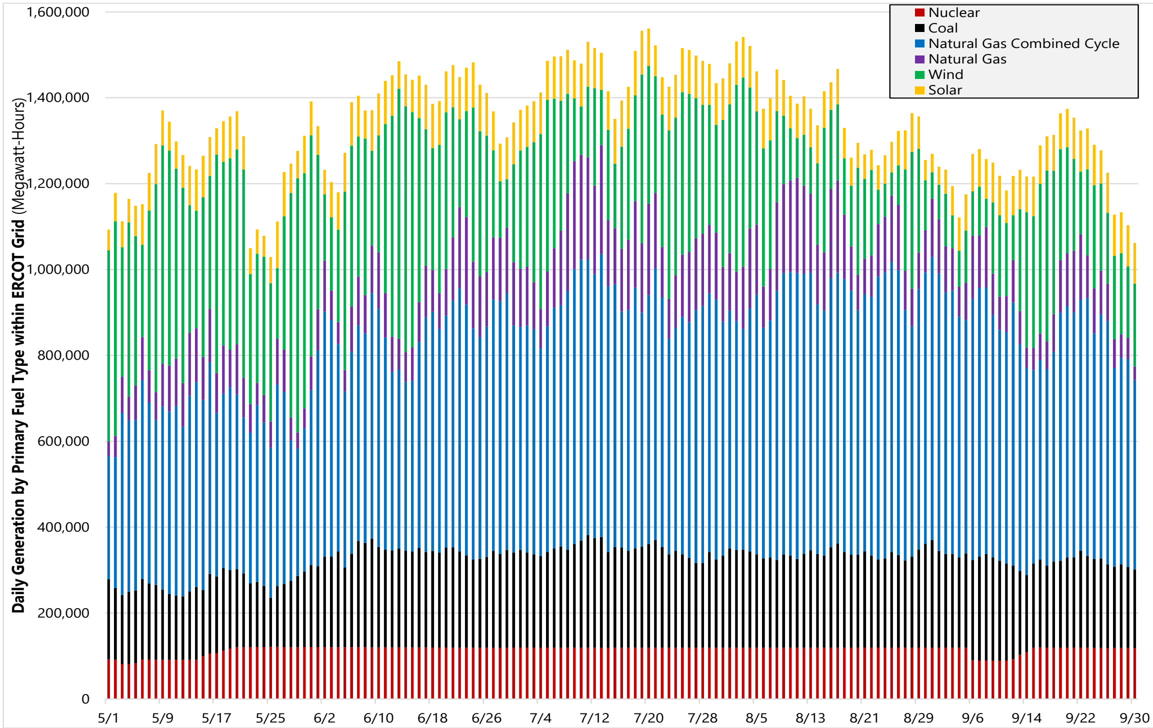


Figure 36. Daily generation by fuel type within the ERCOT grid, May to September 2022.

The daily generation from natural gas turbines and wind (see Appendix A) are combined and presented in Figure 37. The combined daily generation from these two sources hovers between 700,000 and 900,000 MWh, with the natural gas turbines playing the role of swing producer. At any given time, total generation must match total demand to maintain balance on the grid. For example, with nuclear generation constant and wind/solar sources dependent on varying meteorological conditions, the dispatchable fossil fuel sources of coal and natural gas must provide the remaining generation needed to match demand. On days with low wind speeds, natural gas turbine generation must increase so that overall demand on the ERCOT grid is satisfied. Conversely, on days with higher wind speeds, less natural gas turbine generation is needed.

To further demonstrate the highly variable nature of wind and solar sources, the hourly generation from these fuel types is presented for July 1–15, 2022. As Figure 38 shows, wind generation ranged from almost 22,000 MWh during some hours on July 5 to as low as 1,000 MWh during some hours between July 10 and 14. Figure 39 shows that solar generation varies widely as well, but in a much more predictable pattern of zero during overnight hours and peaking at midday with total daily generation not varying much, provided that days are sunny with little or no cloud cover.

The daily generation totals for all 153 days from May 1 through September 30, 2022, were sorted and grouped into three categories, which are 44 low-demand days, 64 medium-demand days, and 45 high-demand days. The intent was to see if and how generation by fuel type would vary across these groups, and Figure 40 presents the results. As expected, generation from the two nuclear plants in Texas was constant. From the low- to high-demand days, coal and solar generation increased slightly, while natural gas generation increased the most, and wind power tended to decrease. This indicates that, on average, the days with the highest electricity demand occur on the hottest days (evident from the increase in solar) and most stagnant days (evident from the decrease in the wind), and the bulk of the increased generation needed on these days comes from natural gas power plants.

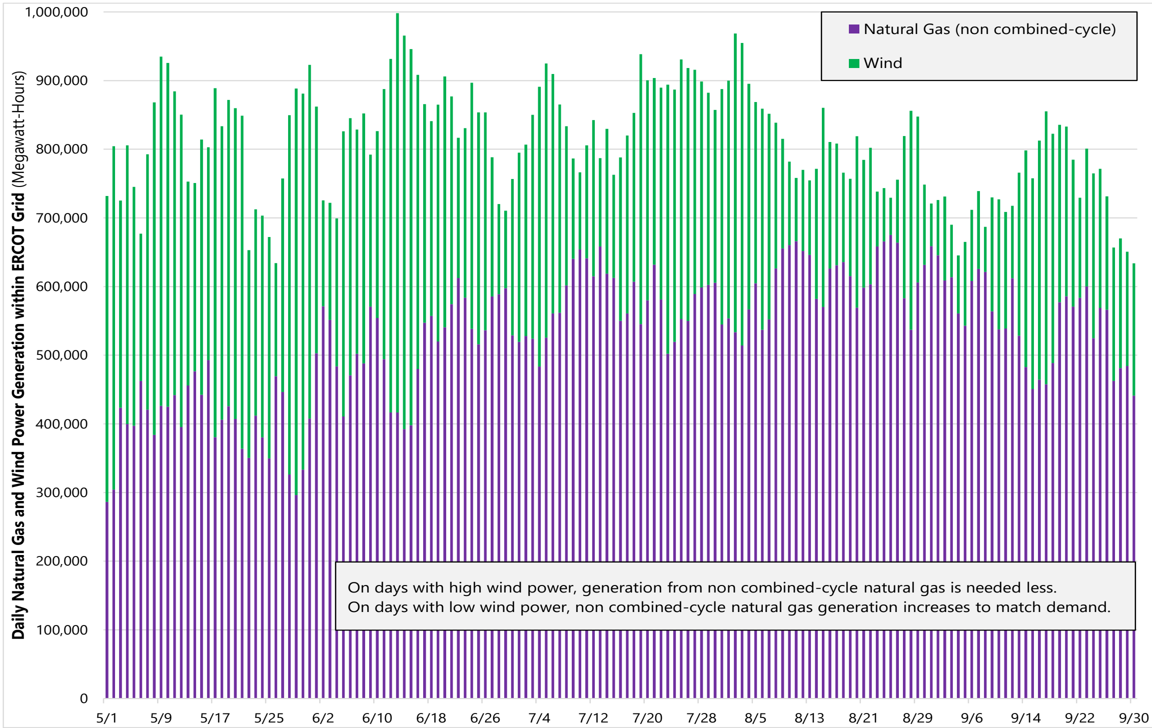


Figure 37. Daily natural gas turbine and wind generation, May to September 2022.

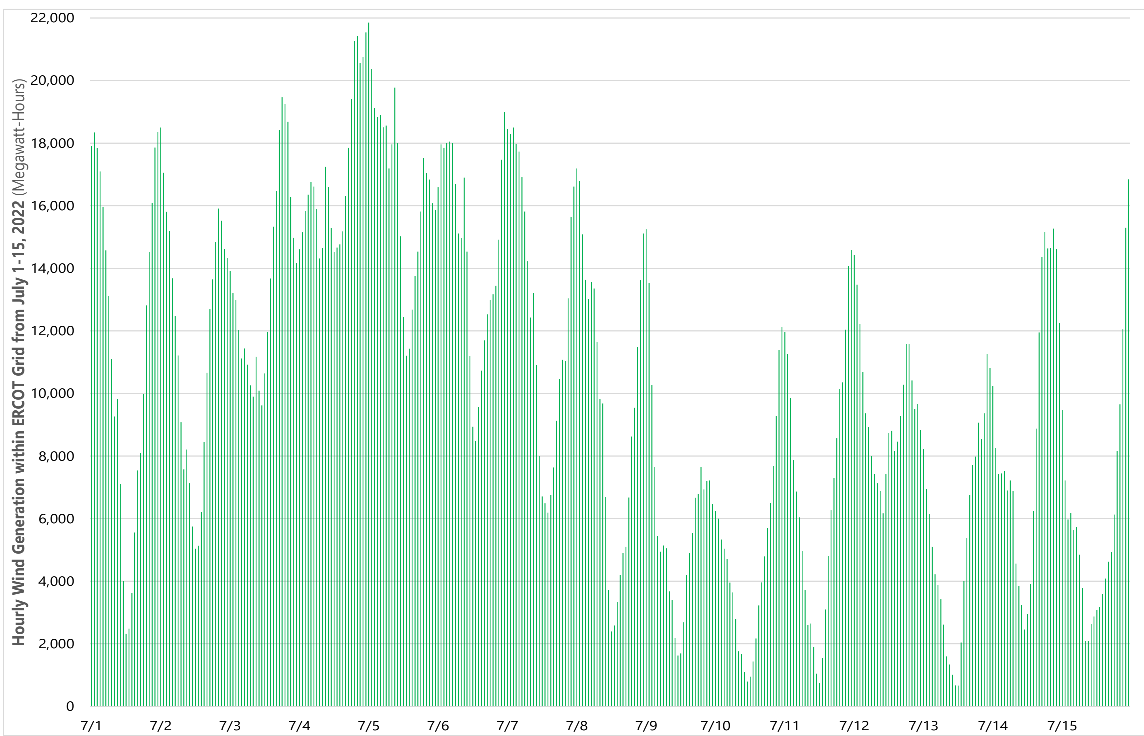


Figure 38. Hourly wind generation in ERCOT, July 1 to 15, 2022.

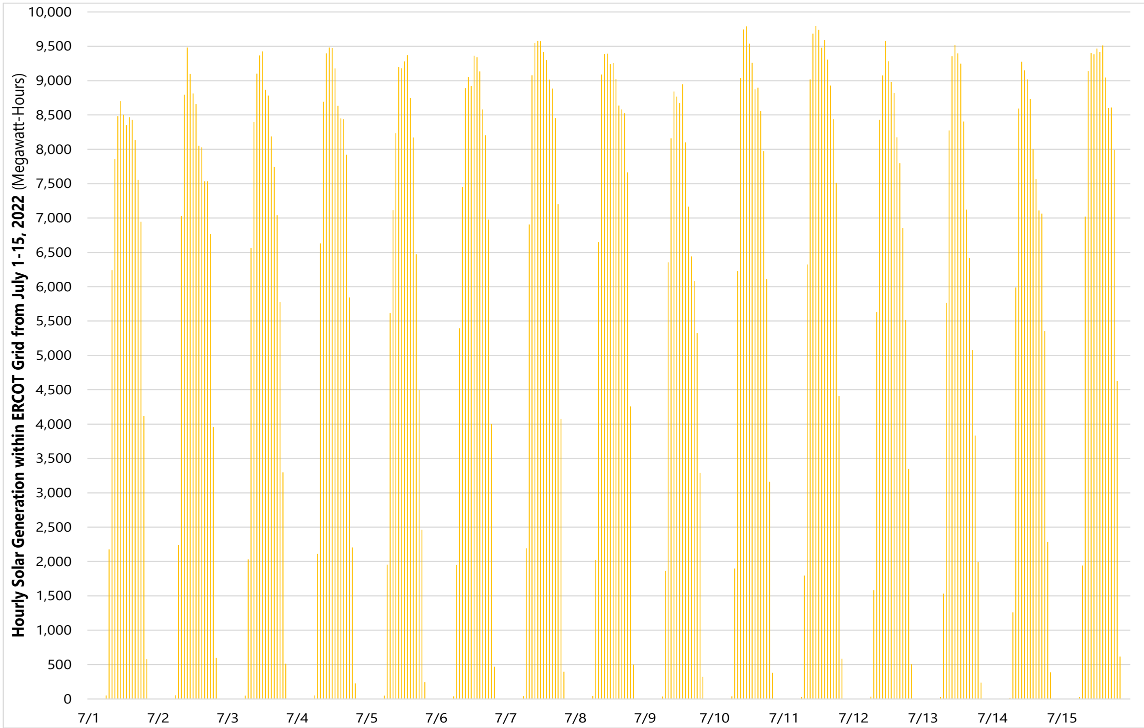


Figure 39. Hourly solar generation in ERCOT, July 1 to 15, 2022.

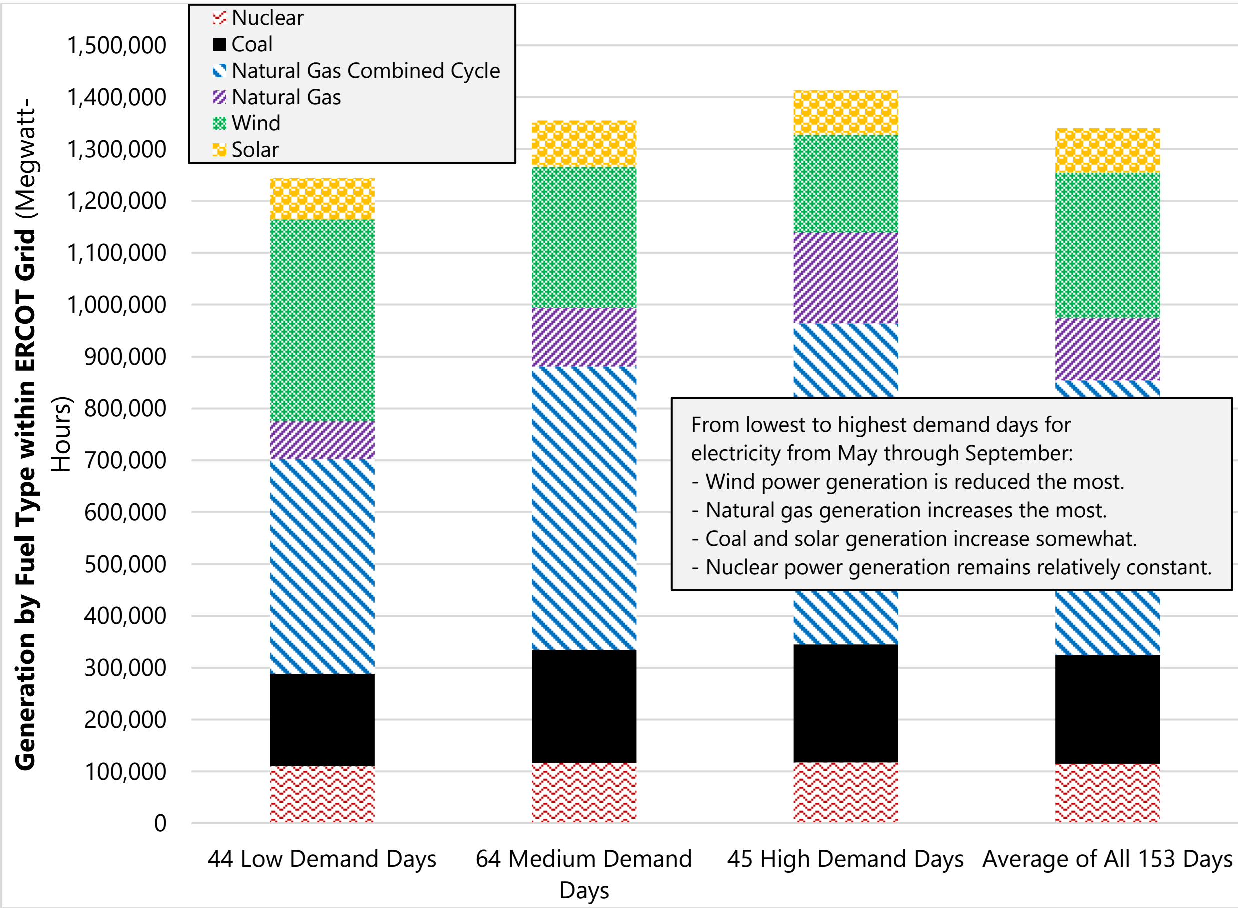


Figure 40. Generation by fuel type on the low-, medium-, and high-demand days in 2022.

Clean Air Markets Program Data

EPA manages the Clean Air Markets Program Data (CAMPD) website, available at https://campd.epa.gov/, which archives hourly electric generation and emissions measurements of NO_X, SO_2, and carbon dioxide (CO_2) from most of the fossil-fuel power plants operating throughout the country [44].

Hourly Electricity Generation for Texas Power Plants in the CAMPD

For the year 2022, 128 fossil fuel power plants from Texas are included in the CAMPD, which included 113 with natural gas as the primary fuel type, 14 with coal as the primary fuel type, and 1 with wood as the primary fuel type. Of the 113 natural gas plants, 3 reported zero generation and emissions during 2022.

From May through September 2022, 3 of the coal plants and 9 of the natural gas plants had relatively flat operating profiles where the hourly generation level was relatively constant. The 12 flat operating profiles and their plant names as listed in the CAMPD are provided in Figure 41 for coal and Figure 42 for natural gas. The profiles for these 12 plants indicate that, on average, their generation does not respond much to hourly changes in electricity demand throughout Texas.

The remaining 112 coal and natural gas power plants in Texas do respond to the hourly changes in electricity demand to different degrees. These 112 plants can be grouped into four categories, as shown in the average hourly operating profiles by category in Figure 43. The four categories are:

- 11 base-load coal plants with spare capacity, mostly overnight.

- 40 base-load natural gas plants with spare capacity, mostly overnight.
- 25 intermediate or load-following natural gas plants with a generation that fluctuates between day and night.
- 36 peaking plants that typically have zero or minimal overnight generation and are run primarily to meet the highest demand during some afternoons.

The operating profiles and plant names as listed in the CAMPD for each of these four groups are available in Appendix B.

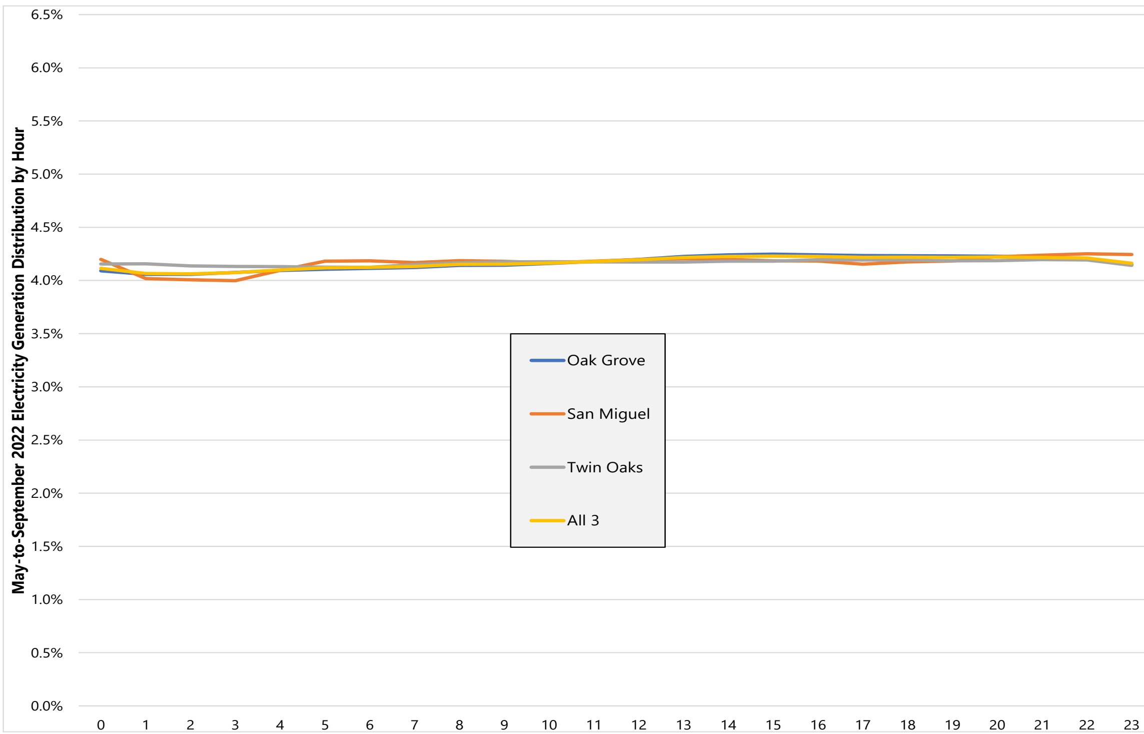


Figure 41. Three coal plants with flat profiles, May to September 2022.

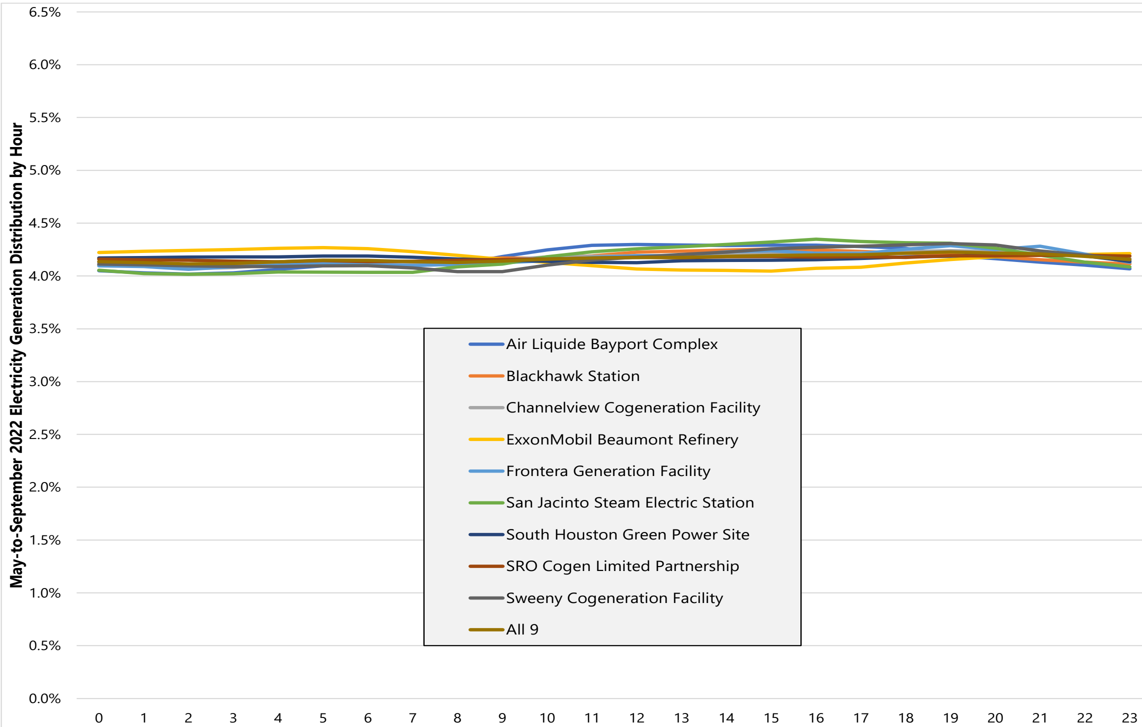


Figure 42. Nine natural gas plants with flat profiles, May to September 2022.

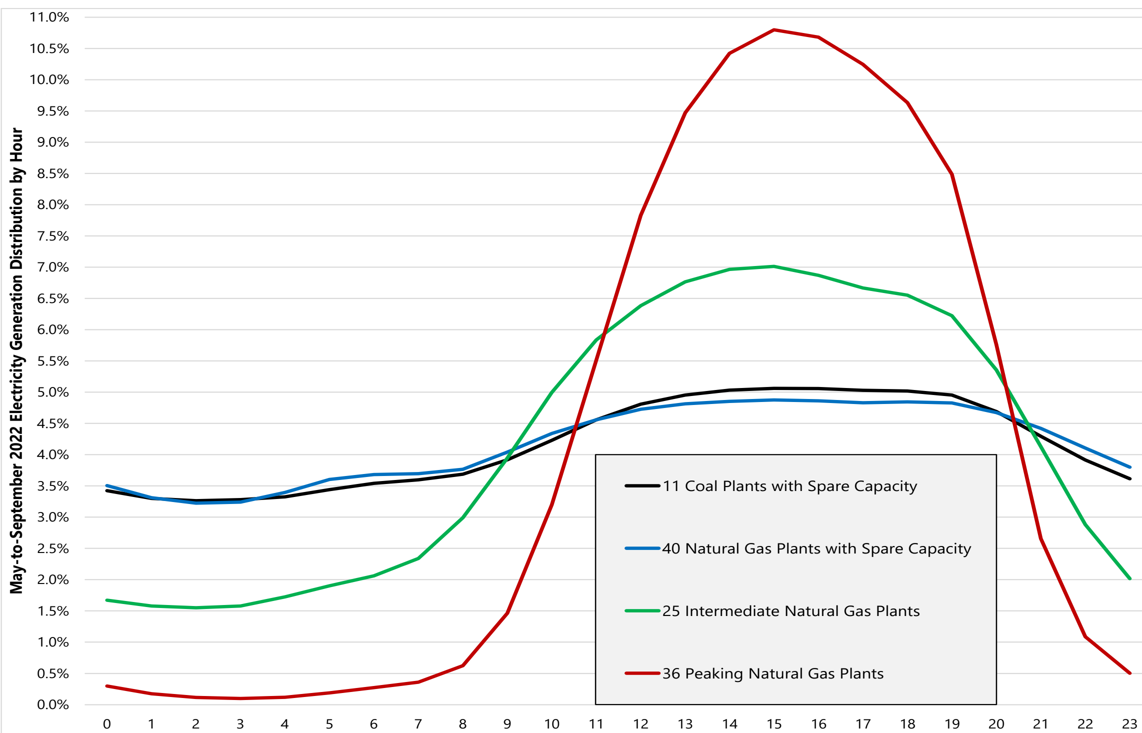


Figure 43. Hourly profiles for coal and natural gas plants, May to September 2022.

For the 124 coal and natural gas plants, the total generation for the 153 days from May to September 2022 was divided into the low-demand days when total generation was below 1 million MWh, the medium-demand days when total generation was between 1 and 1.2 million MWh, and the high-demand days when total generation was above 1.2 million MWh. Table 15 summarizes the average daily generation levels for these three groups.

Table 15. Average Generation on Low/Medium/High Days, May to September 2022

Power Plant Group	44 Low-Demand Days below 1 Million MWh	64 Medium-Demand Days from 1 to 1.2 Million MWh	45 High-Demand Days above 1.2 Million MWh
3 coal plants with flat profiles	58,301	58,045	55,634
11 coal plants with spare capacity	182,742	238,109	270,251
9 natural gas plants with flat profiles	79,210	85,002	89,623
40 natural gas plants with spare capacity	446,821	567,336	631,191
25 intermediate natural gas plants	84,096	140,462	193,085
36 peaking natural gas plants	22,462	26,739	49,466
124 coal and natural gas plants	873,632	1,115,692	1,289,251

Error! Not a valid bookmark self-reference. demonstrates how the average generation levels by power plant group for the low- and medium-demand days compare to those for the high-demand days. As shown, there are relatively small differences across the low, medium, and high days in the generation levels for the coal and natural gas plants with flat operating profiles. Compared to the high days (assigned here at 100 percent for comparison purposes), the coal and natural gas plants with spare capacity generate roughly 70 percent on low days and 90 percent on medium days. The most pronounced differences are with the intermediate and peaking natural gas plants where both groups more than double their generation levels between the low and high days.

Table 16. Average Generation Relative to High-Demand Days

Power Plant Group	44 Low-Demand Days Relative to 45 High Days	64 Medium-Demand Days Relative to 45 High Days	45 High-Demand Days Relative to 45 High Days
3 coal plants with flat profiles	104.8%	104.3%	100.0%
11 coal plants with spare capacity	67.6%	88.1%	100.0%
9 natural gas plants with flat profiles	88.4%	94.8%	100.0%
40 natural gas plants with spare capacity	70.8%	89.9%	100.0%
25 intermediate natural gas plants	43.6%	72.7%	100.0%
36 peaking natural gas plants	45.4%	54.1%	100.0%
124 coal and natural gas plants	67.8%	86.5%	100.0%

Emissions from Texas Power Plants in the CAMPD

For each power plant, the CAMPD reports hourly generation, NO_X emissions, SO_2 emissions, and CO_2 emissions. Aggregated emission rates by power plant were obtained by dividing total emissions for each pollutant by total gross load generation for the 153 days from May to September 2022. Table 17, Table 18, and Table 19 present the aggregated emission rates for NO_X, SO_2, and CO_2, respectively, in units of pounds per MWh.

Table 17. NO_X Emission Rates by Power Plant Group, May to September 2022

Power Plant Group	Minimum NO_X Rate (Pounds per MWh)	Maximum NO_X Rate (Pounds per MWh)	Average NO_X Rate (Pounds per MWh)
3 coal plants with flat profiles	0.69	1.74	0.87
11 coal plants with spare capacity	0.63	2.04	1.31
9 natural gas plants with flat profiles	0.07	0.46	0.15
40 natural gas plants with spare capacity	0.03	1.06	0.19
25 intermediate natural gas plants	0.10	1.93	0.58
36 peaking natural gas plants	0.08	15.67	1.04
124 coal and natural gas plants	0.03	15.67	0.53

Table 18. SO_2 Emission Rates by Power Plant Group, May to September 2022

Power Plant Group	Minimum SO_2 Rate (Pounds per MWh)	Maximum SO_2 Rate (Pounds per MWh)	Average SO_2 Rate (Pounds per MWh)
3 coal plants with flat profiles	1.30	8.55	2.33
11 coal plants with spare capacity	0.21	6.60	2.79
9 natural gas plants with flat profiles	<0.01	0.13	0.01
40 natural gas plants with spare capacity	<0.01	0.01	<0.01
25 intermediate natural gas plants	<0.01	0.01	0.01
36 peaking natural gas plants	<0.01	0.02	0.01
124 coal and natural gas plants	<0.01	8.55	0.72

Table 19. CO_2 Emission Rates by Power Plant Group, May to September 2022

Power Plant Group	Minimum CO_2 Rate (Pounds per MWh)	Maximum CO_2 Rate (Pounds per MWh)	Average CO_2 Rate (Pounds per MWh)
3 coal plants with flat profiles	2,104	2,400	2,167
11 coal plants with spare capacity	1,883	2,371	2,123
9 natural gas plants with flat profiles	802	5,139	1,198
40 natural gas plants with spare capacity	765	1,322	902
25 intermediate natural gas plants	833	1,469	1,069
36 peaking natural gas plants	895	1,862	1,141
124 coal and natural gas plants	765	5,139	1,278

Estimation of EV Charging Demand

This section presents the methodology to estimate of EV charging demand in this study.

TTI has developed an innovative Energy Demand and Emission Estimation Model. This model leverages outputs from a traditional four-step Travel Demand Model (TDM) and incorporates vehicle performance data to accurately estimate energy consumption and emissions for two distinct categories of light-duty vehicles: ICE and EV.

The model provides versatile outputs, including energy consumption categorized by location type (such as home or work), energy consumption and emissions based on trip purpose and time-of-day, and energy consumption and emissions data at the Traffic Analysis Zones (TAZ) identified within a TDM.

The model can be used to assess changes in energy demand, encompassing both electricity and fossil fuels, as well as on-road emissions. Therefore, it allows users to analyze and quantify the impact of various factors such as alterations in travel patterns, advancements in vehicle technology, and policy implementations.

Overview of the model workflow

Figure 44 presents an overview of the model workflow for home-based trips. The workflows for other trip purposes are similar.

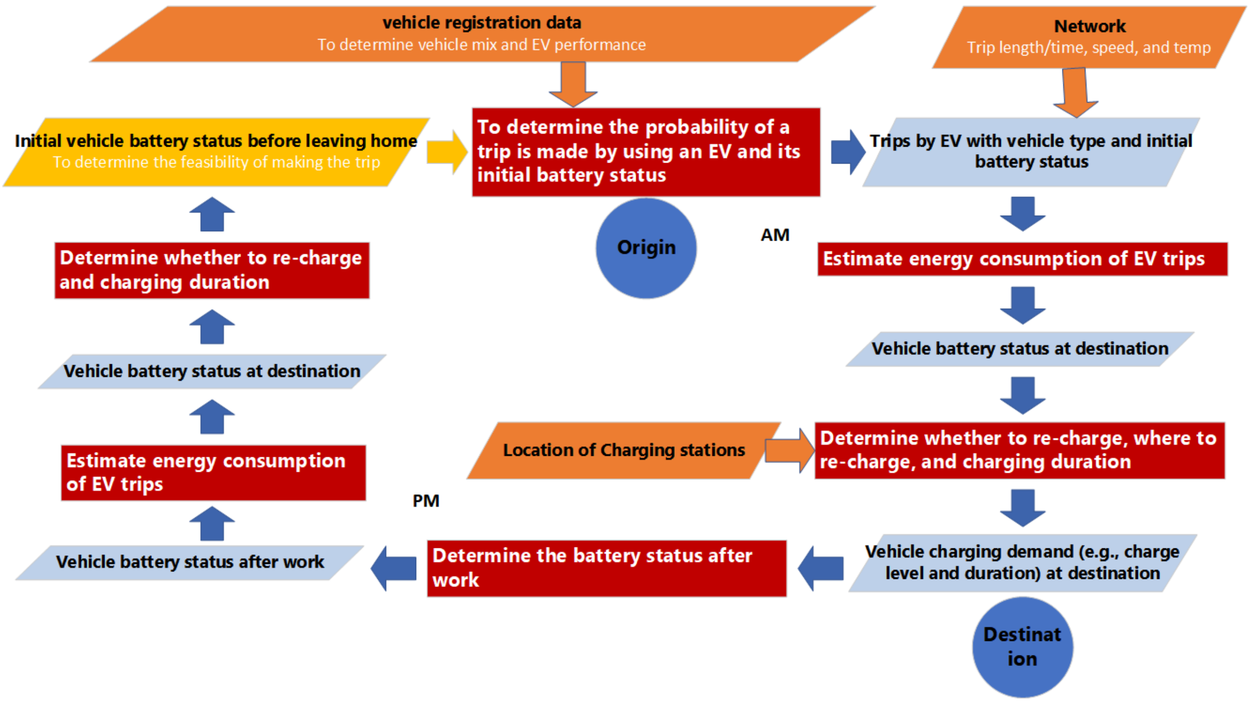


Figure 44: Model Workflow for Home-Based Work Trips /specify which model or which workflow/

The first thing to estimate the PEV charging demand is to estimate the travel demand by EVs. To do so, we used the trips predicted by TDM. These trips are trips made by all the vehicles including EV and ICE.

For each trip between an Origin-Destination (OD) pair in the TDM, the model assigns the trip an LDV, which could be an ICE or PEV. The LDV is randomly selected from local fleet mix subject to constraints such as vehicle performance (e.g., range) and gas/battery status. To estimate the trips by EVs, we assign vehicles to the trips based on the local EV population forecasts. The local fleet mix includes both ICE and PEV and is developed using factors including local registration data and forecasts of future PEV population from EIA's AEO.

The model then estimates the vehicle fuel or energy consumption (i.e., gas or electricity) during the OD trip based on factors such as average OD travel speed and travel time, and vehicle energy consumption rate. The average OD travel speed and travel time are outputs from the TDM. The PEV energy/fuel economy is obtained from the U.S. Department of Energy's Alternative Fuels Data Center [45]. Table 20 presents several examples of PEV's energy/fuel economy.

Table 20: PEV Energy/Fuel Economy

Model	Alternative Fuel Economy City	Alternative Fuel Economy Highway	Alternative Fuel Economy Combined	Conventional Fuel Economy City	Conventional Fuel Economy Highway	Conventional Fuel Economy	Engine Cylinder Count	Electric-Only Range	Total Range
Tonale eAWD			77	29	29	29	4	33	360

Polestar 2 Dual Motor Performance Pack	100	90	95					247	
Pacifica Hybrid			82	29	30	30	6	32	520
Taycan Turbo Cross Turismo	72	72	72					204	
Ioniq Electric	145	121	133					170	

PEV's energy/fuel economy is a function of temperature and vehicle speed. To consider their relationship in the estimation of PEV charging demand, this study adopted the PEV range discount factors due to temperature and vehicle speed developed in [46]. Figure 45 presents the discount factor for PEV energy economy with respect to speed at temperature 32 Fahrenheit and 105 Fahrenheit, respectively. The PEV energy economy is the lowest during low speed, and the economy is the highest at around 32 mph and reduces as speed increases. The discount factors are applied to the energy fuel economy obtained from [45].

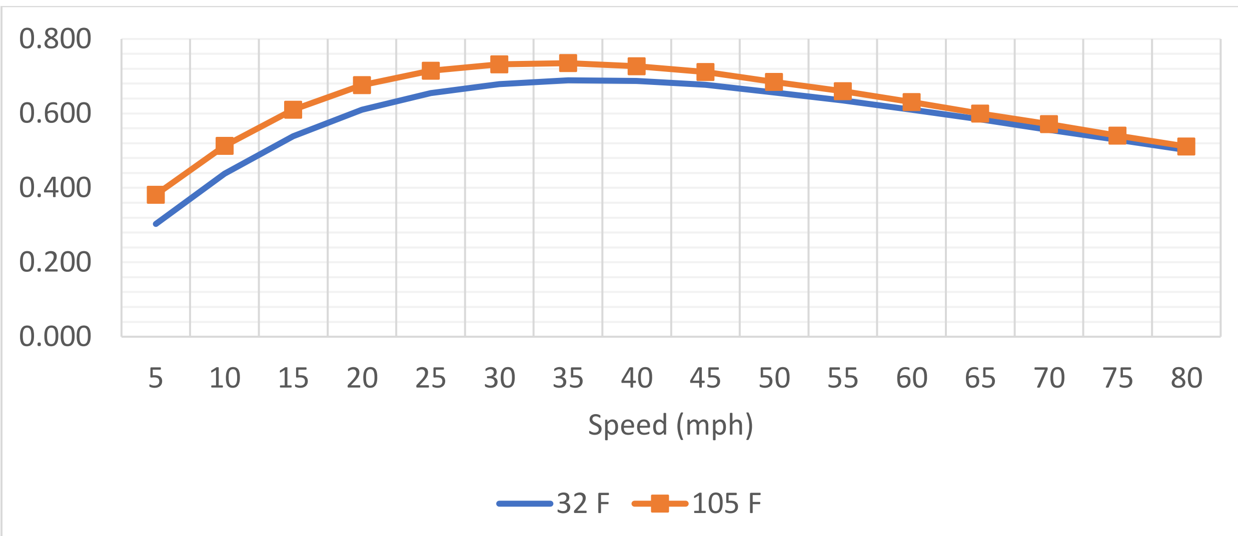


Figure 45: EV Energy Economy Discount Factor

The amount of the energy consumed by PEV from trip origin to trip destination is calculated as follows:

$$E = Travel\_Distance * Optimal\_Energy\_Rate * Discount(Average\_Speed, Temperature)$$

where

$Travel\_Distance$ is the travel distance from trip origin to trip destination. The trip time is obtained from TDM output.

$Optimal\_Energy\_Rate$ is the PEV's energy consumption rate (mile/KwH) at the optimal condition.

$Discount(Average\_Speed, Temperature)$ is the discount factor based on average speed and temperature.

For trips starting from home, this study assumes that the PEV is sufficiently charged. For trips starting at a non-home location, a PEV's initial battery status is determined by selecting from the battery status of the PEVs that have parked at the TAZ and the TAZ is not their home TAZ.

Subsequently, the model calculates the amount of refuel/recharge the vehicle needs and determines the location of the refuel based on the trip purpose, vehicle characteristics (e.g., fuel capacity), and assumptions on driver refueling behaviors. The following assumptions are made on driver refueling behaviors.

- **Refueling assumptions for BEV**

1. At non-home locations, recharge only if current battery level is not enough to get to destination. The amount of recharge is just enough to get to destination,
2. The difference between electricity consumed and recharged at non-home locations will be billed to home recharge.

- **Refueling assumptions for PHEV**

1. Recharge battery whenever possible to avoid using ICE,
2. The difference between electricity consumed and recharged at non-home locations will be billed to home recharge.

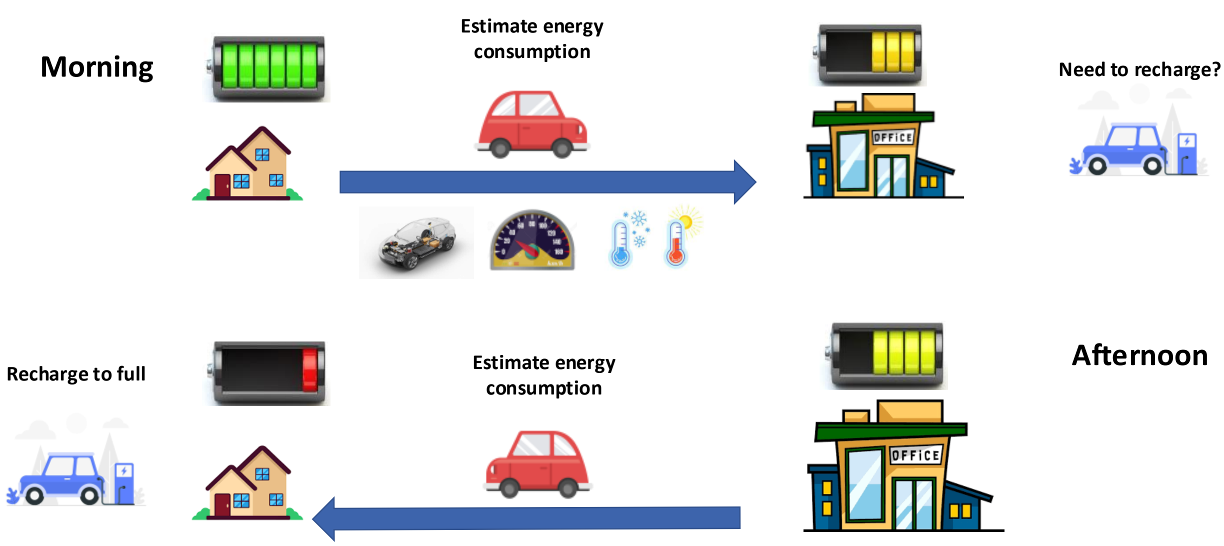


Figure 46: PEV Energy Consumption Example Using Home-Based Trips

We further illustrate the process using home-based work trips shown in Figure 46.

In the morning, the EV leaves home for office. We assume that the EV is sufficiently charged and estimate its energy consumption on the road based on vehicle fuel economy, speed, and temperature. We calculate its battery status at the work location and then evaluate whether a recharge is needed so that the vehicle can reach its next destination (home in this case).

In the afternoon, the EV leaves office for home. We calculate its energy consumption and battery status after it reaches home. We assume that EV will recharge at home for next day's travel.

The TDM usually models the OD trips in a typical weekday. Therefore, the model estimated total PEV charging demand of all the OD trips represents the daily total PEV charging demand. The daily demand will be further disaggregated into hourly charging demand utilizing the PEV charging profile derived from a previous comprehensive study conducted by TTI in [21].

Specific application of the model to the LDV Travel Demand in the Dallas-Fort Worth Region

In this study, the model is applied to estimate the current PEV charging demand and those of future PEV adoption scenarios in the DFW area.

Travel demand

This study utilizes outputs from the NCTCOG Travel Demand Model (TDM) for the years 2019 and 2026. As shown in Figure 47, the TDM encompasses 5,352 TAZs, covering 13 counties in the expansive DFW region, and boasts a network comprising approximately 52,000 links.

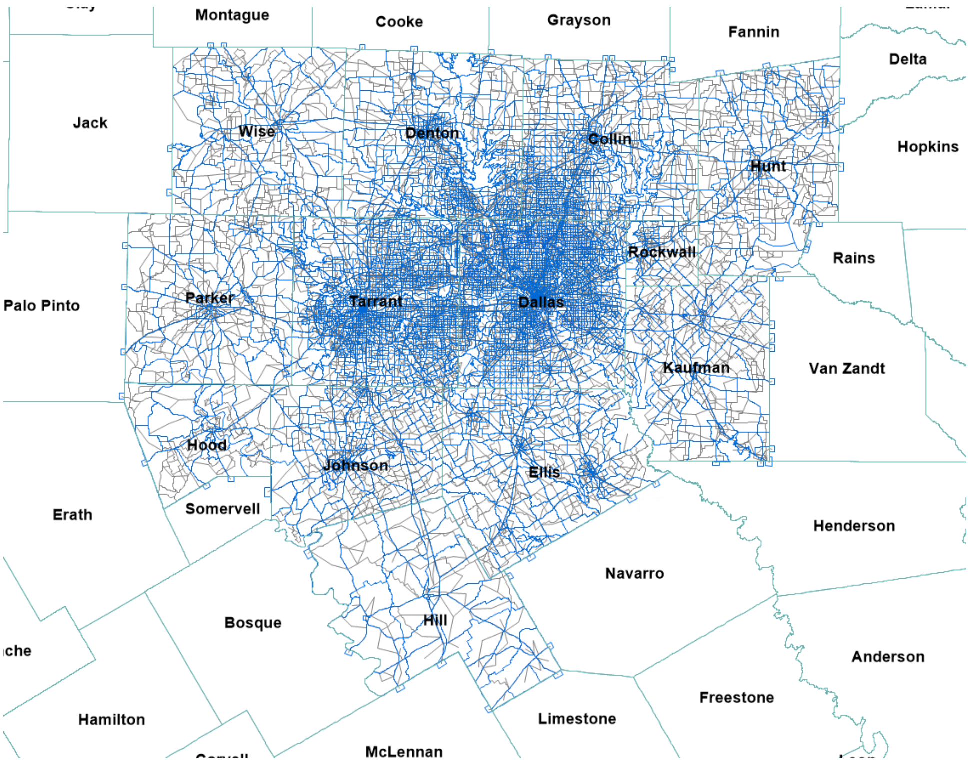


Figure 47: Network and TAZ of the NCTCOG TDM

The TDM contains the OD trips for four trip purposes during three time periods (AM and PM peak and Off-peak). The four trip purposes are:

1. Home-based work trips
2. Home-based nonwork trips
3. Non-home-based non-work trips
4. Non-home-based work trips

The OD trips for 2019 (base year) and 2026 are used. Only the OD trips for passenger cars are considered and all the trips are assumed to use LDV.

Fleet mix

The 2019 fleet mix is developed using the corresponding vehicle registration data at ZIPCODE and county level. The possible scenarios for the 2026 fleet mix are developed by growing the PEV fleet mix in the base year using the growth rates in AEO's EV population forecasts for the Reference, LOP, and HOP scenarios. Figure 48 presents the PEV adoption rate and the BEV market share of different scenarios. The PEV adoption rates in the three possible

2026 scenarios are all significantly higher than that of 2019. The 2026 high-oil-price scenario has the highest PEV adoption rate as the oil price in this scenario is the highest.

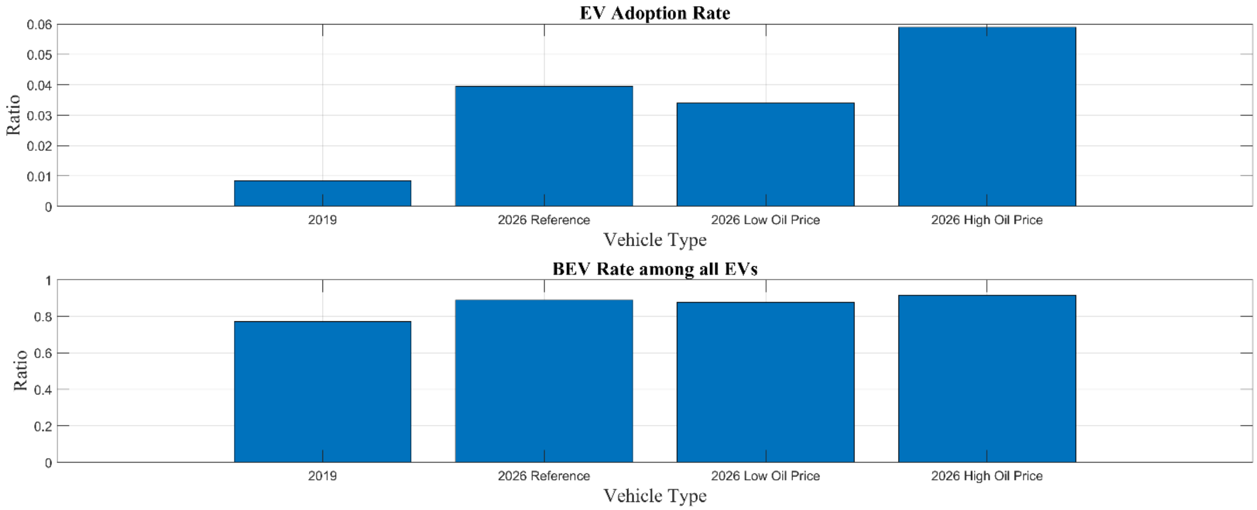


Figure 48: PEV Adoption Rate

Other inputs

The average daily temperature for the OD travel is assumed to be 70 Fahrenheit. The network travel speed and travel time for each year are directly from the TDM outputs.

The distribution of the energy economy of the PEV are shown in Figure 49. Most BEVs have an energy economy between 2-4 miles/KWH.

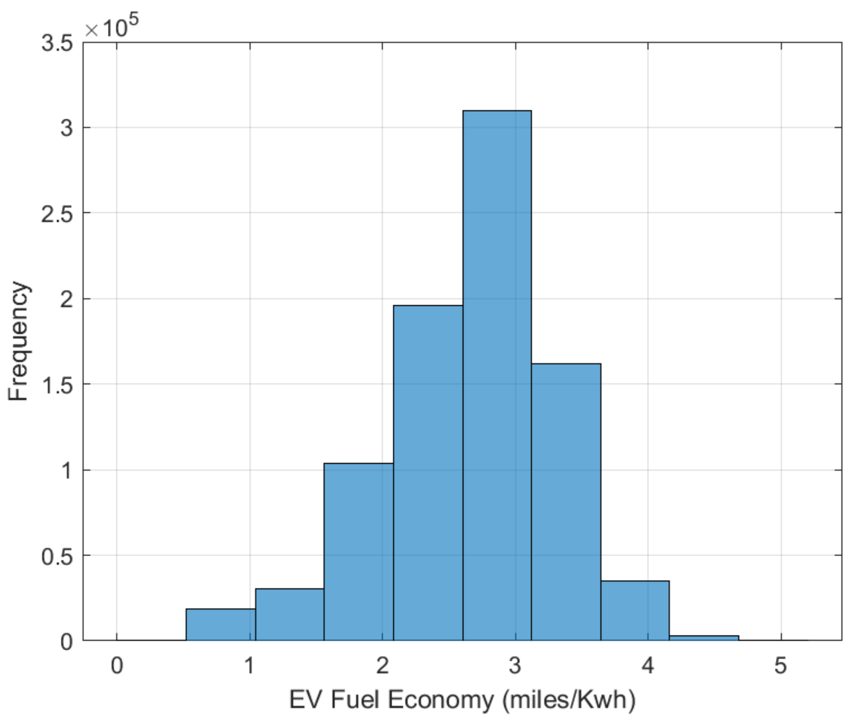


Figure 49: EV Energy Economy

Model outputs

Figure 50 summarizes the total charging demand (in KWH) for each scenario. The demand in 2019 is lower than the demand in all the three scenarios in 2026. The charging demand in the HOP scenario is the highest while the one in the LOP scenario is the lowest for the 2026 scenarios. This is consistent with the PEV adoption rates shown in Figure 48.

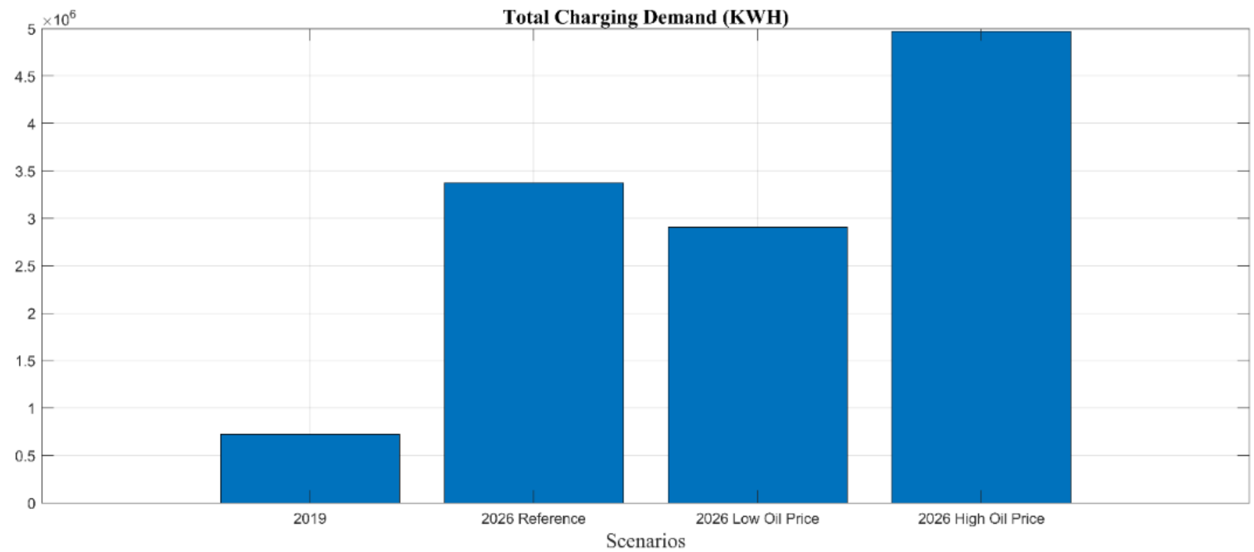


Figure 50: Total Charging Demand

Figure 51 presents the distribution of the charging demand among the TDM area in 2019 and the distribution of demand of the HOP scenario in 2026. It can be observed that almost all the counties and TAZs are projected to have a higher charging demand in 2026 than 2019 and the counties with a higher PEV adoption rate tend to have a higher charging demand.

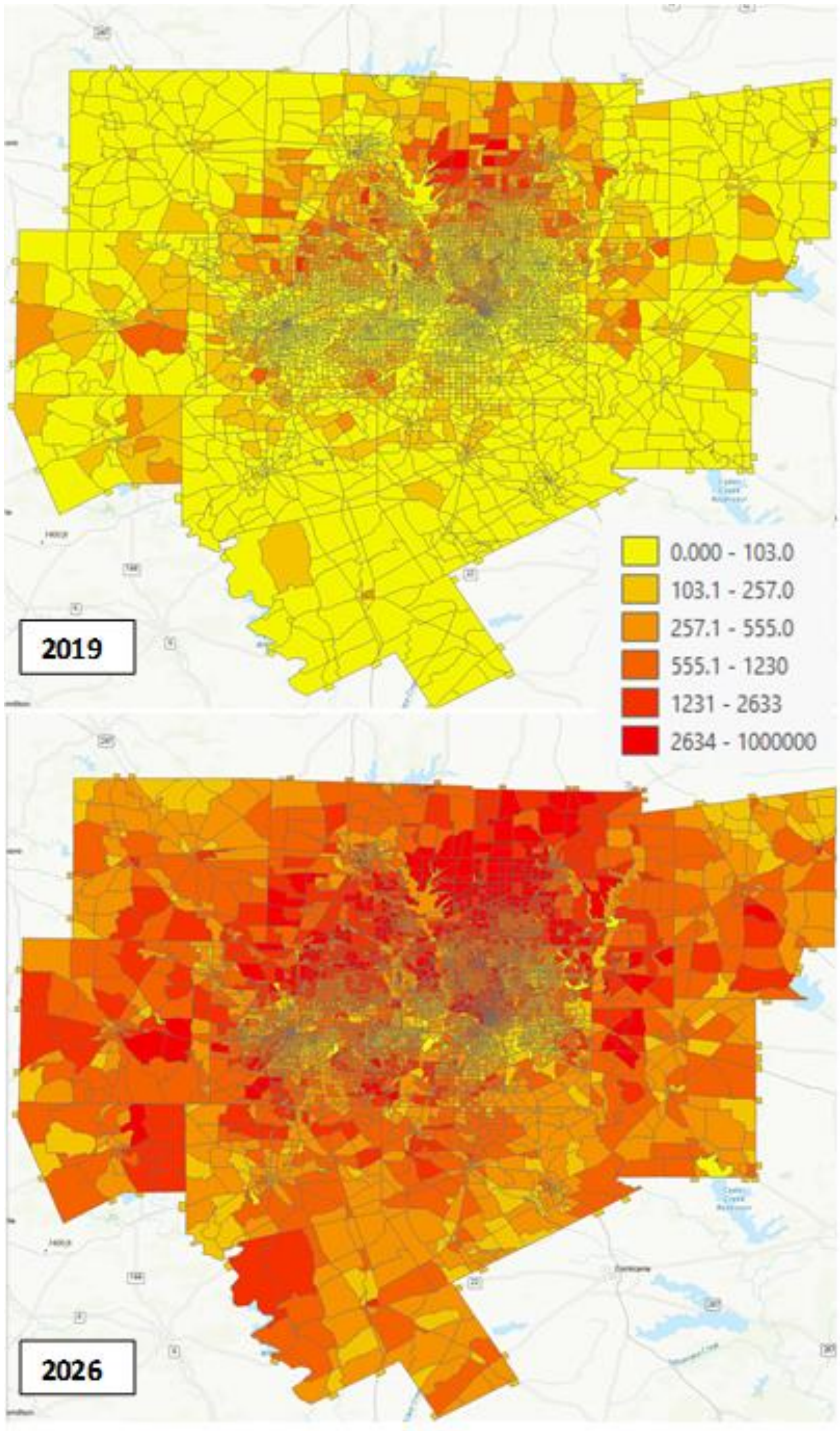


Figure 51: Distribution of the Charging Demand

Further, two hourly charging profiles are produced from the total charging demand for each scenario. Figure 52 presents the charging profiles for the 2019 charging demand. One is the managed charging profile which represents pushing most of the PEV charging demand from the peak energy demand hours to after midnight. The other one is the unmanaged charging profile which represents starting charging when a PEV arrives at its destination.

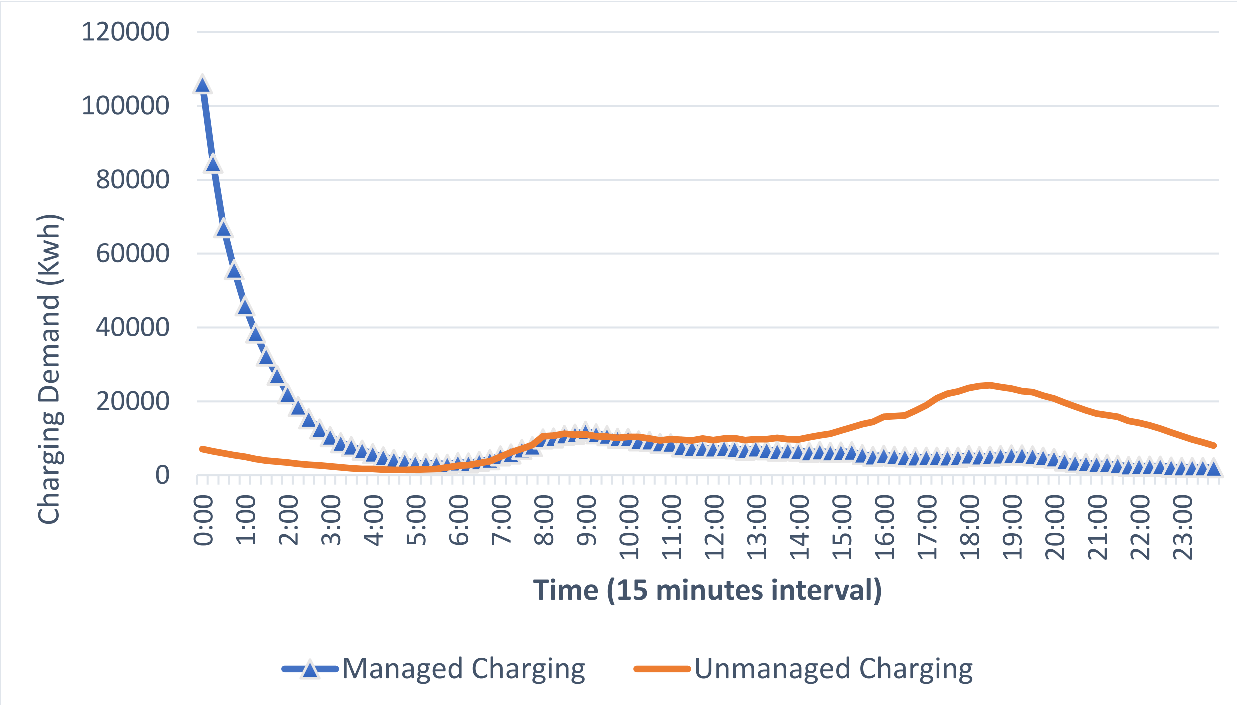


Figure 52: Hourly Distribution of the Charging Demand

Assignment of Increased Generation to Charge EVs

A balance must be always maintained between the amount of electricity generated and consumed within a large grid, such as the one managed by ERCOT. When additional electricity is needed to match an increase in demand, non-dispatchable sources (e.g., wind and solar) cannot meet the net increase or marginal power required. Instead, dispatchable fossil fuel sources from natural gas and/or coal must be relied upon to meet short-term increases in demand because additional fuel can readily be added to existing EGUs. Wind turbines and solar panels are passive sources of power as the operator cannot add more fuel in the form of wind and sun. While nuclear power can technically be classified as a dispatchable source of electricity, the flat operating profile precludes it from being a source of marginal power that regularly responds to fluctuating demand.

To estimate the increased generation for charging EVs, the marginal power required will be assigned primarily to natural gas and coal plants. This approach may not be intuitive for some people but does reflect how generation sources connected to the grid respond to short-term increases in demand. When individuals request more electricity from the grid (e.g., by turning on a light, running an air conditioner, or charging an EV), additional power is rarely generated from the non-emission sources of wind and solar to match that increase in demand. Exceptions can occur if the wind or solar generation is being temporarily curtailed, which happens when the grid cannot momentarily handle the total amount of wind/solar power that could be generated. In such instances, the potential wind/solar output is deliberately reduced so that the grid remains balanced and is not temporarily overloaded with excess supply. Wind and/or solar sources can provide the marginal power needed if the additional demand happens to occur during these infrequent times of curtailment.

Vehicles powered by gasoline and diesel fuel emit tailpipe pollutants at the time and location of the vehicle's operation. In contrast, the power plant stack pollutants emitted for EV charging are separated in space and time from the vehicle's operation. While the charging of a light-duty EV can occur at any time of day, most of it occurs during overnight hours at the owner's residence. This timing matches well with available capacity from all fossil fuel plants on the grid, particularly the large base-load power plants that typically operate at their lowest generation levels during overnight hours.

Figure 53 summarizes the average available generation by the hour from Texas power plants from May to September 2022.

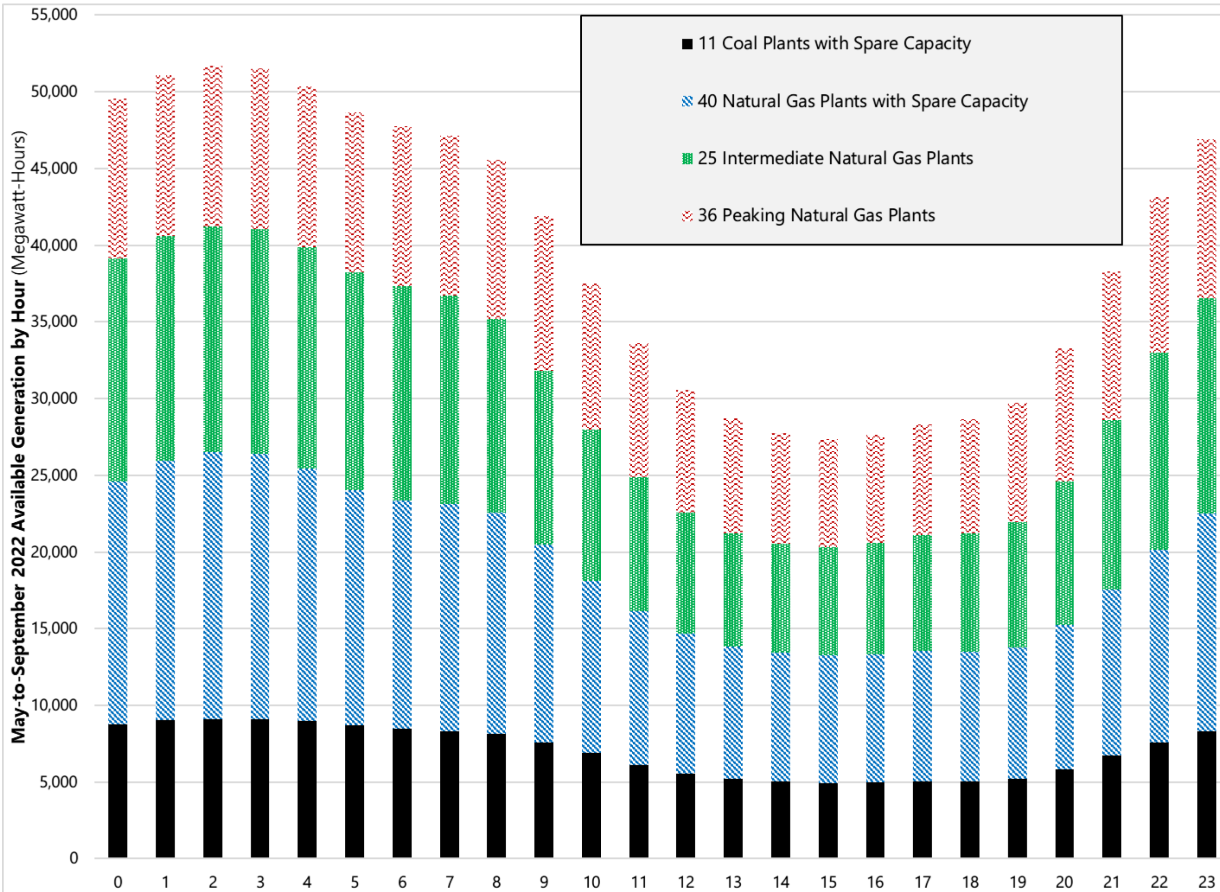


Figure 53. Average available hourly generation, May to September 2022.

As Figure 53 shows, the amount of generation capacity available overnight is roughly double that available in the middle of the afternoon. During any given hour, the amount of available capacity from large base-load plants (black and blue) is roughly equal to the available capacity from intermediate and peaking plants (green and red). However, the large base-load plants that tend to operate continuously are more likely to increase their generation for charging EVs, particularly during overnight hours. Many power plants are equipped with multiple EGUs, and starting an individual EGU can take several minutes for a gas turbine or hours for a steam turbine. However, the generation level of an EGU that is already running can readily be increased, provided that its maximum operating capacity has not been reached.

Estimation of the In-Use Peak for Texas Power Plants

To obtain an estimate of the in-use operational peak for each Texas plant, the maximum hourly generation level was obtained during 2022 from the CAMPD. Then, the difference between this peak and the average hourly generation from May to September 2022 was taken.

For example, the W.A. Parish plant in the greater Houston area is fueled primarily by coal. The plant generated more electricity during 2022 than all non-nuclear plants in Texas. During its peak hour of operation in 2022, W.A. Parish generated 3,523 MWh. If it operated at this level for all 24 hours of each day, W.A. Parish would generate a total of 84,552 MWh. The daily average generation for W.A. Parish from May to September 2022 was 42,950 MWh, which leaves an average available capacity of 41,602 MWh daily. Figure 54 demonstrates how this available capacity for W.A. Parish varies on an hourly basis. Additional examples of this approach are presented for the large Forney natural gas base-load plant in Dallas in Figure 55, the intermediate O.W. Sommers natural gas plant in the San Antonio area in Figure 56, and the peaking Ray Olinger natural gas plant in Dallas in Figure 57.

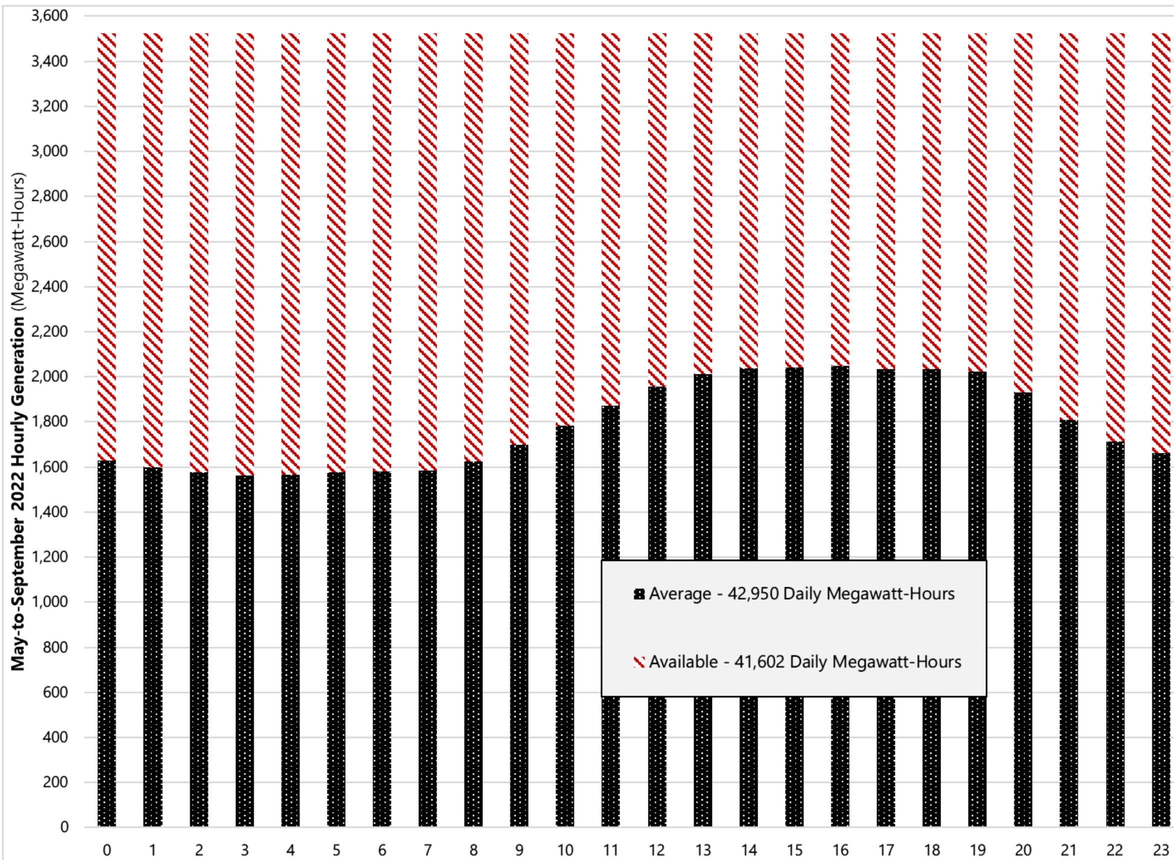


Figure 54. Large coal plant example: W.A. Parish in the Houston area.

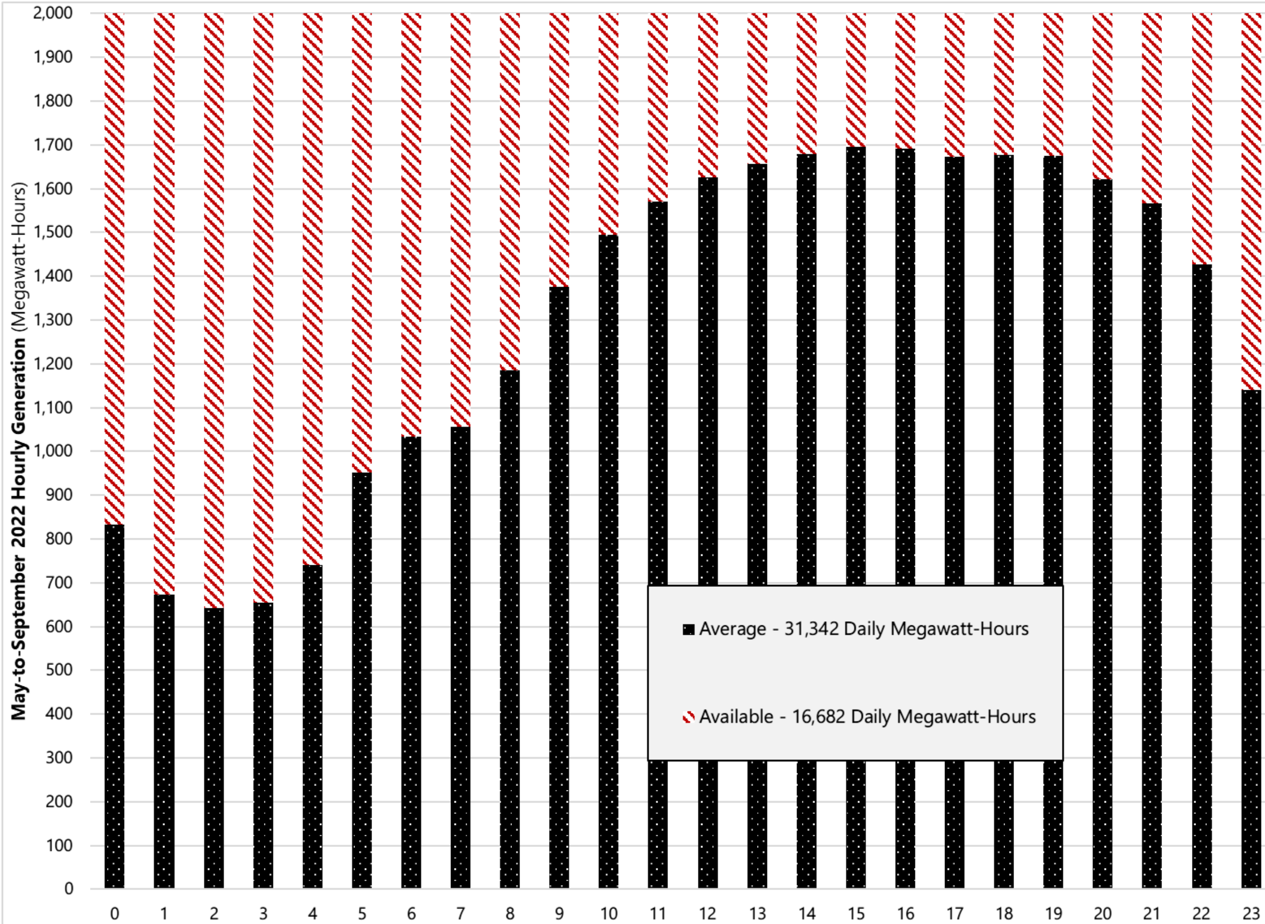


Figure 55. Large natural gas plant example: Forney in the Dallas area.

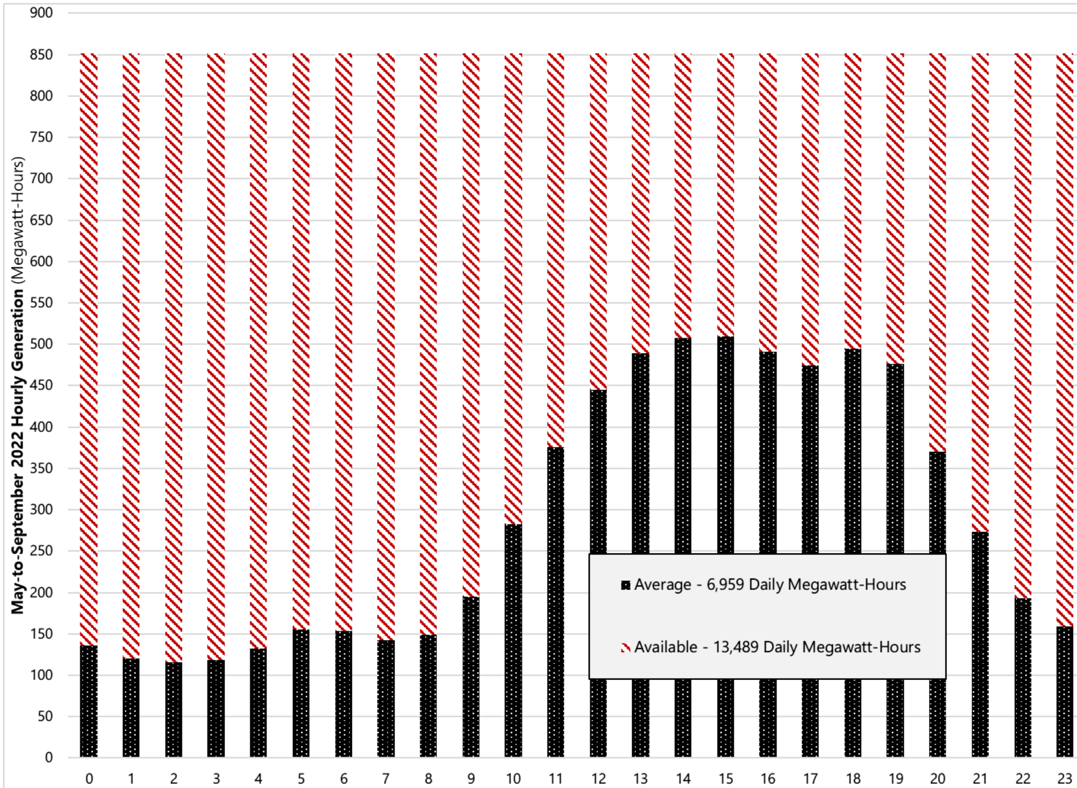


Figure 56. Intermediate natural gas plant example: O.W. Sommers in San Antonio.

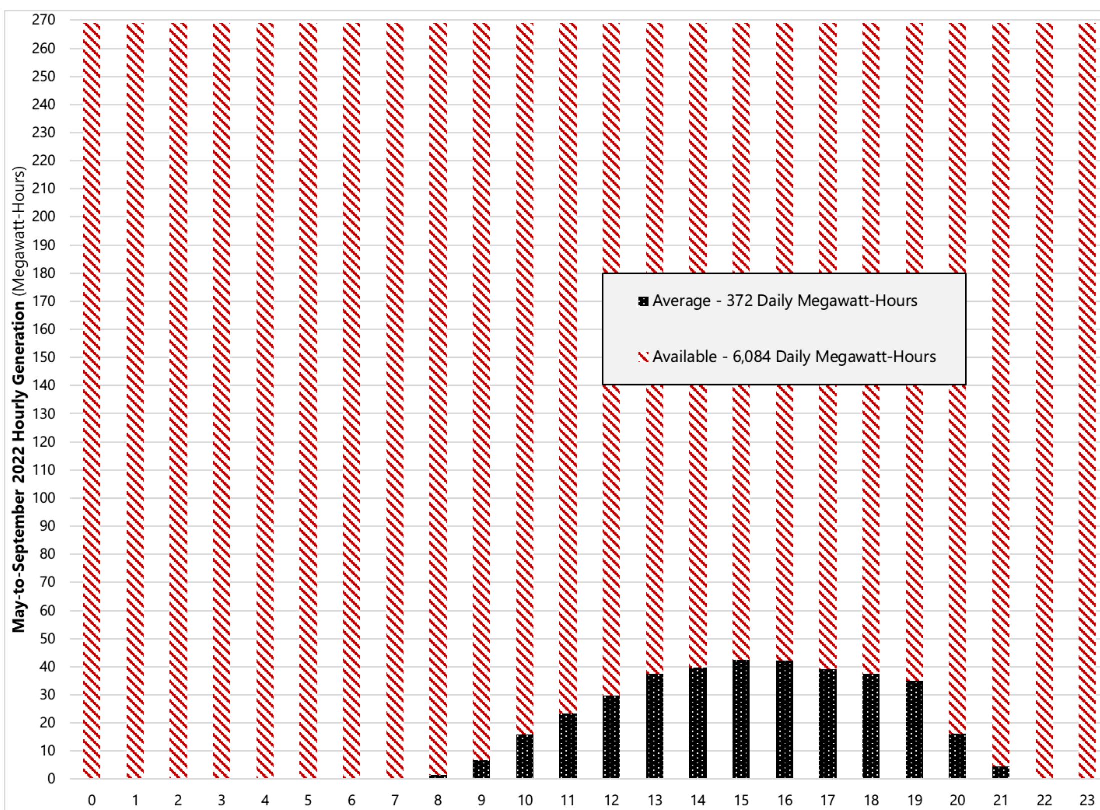


Figure 57. Peaking natural gas plant example: Ray Olinger in the Dallas area.

For each plant, the actual maximum operating capacity is typically higher than the peak hour of operation during 2022. However, most plants do not operate at their maximum capacity continuously. For this analysis, an in-use operational peak was needed based on recently available data, so it was extracted from the CAMPD dataset for 2022 rather than assuming that multiple plants will operate at their full nameplate capacity.

Electricity Generation Scenarios to Meet EV Charging Demands

As discussed previously in the section "Overview of Electrical Generation for Texas," the 153 days from May to September 2022 were divided into groups of low-, medium-, and high-demand days. The total demand varies significantly for each day, along with the hourly generation available from non-emission sources such as wind and solar. This variability makes it difficult to select a single scenario for allocating the charging of EVs to individual power plants by the time of day. Instead, the three scenarios summarized in Table 21 are planned for allocating the hourly generation needed for charging EVs to specific power plants.

Table 21. Scenarios for Allocating Electricity Generation for EV Charging to Power Plants

Scenario **Description**	51 Large Base-Load **Power Plants**	25 Intermediate **Power Plants**	36 Peaking **Power Plants**
Low impact	All 24 hours		
Medium impact	Overnight hours	Daytime hours	
High impact	Overnight hours	Morning hours	Afternoon hours

Under each scenario, most of the EV charging occurs during overnight hours, so the majority of the EV charging daily will still get allocated to the large base-load plants under the medium- and high-impact scenarios. Since the intermediate and peaking plants are less likely to be operated during overnight hours, it is reasonable to assume that large base-load plants are the ones most likely to increase generation levels to match EV charging demand.

Even though the majority of charging will occur overnight, it is also reasonable to assume that some EV charging will occur during all hours of the day. On days with lower overall demand and higher wind speeds, the generation from large base-load plants is reduced, and this leaves additional capacity for EV charging throughout the day. Conversely, on days with high overall demand and low wind speeds, large base-load plants may not be able to handle the additional EV charging demand during all daytime hours, which means that a combination of intermediate and peaking plants will be needed.

Power Plant Emissions for Meeting EV Charging Demands

NO_X is the primary precursor of concern for ozone formation. Table 17 shows that the average NO_X emission rates are 0.19 pounds per MWh for the 40 large natural gas plants, 0.58 pounds per MWh for the 25 intermediate natural gas plants, and 1.04 for the 36 peaking natural gas plants. For each MWh of generation needed from natural gas plants, the 25 intermediate plants would emit three times the NO_X of large base-load plants, and the 36 peaking plants would emit over five times the NO_X per MWh.

Ozone concentrations measured in metropolitan areas tend to reach their highest levels on high-temperature days with low wind speeds. Since the eight-hour ozone standard is based on concentrations from the highest ozone days that occur within a given year, it is appropriate to model a high-impact scenario to estimate how the ozone design value for each monitor could be affected by allocating hourly generation and NO_X emissions to a combination of large base-load, intermediate, and peaking plants. The following is a general outline of the allocation approach:

1. Determine the total amount of generation needed in units of MWh for charging EVs daily from May to September throughout Texas.
2. Allocate the generation needed by the hour of the day, with the bulk of EV charging occurring overnight.

3. Obtain a simplified charging distribution profile by taking the inverse of hourly VMT from the light-duty fleet, which mathematically assigns charging times when vehicles are least likely to be operated, so the least amount of charging would occur during rush hour periods.
4. For each hour, assign the amount of generation to each power plant using software such as PowerWorld to allocate increases in marginal generation to the next lowest cost producer(s) on the grid.
5. Once the hourly generation for each plant is known for each scenario, multiply the pollutant emission rates in units of pounds per MWh (e.g., for NOX, SO2, CO2, etc.) by the assigned hourly generation to estimate the incremental hourly emissions.

Ozone formation is heavily dependent on the spatial and temporal distribution of NO_X emissions on stagnant days that are conducive to the accumulation of high pollutant concentrations. All the steps outlined here are necessary to estimate the appropriate hours and locations of the NO_X emission increases that will result from EV charging. Additional NO_X emitted nearby or upwind of a metropolitan area will likely cause a temporary increase in ground-level ozone that will eventually dissipate when nighttime hours arrive. Additional NO_X emitted far away or downwind of a metropolitan area typically has little or no impact on local ozone formation. Also, NO_X increases or decreases that happen to occur on a windy day typically have diminished impacts on local ozone formation because higher winds will typically preclude the accumulation of high pollutant concentrations. If the hourly EGU NO_X emissions are averaged over multiple weeks or months, their full impact on the highest ozone days can easily be underestimated in an ozone modeling analysis.

Conversely, CO_2 is a stable non-reactive pollutant that has a long life and accumulates in the earth's atmosphere. Unlike with NO_X impacting local ozone formation daily, the spatial and temporal distribution of CO_2 emissions on any given day is not critical. In other words, a net reduction in CO_2 emissions that can be achieved anywhere in the world at any time is beneficial, but a net reduction in NO_X emissions must be achieved at specific times and places to be optimally beneficial for reducing local ozone formation. Since global CO_2 emissions are not dependent on space and time in the way that NO_X emissions are, using EGU CO_2 emissions averaged over multiple weeks and months is acceptable for estimating total CO_2 contributions to GHG concentrations.

A common misperception is that strategies for reducing GHG emissions such as CO_2 on a global basis will have equivalent reductions in concentrations of pollutants such as ozone on a local basis. This is not the case since a 10 percent reduction in CO_2 for a specific scenario will not automatically correlate with a 10 percent reduction in either NO_X emissions or local ozone concentrations.

Estimating the Maximum Possible On-Road Emissions Reductions from EVs

This section discusses the challenges in estimating on-road emissions reductions that can be achieved from EVs for different EV population scenarios.

Overview of EV and Light-Duty Emissions Standards

A difficult challenge in modeling the emission impacts of EVs is determining a net reduction that can or will occur from on-road tailpipe emissions on a fleet-wide basis. When comparing the zero-level emissions of an individual EV with a gasoline-powered vehicle, such a task is straightforward if it is assumed that the model year and VMT are constant between the EV and gasoline vehicle. For a tailpipe pollutant such as NO_X, it is simply the emission rate in grams per mile (gpm) of the gasoline vehicle multiplied by the VMT for a given hour, day, or year. In this example, the NO_X emission rate depends on the federal certification standard that is applied for the model year of the EV and gasoline vehicle.

When evaluating an entire on-road fleet rather than two specific vehicles side by side, this task becomes difficult due to how federal emissions standards are structured. The emissions standards required of auto manufacturers are based on an average of all the vehicles produced for sale within a given model year. Provided that the fleet average standard for a specific pollutant is above 0 gpm, an EV produced for sale will exceed (i.e., be lower than) the fleet average emissions requirements. However, the applicable regulations allow auto manufacturers to produce vehicles that emit higher than the fleet average provided that the emission rate average is not exceeded for all vehicles produced for sale within that model year.

For example, assume that the fleet average emissions standard for pollutant X in model year Y is 1 gpm. For that model year, auto manufacturers have options for the mix of vehicles that are produced:

- All vehicles produced are powered by gasoline and emit 1 gpm.
- Half of the vehicles produced are EVs at 0 gpm, and half are gasoline vehicles that emit 2 gpm.
- One-third of the vehicles produced are EVs at 0 gpm, one-third are gasoline vehicles that emit 1 gpm, and one-third are gasoline vehicles that emit 2 gpm.

In each of these three simplified scenarios, the fleet average of 1 gpm for pollutant X in model year Y is achieved. The sales of the EVs did not result in additional reductions above and beyond the fleet average required for that model year. Instead, the sales of zero-emitting EVs offset the sales of vehicles with emission rates higher than the fleet average.

For the pollutants of NO_X and non-methane organic gases (NMOG), the most recent regulations for LDVs are referred to as Tier 3 and phase in for the 2017 through 2025 model years [47]. For 2025 and later model year vehicles, auto manufacturers are required to achieve a fleet average emission rate of 30 milligrams/mile of NO_X and NMOG combined. The Tier 3 standards refer to this fleet average category as Bin 30. Under Tier 3, there are seven different bins that vehicles get certified to:

- Bin 0 is for battery-powered EVs and hydrogen-powered fuel cell vehicles.
- Bin 30 is the fleet average for 2025 and later year vehicles.
- In addition to Bins 0 and 30, vehicles can be certified to Bins 20, 50, 70, 125, and 160.

The highest-emitting category allowed under Tier 3 is Bin 160 for 160 milligrams/mile emitted from NO_X and NMOG combined. Under the previous system of Tier 2 standards, Bin 160 was the fleet average required from the 2007 through 2016 model years but was referred to as Bin 5 under Tier 2. Under Tier 3, an auto manufacturer can achieve the Bin 30 fleet average by producing 3 Bin 160 gasoline (or diesel) vehicles for every 13 Bin 0 EVs:

1. Gasoline vehicles (19 percent of sales): 3 vehicles × 160 milligrams/mile = 480 milligrams/mile.
2. EVs (81 percent of sales): 13 × 0 milligrams/mile = 0 milligrams/mile.
3. Gasoline and EVs (100 percent of sales): 480 + 0 = 480 milligrams/mile.
4. Fleet average: 480 milligrams/mile divided by 16 vehicles = 30 milligrams/mile average.

Table 22 summarizes this compliance scenario and others. In each case, the sale of Bin 0 EVs helps the fleet average to be achieved but not exceeded, so there is no incremental or marginal emissions reduction achieved from the sale of EVs. There can be a tendency to identify the portion of EV sales within a given model year and assume that it represents extra emissions to be removed from an on-road emissions inventory. If it is not acknowledged that EV sales offset those of higher-emitting vehicles, fleet-wide emission rates inevitably get underestimated because the net emissions reduction from EVs alone gets double counted.

Table 22. Gasoline and EV Sales Compliance Options under Tier 3 Standards

Tier 3 Bin	Gasoline Sales	Bin 0 EV Sales	Gasoline and EV Sales	Total Emissions (mg/Mile)	Fleet Average (mg/Mile)	Gasoline Sales Portion	EV Sales Portion
Bin 30	1	0	1	30	30	100%	0%
Bin 50	3	2	5	150	30	60%	40%
Bin 70	3	4	7	210	30	43%	57%
Bin 125	6	19	25	750	30	24%	76%
Bin 160	3	13	16	480	30	19%	81%

When projecting to future years, it is impossible to ascertain the precise number of Bin 0 EVs that will be sold along with those in the various other Tier 3 emissions certification bins because manufacturers have multiple compliance options. Due to this uncertainty, version 3 of the Motor Vehicle Emission Simulator (MOVES3) model from EPA assumes that the emission rates by model year for each vehicle type are based on the fleet average required of manufacturers. For example, MOVES3 assumes that all 2025 and later year LDVs are in Bin 30 simply because that represents the fleet average required. This assumption effectively assigns a 0 percent contribution from the other certification bins: Bin 0, Bin 20, Bin 50, Bin 70, Bin 125, and Bin 160.

In theory, MOVES3 could assign specific portions of each model year to Bin 0. However, MOVES3 would then have to increase the non-EV emission rates reported to ensure that the light-duty fleet average requirement is maintained. For example, assume that 40 percent of the LDVs sold in the 2030 model year were EVs and therefore certified to Bin 0. To maintain an overall fleet-average emission rate of 30 milligrams/mile, MOVES3 would have to assume the remaining 60 percent of the 2030 model year vehicles would be certified to Bin 50, based on calculations shown in Equation 20.

$$(40\% \times 0\, milligrams/mile) + (60\% \times 50\, milligrams/mile) = 30\, milligrams/mile\ fleet\ average \qquad (20)$$

Under this approach, the non-EV emission rates from MOVES3 would have to be increased to stay consistent with the 30 milligrams/mile fleet average requirements of the Tier 3 regulations for 2025 and later model year vehicles. In its *Exhaust Emission Rates for Light-Duty Onroad Vehicles in MOVES3* technical report [48], EPA addresses the challenges of modeling specific emissions reductions from EVs. Excerpts from Section 5.2, “Light Duty EVs,” are as follows:

> EPA is aware that manufacturers can include EVs and HEVs in their computation of average emissions for compliance with Tier 3 standards. Thus, if a manufacturer sells a large number of zero or low-emitting vehicles, the manufacturer would be allowed to increase the average emissions of other vehicles.
>
> We must caution that MOVES does not account for potential associated increases in emissions from conventional LDVs. If the future fraction of EVs is large, and manufacturers take advantage of the flexibility allowed by the Tier 3 regulations, this could lead to underestimation of light-duty NMOG and NO_X emissions from conventional (i.e. gasoline, diesel, and E85) vehicles [48].

How EPA models light-duty exhaust emission rates in MOVES3 is consistent with the April 2014 federal rule titled *Final Rule for Control of Air Pollution from Motor Vehicles: Tier 3 Motor Vehicle Emission and Fuel Standards* [47]. Applicable excerpts related to EVs are as follows:

> Compliance with the more stringent Tier 3 fleet average standards will require vehicle manufacturers to certify a significant amount of vehicles to bin standards that are below the

Bin 30 fleet average standard to offset other vehicles that are certified to bin standards that remain somewhat above the Bin 30 fleet average even after significantly reducing their emissions.

There is also the very limited ability for vehicle manufacturers to certify vehicles below the stringent Tier 3 fleet average exhaust emissions standard since Bin 20 and Bin 30 standards for individual vehicle certification test groups are approaching the engineering limits of what can be achieved for vehicles using an ICE and Bin 0 can only be achieved by electric-only vehicle operation.

The result is that there is a very limited ability to offset sales of vehicles certified above the 30 milligrams per mile fleet average emission standard.

Modeling Scenario Where All EVs Sold Provide Extra Reductions

Rather than modeling the most likely scenario where EV sales are used to meet fleet average standards, a method can be employed to estimate the maximum possible emissions reductions that could be achieved from EVs. For each model year that Bin 0 EVs either were or will be sold, it would be assumed that all non-EVs (i.e., those powered by gasoline, diesel fuel, etc.) meet the fleet average requirements, thus allowing EV sales to achieve marginal emissions reductions beyond what is required of auto manufacturers. For each model year, this marginal reduction is the difference between zero and the applicable fleet average emissions required. For example, the maximum possible benefit of all EVs sold in 2025 and later would be the emissions difference between Bin 0 and Bin 30 standards.

This approach was taken in an analysis done by TCEQ in December 2020 under Senate Bill 604 [49]. For the 2028 future year, it was projected that 486,811 EVs would be operating in Texas. Under the extreme case where all of these EVs were not needed to meet Tier 3 fleet average emission rates, the net additional reduction in NO_X emissions estimated was only 0.63 tons per day (tpd) (0.8 percent) out of 77.65 tpd for the light-duty fleet from all 254 Texas counties (see Appendix B of the TxDMV *Study on Imposing Fees on Alternatively Fuel Vehicles* report [49]). If 0.63 tpd of NO_X were removed from an on-road emissions inventory, the modeled ozone response would be negligible, even if all of that 0.63 NO_X tpd was removed in a single metropolitan area.

Both the December 2020 Senate Bill 604 analysis [49] and a July 2019 TCEQ presentation [50] show that obtaining a sizeable ozone response in a photochemical model would entail extremely unrealistic EV penetration scenarios. This is primarily because the NO_X and VOC emission rates from modern gasoline vehicles are less than 1 percent of uncontrolled levels from the 1960s before emissions standards existed. So, the net difference in NO_X and VOC emissions between a new gasoline vehicle and a new EV is very small, even before the sources of electricity to charge the EVs are considered.

Light-Duty Emissions Inputs Currently Available from TCEQ

TCEQ currently has a 2019 ozone modeling episode with emissions inputs available for the 2019 base case and future years of 2023 and 2026 [51]. In the latter year, the light-duty on-road inventory is comprised of 1996–2026 model year vehicles, with the bulk of the light-duty activity coming from vehicles meeting Tier 2 (2004–2016 model years) and Tier 3 (2017 and later model years) standards. The fleet average emission rates for both vehicle groups are quite low compared with older vehicles that met earlier standards upon manufacture.

Table 23 summarizes the 2026 summer weekday on-road emissions for all 254 Texas counties of the current TCEQ modeling files that were developed using the MOVES3 model. The large majority of the EVs currently available are for the light-duty portion of the fleet. MOVES3 categorizes these vehicles as passenger cars and passenger trucks, the latter of which includes many sport utility vehicles, minivans, pickups, etc.

Table 23. 2026 Summer Weekday On-Road Emissions for 254 Texas Counties

MOVES3 Fuel and Source Use Type	NO_X (tpd)	VOC (tpd)	CO (tpd)	SO_2 (tpd)	NH_3 (tpd)
Gasoline passenger car	26.90	72.80	1,637.62	1.27	13.23
Diesel passenger car	0.37	0.35	21.93	0.01	0.06
Gasoline passenger truck	22.36	32.63	731.59	0.52	4.51
Diesel passenger truck	2.93	0.31	6.04	0.01	0.07
Gasoline light commercial truck	8.21	9.31	218.84	0.14	1.18
Diesel light commercial truck	3.55	0.37	4.48	0.01	0.06
Gasoline motorcycle	0.35	3.39	7.00	0.00	0.03
Gasoline school bus	0.01	0.01	0.26	0.00	0.00
Diesel school bus	2.98	0.22	1.80	0.01	0.05
Diesel transit bus	1.74	0.06	1.34	0.00	0.02
Diesel other bus	1.16	0.05	0.75	0.00	0.01
Gasoline motor home	0.35	0.25	7.23	0.00	0.02
Diesel motor home	1.79	0.18	1.07	0.00	0.01
Gasoline refuse truck	1.62	0.83	17.49	0.00	0.05
Diesel refuse truck	2.89	0.11	1.85	0.00	0.03
Gasoline single-unit short-haul truck	3.56	4.32	68.41	0.08	0.57
Diesel single-unit short-haul truck	19.70	0.53	17.23	0.05	0.50
Gasoline single-unit long-haul truck	0.10	0.23	5.13	0.01	0.06
Diesel single-unit long-haul truck	1.69	0.05	1.60	0.01	0.05
Gasoline combination short-haul truck	0.85	1.11	101.99	0.02	0.09
Diesel combination short-haul truck	47.82	1.58	31.65	0.09	0.56
Diesel combination long-haul truck	168.26	6.26	117.11	0.27	1.76
MOVES3 fuel and source use type total	319.18	134.93	3,002.40	2.49	22.92

Note: NH_3 = ammonia.

Table 24 provides a summary of the light-duty emissions for these categories by geographic area for a 2026 summer weekday.

Table 24. 2026 Summer Weekday Light-Duty Emissions by Texas Geographic Area

Texas Geographic Area	NO_X (tpd)	VOC (tpd)	CO (tpd)	SO_2 (tpd)	NH_3 (tpd)
Five-county AUS	3.42	7.05	154.06	0.13	1.24
Three-county BPA	0.77	1.52	39.07	0.02	0.24
Ten-county DFW	12.50	26.94	602.51	0.51	4.98
ELP	1.93	3.72	60.27	0.04	0.44
Eight-county HGB	10.19	22.56	519.64	0.43	4.19
Five-county SAN	4.35	9.33	190.27	0.13	1.29
Remaining 222 Texas counties	19.39	34.96	831.36	0.54	5.48
254-county Texas total	52.56	106.09	2,397.17	1.80	17.87

Note: AUS = Austin; BPA = Beaumont/Port Arthur

Emissions Impact

This section covers the work performed for Task 4. Emissions corresponding to the three scenarios developed in Task 3 are characterized, including on-road mobile sources and EGUs.

EGU Impacts

This section summarizes the methodology used to obtain realistic calculations of spatiotemporal operational emissions from coupled transportation and power grid sectors, as described in the journal article "Spatiotemporal Operational Emissions Associated with Light-, Medium-, and Heavy-Duty Transportation Electrification," written by Wert et al. [52].

This journal article presents a strategy for calculating the spatiotemporal operational emissions from road transportation and the electric grid. The quantification of these operational emissions enables the authors to assess the impacts that the increased electrification of transportation could have on overall emissions from the transportation sector. Ultimately, this article aims to demonstrate the hourly impact of both light-duty (LD) and medium-and-heavy-duty (MHD) EVs on a realistic coupled infrastructure model that incorporates actual transportation networks and electric grid models.

Methodology

Charging Demand

For LD EVs, Wert et al. assumed an uncontrolled charging scenario where most of the EVs are charged overnight at the owner's residence using the most affordable charging infrastructure, which is the level 1 charger.

For MHD EVs, the charging demand was simulated based on three factors: VMT, the distance travelable on a full charge, and the likelihood of trips ending at depots by trucks and time of day. The MHD EV VMTs were obtained from travel demand models (TDMs), their full-charge distance was developed by comparing online repositories for EV trucks, and the likelihood of the trucks ending their trips at depots was estimated using a Bayesian network model based on commercial vehicle survey data. Wert et al. also assumed that the MHD EVs are primarily charged using 100 kW Level 3 chargers.

Spatial and Temporal Mapping of the EV Load

Wert et al. based the load-mapping methodology on the methods documented in an earlier work [53]. To map the EV loads, the authors first used the transmission substation coordinates to create Voronoi polygons[2] representing the service area of each substation. Then, for each EV charging location, the authors determined the substation service area within which the charging location falls. Finally, the EV charging load was added to the model.

To map the load temporally, Wert et al. developed an hourly time series of bus-level[3] load for a year. Using the coordinates of each bus, the authors determined the unique electricity consumption profile at each location. The composition of residential, commercial, and industrial loads at each bus, along with location-specific building- and facility-level load time series, were used to create the bus-level load time series.

Finally, the spatial and temporal components were combined by assigning the load time series as a load at the bus level within its designated substation area.

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[2] In geographic information systems, Voronoi polygons, also called area-of-influence polygons, are shapes that cover spaces. They are made around specific points (called Voronoi centers). Each polygon includes all the points that are nearer to its center than to the center of any other polygon.

[3] A *bus* is the term for an electrical node.

Time Step Simulation

Using generator cost curves, unit commitment was calculated for each scenario to determine which generators in the electrical grid would be online. Then, an optimal power flow (OPF) was calculated for each hour within the 24-hour simulation period. This calculation provided an hourly cost-optimized dispatch of the generators that is feasible within the operational constraints of the system. The AC OPF is used to find the state of the power system that minimizes the cost of real power generation. This solution must satisfy both power balance equations and system operating constraints, accounting for generator power limits, bus voltage, and thermal line limits. Wert et al. point out that the AC OPF considers reactive power limitations, making it a more realistic model compared to the commonly used DC OPF.

Wert et al. also included weather data in their modeling because the output from renewable energy sources, such as wind and solar, is directly related to weather conditions.

Operational Emissions

For grid emissions, emission calculations were performed using the grid dispatch information specific to each scenario, along with the pollutant emission rates categorized by fuel type from the GREET model. Emission factors for 2030 were applied for coal, natural gas, and petroleum coke whereas nuclear and renewable energy generation sources were assumed to have no operational emissions. For every generator and each pollutant, the energy contribution of the generator was multiplied by the emission factor corresponding to its fuel type for that specific pollutant. This process was repeated for each generator and type of pollutant.

For transportation emissions, assuming a one-to-one replacement of ICE vehicles with their EV counterparts, the emission reductions for each pollutant type were calculated by multiplying the hourly VMT by the average grams/mile emissions of that pollutant type for both LD and MHD EVs.

Summary Findings

Wert et al. successfully developed a coupled infrastructure model of the transportation network and electric grid. The datasets used to create this model were all publicly available, enhancing transparency and reproducibility. The authors were able to calculate detailed spatial and temporal impacts from ICE vehicles, as well as from LD and MHD EVs, on ozone generation and its related health effects. The model also simulated the potential effects of additional charging demand resulting from an increased volume of EVs on the electric grid. Importantly, the charging behaviors of different EV types were considered in this model. The authors concluded that this methodology could be applied to any power grid model that includes geographical data, generator costs, and fuel type information.

The TTI project research team collaborated with the authors of this study in developing hourly generation levels from power plants in the ERCOT grid to supply electricity for 2019 and 2030 to the 12 counties in the DFW area, falling under the jurisdiction of NCTCOG. The TTI project research team provided the authors with the latest NCTCOG TDM data, along with our estimated future DFW EV counts based on scenarios derived from the latest EIA AEO. Figure 58 (base) and Figure 59 (EV scenario) show samples of the 2030 hourly dispatch in MWh by fuel type for all power plants in the system. The resulting output (hourly generation from power plants) was combined with plant-specific emission rates to estimate the incremental emissions increase for charging EVs. This increase in charging emissions for EVs can then be compared with the maximum possible emissions reductions from EV adoption that will be presented in the section "Estimating Maximum Possible Additional Emissions Reductions for EV Population Scenarios."

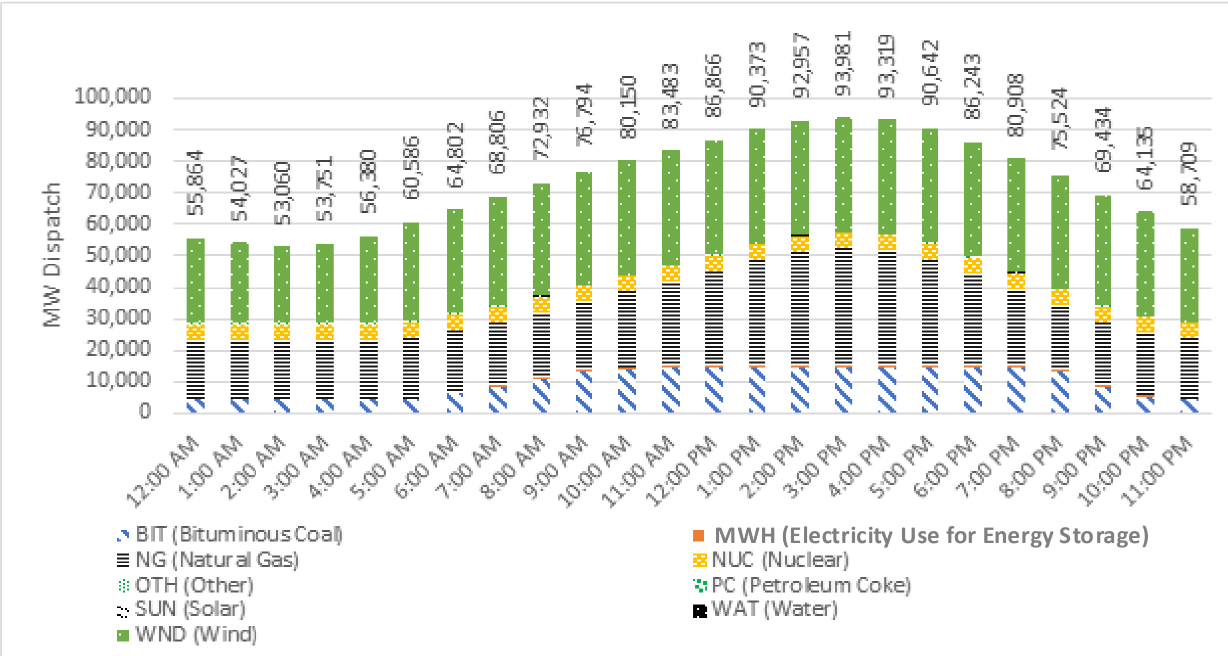

Figure 58. Hourly MW dispatch by fuel type (2030 base).

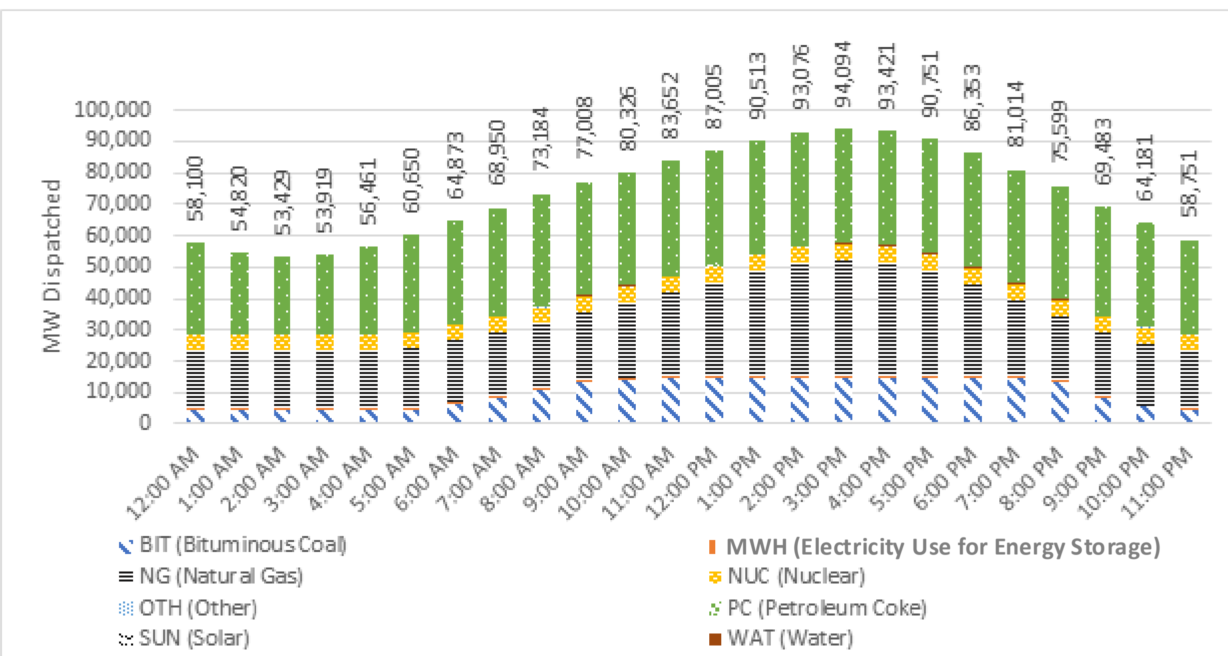

Figure 59. Hourly MW dispatch by fuel type (2030 EV scenario).

The results in Figure 58 and Figure 59 are estimates of the electricity produced and made available to the generator substations associated with each power plant. On a 24-hour basis, the net increase in generation is 5,887 MWh between the 2030 base and EV charging scenarios. The 2021 version of the Emissions and Generation

Resource Integrated Database (eGRID) from EPA reports that the transmission and distribution losses in the ERCOT grid are approximately 4.4 percent. Applying this grid loss factor to the generation increase of 5,887 MWh yields 259 MWh, and this results in a reduced amount of 5,628 MWh for charging EVs at the load substations adjacent to the residential, commercial, and industrial areas where electricity is consumed.

For the 2030 scenarios, the datasets include 1,058 generator buses (or nodes) associated with the generation sources throughout the modeled ERCOT grid. A plant with multiple generating units will typically have a separate node for each unit. Table 25 summarizes the 1,058 generator nodes in the modeled ERCOT grid by fuel type.

Table 25. 2030 Generator Nodes by Fuel Type within the Modeled Grid

Fuel Type	Number of Generator Nodes
Coal	23
Natural gas	502
Petroleum coke	2
Nuclear	4
Water (hydroelectric)	22
Wind	293
Solar	178
Storage	18
Other	16
Total	1,058

The 1,058 nodes were matched to the Office of Regulatory Information Systems (ORIS) code for each power plant in the 2021 eGRID dataset. For example:

- W.A. Parish is a large power plant fueled primarily by coal in the greater Houston area with an ORIS code of 3470.
- Forney is a large power plant fueled by natural gas in the greater Dallas area with an ORIS code of 55480.

For each fossil fuel power plant, the 2021 eGRID dataset includes emission rates in units of pound per MWh of net generation for:

- The criteria pollutants of NO_X, SO_2, and particulate matter at a threshold of 2.5 microns ($PM_{2.5}$).
- The GHG pollutants of CO_2, methane (CH_4), and nitrous oxide (N_2O).

At the time of this analysis, the 2022 eGRID dataset was not yet available, so the 2021 eGRID emission rates were used instead. EPA also includes generation and emissions measurements in the CAMPD set for power plants, and the full 2022 version was available. However, the CAMPD only includes emissions for the pollutants of NO_X, SO_2, and CO_2. Also, the generation levels reported in the CAMPD are for gross load and not net generation. A plant that provides electricity to the grid typically has to consume a portion of the electricity it generates for operations. The total amount of electricity generated by the plant is the gross load, while the amount provided to the grid is the net generation. The 2030 base and EV charging scenarios estimated the amount of generation provided to the grid by each plant, so emissions as a function of net generation (and not as a function of gross load) should be applied to estimate total emissions impacts.

Table 26 provides examples of the 2021 eGRID emission rates for the W.A. Parish and Forney power plants. For NO_X, eGRID provides emission rates based on both ozone season and annual operating data. For the remaining pollutants, eGRID provides emission rates based on annual operating data only.

Table 26. Sample 2021 eGRID Emission Rates for the W.A. Parish and Forney Power Plants

Texas Power Plant	2021 eGRID Emission Rates (Pounds per MWh of Net Generation)						
	Ozone Season NO_X	Annual NO_X	Annual SO_2	Annual $PM_{2.5}$	Annual CO_2	Annual CH_4	Annual N_2O
W.A. Parish	0.807	0.763	4.572	0.185	2,052.578	0.235	0.034
Forney	0.247	0.244	0.004	0.026	863.643	0.016	0.002

For the power plants fueled by coal, natural gas, and petroleum coke, the hourly generation for each scenario was multiplied by the plant-specific emission rates for each pollutant. As an example, Table 27 provides the daily generation totals for both 2030 scenarios for the W.A. Parish and Forney plants. As shown, the net generation increase for EV charging is 26 MWh for W.A. Parish and 99 MWh for Forney.

Table 27. 2030 Daily Modeled Generation Scenarios for the W.A. Parish and Forney Power Plants

Texas Power Plant	Total Modeled Generation over 24 Hours (MWh)		
	2030 Base	2030 EV Charging	2030 Net Increase
W.A. Parish	60,660.20	60,685.96	25.76
Forney	17,416.48	17,515.37	98.89

The rates from Table 26 were multiplied by the generation levels in Table 27 to develop the total emissions estimates in Table 28 and Table 29 for W.A. Parish and Forney, respectively. This multiplication step was performed for each hour, but only the daily totals are reported here.

Table 28. 2030 Emissions for Modeled Generation Scenarios at the W.A. Parish Power Plant

2030 Generation Scenario	2030 Daily Modeled Emissions for W.A. Parish Power Plant (Pounds per Day)					
	NO_X	SO_2	$PM_{2.5}$	CO_2	CH_4	N_2O
2030 base	48,952.8	277,338.4	11,252.1	124,509,792	14,255.1	2,062.4
2030 EV charging	48,973.6	277,456.2	11,256.8	124,562,666	14,261.2	2,063.3
2030 net increase	20.8	117.8	4.7	52,874	6.1	0.9

Table 29. 2030 Emissions for Modeled Generation Scenarios at the Forney Power Plant

2030 Generation Scenario	2030 Daily Modeled Emissions for Forney Power Plant (Pounds per Day)					
	NO_X	SO_2	$PM_{2.5}$	CO_2	CH_4	N_2O
2030 base	4,301.9	69.7	447.0	15,041,621	278.7	34.8
2030 EV charging	4,326.3	70.1	449.6	15,127,027	280.2	35.0
2030 net increase	24.4	0.4	2.6	85,406	1.5	0.2

Similar calculations were performed for all fossil fuel plants in the modeled grid that had non-zero generation assigned to them. The eGRID dataset does not include emission rates for PM_{10}, VOC, and CO. A study performed by Argonne National Laboratory titled *Updated Greenhouse Gas and Criteria Air Pollutant Emission Factors and Their Probability Distribution Functions for Electric Generating Units* developed region-specific emission rates for power plants by fuel type. Table 30 provides the PM_{10}, VOC, and CO rates for the Texas Reliability Entity (TRE) under the authority of the North American Electric Reliability Corporation for coal and natural gas plants. As shown, PM_{10} rates for coal plants are obtained using a multiplier with $PM_{2.5}$ rates, while the PM_{10} rates for natural gas plants are equivalent to the $PM_{2.5}$ rates.

Table 30. Argonne PM_{10}, VOC, and CO Emission Rates by Fuel Type for Texas Power Plants

TRE Power Plant Fuel Type	Argonne Emission Rates for TRE (Pounds per MWh)		
	PM_{10}	VOC	CO
Coal	Multiply $PM_{2.5}$ by 1.0367	0.0390	0.5542
Natural gas	Multiply $PM_{2.5}$ by 1.0000	0.0197	0.2229

These PM_{10}, VOC, and CO rates were appended to the 2021 eGRID emission rates to obtain hourly emissions from the modeled generation levels. Table 31 provides the daily emission totals for all fossil fuel plants modeled within the ERCOT grid.

Table 31. 2030 Emissions for Modeled Generation Scenarios at All Fossil Fuel Plants

2030 Generation Scenario	Fossil Fuel Power Plant Emissions (Tons per Day)								
	NO_X	VOC	CO	SO_2	$PM_{2.5}$	PM_{10}	CO_2	CH_4	N_2O
2030 base	391.34	10.51	132.49	413.57	31.33	31.97	572,607	38.49	5.39
2030 EV charging	392.01	10.53	132.76	414.58	31.39	32.03	573,813	38.56	5.40
2030 net increase	0.67	0.02	0.27	1.01	0.06	0.06	1,206	0.07	0.01

Both the modeled generation output and the eGRID datasets include the latitude and longitude of the power plants. The latitude and longitude coordinates were converted to X-Y coordinates in the Lambert conformal conic projection used for most North American photochemical modeling applications. These X-Y locations were matched to the hourly emissions per plant to create output files that can be used for developing photochemical modeling input files to estimate ozone and PM impacts.

Estimating Maximum Possible Additional Emissions Reductions for EV Population Scenarios

The section "Overview of EV and Light-Duty Emissions Standards" provides an overview of how auto manufacturers use zero-emitting EVs to meet the fleet average emissions standards required for each model year. EVs are certified to Bin 0 under Tier 3 standards for 2017 and newer model years, and sales of these EVs allow manufacturers to provide vehicles in higher-emitting bins (e.g., Bin 50, Bin 70, and Bin 160) to ensure that fleet averages are met for regulated pollutants. As a result, EV sales allow manufacturers as a whole to achieve but typically not exceed fleet average standards per model year, so each EV purchased usually offsets the sale of one or more non-EVs that emit at a rate higher than the fleet average.

The section "Modeling Scenario Where All EVs Sold Provide Extra Reductions" summarizes a methodology that estimates the maximum possible additional emissions reductions that could be achieved from the sales of EVs for each model year. A simplified assumption is made that all non-EVs in the higher-emitting bins meet the fleet average standard for each model year, and the net difference is taken between the fleet average emission rate and zero for each pollutant to estimate the maximum potential reductions that could be achieved from EV sales.

The section "Light-Duty Emissions Inputs Currently Available from TCEQ" discusses on-road emissions input files developed with MOVES3 available from TCEQ for modeling ozone impacts in the 2026 future year.

The DFW area portion of the 2026 on-road files from TCEQ was developed by NCTCOG based on the TDM for 12 DFW area counties: Collin, Dallas, Denton, Ellis, Hood, Hunt, Johnson, Kaufman, Parker, Rockwall, Tarrant, and Wise. Table 32 summarizes the 2026 summer weekday activity and emissions for the source use type of passenger cars for the 12 DFW counties, while Table 33 provides a similar summary for passenger trucks. Emissions are reported for NO_X, VOC, CO, SO_2, NH_3, $PM_{2.5}$, PM_{10}, CO_2, CH_4, and N_2O.

Table 32. 2026 Summer Weekday Passenger Car Activity and Emissions for DFW Counties

DFW County	Vehicle Population	Daily VMT	2026 Summer Weekday Passenger Car Emissions (Tons per Day)									
			NO_X	VOC	CO	SO_2	NH_3	$PM_{2.5}$	PM_{10}	CO_2	CH_4	N_2O
Collin	709,583	22,587,962	0.91	2.74	57.26	0.05	0.50	0.05	0.06	7,532	0.20	0.11
Dallas	1,702,546	69,119,519	2.73	7.55	180.98	0.15	1.55	0.14	0.16	23,417	0.60	0.29
Denton	564,020	17,481,899	0.74	2.18	43.41	0.04	0.38	0.04	0.05	5,755	0.16	0.09
Ellis	114,550	5,901,075	0.22	0.50	13.74	0.01	0.13	0.01	0.01	1,785	0.04	0.02
Hood	39,472	1,249,993	0.07	0.18	3.75	0.00	0.03	0.00	0.00	394	0.01	0.01
Hunt	55,863	2,874,790	0.13	0.28	7.92	0.01	0.06	0.01	0.01	864	0.02	0.01
Johnson	100,332	3,710,070	0.15	0.40	8.85	0.01	0.08	0.01	0.01	1,144	0.03	0.02
Kaufman	77,734	5,064,294	0.18	0.36	11.53	0.01	0.11	0.01	0.01	1,533	0.03	0.01
Parker	83,166	3,742,994	0.15	0.34	8.28	0.01	0.08	0.01	0.01	1,123	0.03	0.01
Rockwall	68,090	2,139,293	0.09	0.26	5.41	0.00	0.05	0.01	0.01	675	0.02	0.01
Tarrant	1,319,909	43,489,574	1.83	5.36	109.66	0.09	0.96	0.10	0.11	14,345	0.39	0.21
Wise	40,503	2,542,569	0.10	0.21	6.70	0.01	0.05	0.00	0.01	763	0.02	0.01
Total	4,875,768	179,904,033	7.29	20.37	457.50	0.39	3.98	0.39	0.44	59,333	1.55	0.79

Table 33. 2026 Summer Weekday Passenger Truck Activity and Emissions for DFW Counties

DFW County	Vehicle Population	Daily VMT	2026 Summer Weekday Passenger Truck Emissions (Tons per Day)									
			NO_X	VOC	CO	SO_2	NH_3	$PM_{2.5}$	PM_{10}	CO_2	CH_4	N_2O
Collin	95,048	4,976,469	0.57	0.71	17.89	0.02	0.13	0.02	0.02	2,294	0.06	0.03
Dallas	326,581	15,009,051	1.96	2.54	57.65	0.05	0.39	0.06	0.06	7,092	0.20	0.10
Denton	96,336	3,959,332	0.49	0.66	14.11	0.01	0.10	0.02	0.02	1,807	0.05	0.03
Ellis	36,913	1,562,112	0.21	0.26	5.77	0.00	0.04	0.01	0.01	678	0.02	0.01
Hood	14,873	411,950	0.07	0.10	1.85	0.00	0.01	0.00	0.00	184	0.01	0.00
Hunt	21,971	1,029,146	0.15	0.18	4.45	0.00	0.03	0.00	0.00	448	0.01	0.01
Johnson	38,404	1,159,828	0.17	0.24	4.37	0.00	0.03	0.01	0.01	513	0.02	0.01
Kaufman	26,679	1,380,860	0.18	0.20	4.95	0.00	0.04	0.01	0.01	598	0.02	0.01
Parker	33,225	1,146,227	0.16	0.21	4.02	0.00	0.03	0.00	0.01	495	0.01	0.01
Rockwall	15,862	506,376	0.07	0.10	1.93	0.00	0.01	0.00	0.00	225	0.01	0.00
Tarrant	272,120	11,485,053	1.47	1.96	42.55	0.03	0.29	0.04	0.05	5,323	0.15	0.08
Wise	19,621	846,532	0.12	0.15	3.45	0.00	0.02	0.00	0.00	364	0.01	0.01
Total	997,634	43,472,936	5.62	7.32	162.98	0.13	1.12	0.17	0.19	20,020	0.57	0.29

A typical approach taken with on-road emissions inventory development is to obtain emission rates for each source use type from a model, such as MOVES3, and multiply them by activity estimates from transportation datasets, such as the output from a TDM. For example, NO_X emission rates in units of gpm for gasoline passenger cars are estimated with MOVES3, and these rates are multiplied by estimates of VMT from either the local TDM or the Highway Performance Monitoring System dataset managed by TxDOT. For the calendar year specified in the run specification, the MOVES3 model assumes that vehicles from ages 0–30 are in operation. For example, the 31 model years from 1993 through 2023 are assumed to be in operation during the 2023 calendar year. When the 2026 future year is modeled with MOVES3, it is assumed that the 31 model years from 1996 through 2026 are in operation. In most MOVES3 modeling applications, the emission rates for each fuel type and source use type are averages weighted across 31 model years in operation.

As an example, Figure 60 presents Dallas County NO_X, VOC, and CO emission rates for the 1996 through 2026 model years operating on a summer weekday in 2026. As shown, older Tier 1 vehicles from the 1990s have higher emission rates than the national low-emission vehicles from 2001 through 2003. In turn, the national low-emission vehicles have higher emission rates than the Tier 2 vehicles that were sold from 2004 through 2016. The most recent Tier 3 vehicles, which have the lowest emission rates, started entering the fleet in 2017. The NO_X rates shown in blue range from a high of 1.54 gpm for the 1996 model year to a low of 0.01 gpm for the 2026 model year. In general, newer vehicles accumulate more miles per day than older ones, and this is reflected in the daily average VMT ranging from 19.3 miles for the 1996 model year to 49.9 miles for the 2026 model year. Due to attrition, the population size for older vehicles is smaller than for newer vehicles. Combining the different emission rates, miles traveled, and populations across model years results in a weighted average NO_X emission rate of 0.036 gpm for passenger cars operating in 2026, The full range by model year spans from 0.01 to 1.54 gpm.

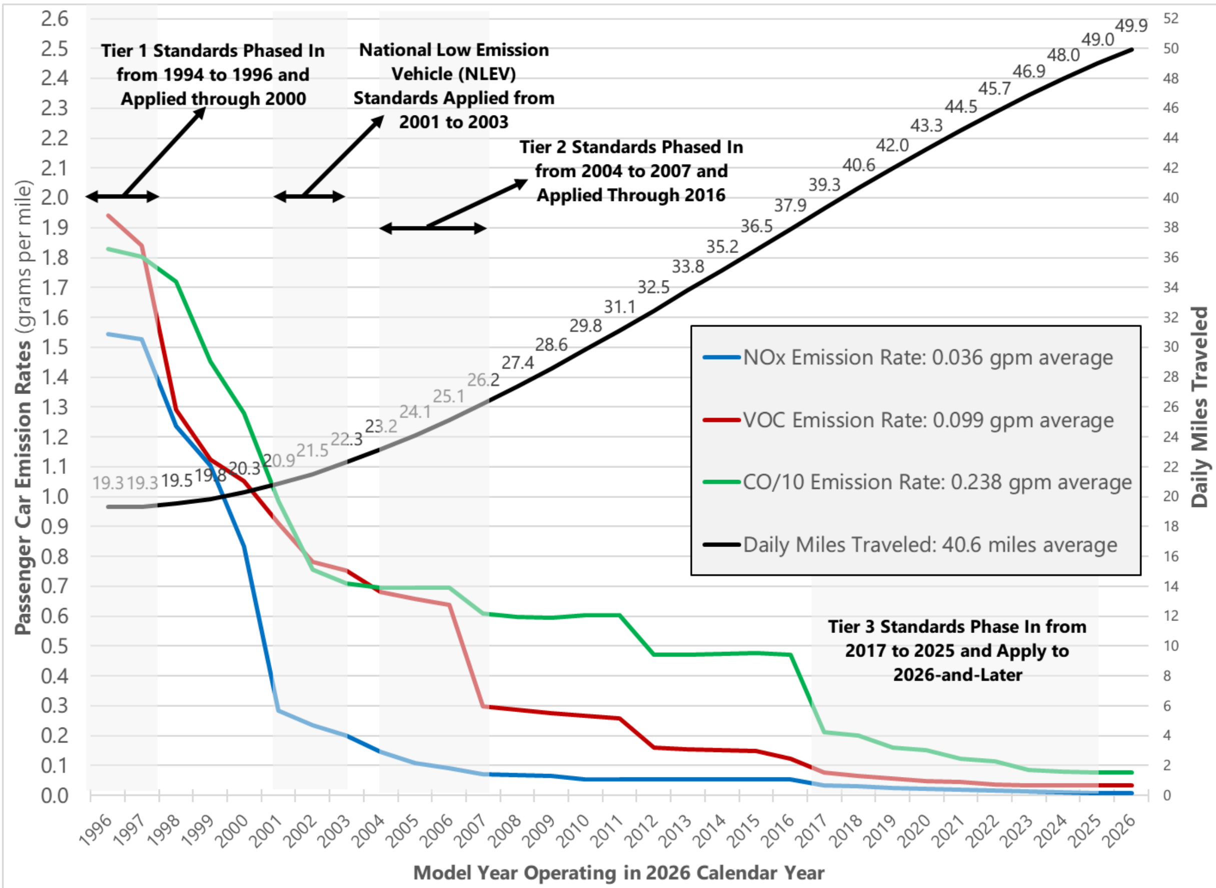

Figure 60. Dallas County NO_X, VOC, and CO passenger car activity and emission rates.

To estimate the maximum possible additional emissions reductions that can be achieved from EVs, it must be assumed that manufacturers over comply with regulations for emissions standards and do not use EVs to meet fleet average requirements. Application of this methodology requires the following information for a calendar year of interest such as 2026:

- EV population by model year and MOVES source use type (e.g., passenger car or passenger truck).
- Fleet average emission rates by model year and pollutant for each MOVES source use type.
- Daily VMT by model year for the source use type.

Since the operational (i.e., not while charging) tailpipe emissions rate for EVs is zero, multiplying these three items together will yield the maximum possible additional emissions reductions that can be achieved from EV sales. An example of this process is provided for Dallas County, and then summary results are presented for the entire DFW area. Table 14 in the section “NCTCOG EV Adoption” contains a projected Dallas County population of 52,174 EVs operating in 2026 for the baseline scenario. Table 38, “Light-Duty Vehicle Sales by Technology Type,” from the AEO 2011–2023 datasets were obtained for the West South-Central region that includes Texas. This table provides estimates of light-duty EVs by model year out to 2050 for the categories of cars and light trucks, which align with the MOVES source use types of passenger cars and passenger trucks, respectively. For the 2026 calendar year, an EV age distribution from the AEO for the years 2008–2026 was obtained for both passenger cars and light trucks.

This age distribution was applied to the 52,174 total EV projection for Dallas County to obtain the EV population by model year and source use type shown in Table 34.

Table 34. Projected Dallas County Distribution of Light-Duty EVs by Model Year in 2026

Model Year	Passenger Car EVs	Passenger Truck EVs	Total Light-Duty EVs
2008	1	1	2
2009	1	4	5
2010	7	10	17
2011	59	8	67
2012	70	10	80
2013	106	12	118
2014	829	14	843
2015	1,149	129	1,278
2016	530	108	638
2017	568	109	677
2018	1,898	111	2,009
2019	2,586	511	3,097
2020	1,249	401	1,650
2021	2,605	2,528	5,133
2022	3,929	1,631	5,560
2023	4,124	1,991	6,115
2024	4,412	2,674	7,086
2025	4,798	3,457	8,255
2026	5,314	4,230	9,544
Total	34,235	17,939	52,174

The MOVES3 model was run for all 12 counties in the DFW TDM network for a 2026 summer weekday scenario using the run specification and county database inputs developed by NCTCOG. The model year output option was activated so that emissions for the 1996–2026 model years would be reported for all pollutants in the *movesoutput* table in the output database of each run. These emissions totals were divided by the VMT for each source use type and model year from the *movesactivityoutput* table in the output database of each run. This process yielded aggregate emission rates in units of gpm for each pollutant, and this is how the NO_X, VOC, and CO emission rates presented in Figure 47 were obtained. Table 35 provides an excerpt of this output for the 2017–2026 model years in Dallas County for multiple pollutants. These model years were chosen because they represent vehicles meeting the most recent Tier 3 emissions standards that began phasing in with the 2017 model year. A comparison of Table 34 and Table 35 shows that the passenger car EV population estimates for 2017–2026 match those for Dallas County.

Table 35. Dallas County Passenger Car Emission Rates for the 2017–2026 Model Years

On-Road Emissions Inventory Parameter	Model Year for Dallas County Passenger Cars Operating in 2026									
	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026
EV population estimate	568	1,898	2,586	1,249	2,605	3,929	4,124	4,412	4,798	5,314
Daily VMT	39.3	40.6	42.0	43.3	44.5	45.7	46.9	48.0	49.0	49.9
NO_X (grams per mile)	0.0348	0.0316	0.0263	0.0234	0.0197	0.0169	0.0136	0.0113	0.0089	0.0089
VOC (grams per mile)	0.0770	0.0653	0.0573	0.0478	0.0446	0.0366	0.0349	0.0330	0.0337	0.0333
CO (grams per mile)	2.1332	2.0131	1.6175	1.5158	1.2210	1.1322	0.8517	0.7895	0.7579	0.7581
SO_2 (grams per mile)	0.0021	0.0020	0.0020	0.0019	0.0018	0.0018	0.0018	0.0018	0.0017	0.0017
NH_3 (grams per mile)	0.0206	0.0206	0.0206	0.0205	0.0169	0.0169	0.0169	0.0169	0.0169	0.0168
$PM_{2.5}$ (grams per mile)	0.0022	0.0023	0.0020	0.0018	0.0014	0.0014	0.0012	0.0012	0.0012	0.0012
PM_{10} (grams per mile)	0.0025	0.0026	0.0023	0.0021	0.0016	0.0016	0.0013	0.0013	0.0013	0.0013
CO_2 (grams per mile)	322.44	307.79	295.18	285.01	279.19	274.59	268.98	265.84	262.00	257.74
CH_4 (grams per mile)	0.0089	0.0083	0.0070	0.0064	0.0056	0.0051	0.0043	0.0039	0.0036	0.0036
N_2O (grams per mile)	0.0037	0.0037	0.0037	0.0037	0.0037	0.0037	0.0037	0.0037	0.0037	0.0037

For each model year, the EV population estimates are multiplied by the daily VMT and emissions rate for each pollutant. Table 36 presents the results. For most pollutants, the emissions are reported in units of grams, but the CO_2 emissions are reported in units of kilograms.

Table 36. Maximum Passenger Car EV Emissions Reductions in 2026 for Dallas County

On-Road Emissions Inventory Parameter	Model Year for Dallas County Passenger Cars Operating in 2026									
	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026
EV population estimate	568	1,898	2,586	1,249	2,605	3,929	4,124	4,412	4,798	5,314
Daily miles traveled	39.3	40.6	42.0	43.3	44.5	45.7	46.9	48.0	49.0	49.9
Total miles traveled	22,320	77,147	108,538	54,038	115,976	179,676	193,350	211,677	235,104	265,412
NO_X emissions (grams)	776	2,440	2,851	1,265	2,281	3,037	2,630	2,399	2,093	2,363
VOC emissions (grams)	1,720	5,041	6,219	2,580	5,170	6,574	6,756	6,985	7,922	8,845
CO emissions (grams)	47,612	155,302	175,560	81,910	141,608	203,435	164,682	167,115	178,185	201,214
SO_2 Emissions (grams)	48	158	212	102	214	326	344	371	406	450
NH_3 emissions (grams)	460	1,589	2,232	1,109	1,965	3,042	3,271	3,577	3,967	4,472
$PM_{2.5}$ emissions (grams)	50	179	218	100	166	257	228	250	277	313
PM_{10} emissions (grams)	56	202	246	113	188	291	258	282	313	354
CO_2 emissions (kilograms)	100,140	330,399	445,768	214,271	450,462	686,354	723,484	782,775	856,780	951,456

On-Road Emissions Inventory Parameter	Model Year for Dallas County Passenger Cars Operating in 2026									
	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026
CH_4 emissions (grams)	199	641	756	346	652	916	835	824	854	962
N_2O emissions (grams)	83	287	403	200	429	664	713	780	864	973

A similar approach was taken for all 2008–2026 model years for passenger cars and passenger trucks in the 12 DFW area counties for the baseline EV population scenario. This process was then repeated for the high- and low-oil-price scenarios. Table 37 presents the full results. The results in Table 37 for each scenario are the maximum possible *additional* emissions reductions that could be achieved if auto manufacturers did not use EVs to meet the required emissions standards for each model year.

Since such overcompliance on the part of manufacturers is unlikely to occur, these results present an upper bound on the emissions reductions that could be achieved for each of the three scenarios. As shown, the high-oil-price scenario leads to the highest projected EV population of 261,485 and therefore the highest possible emissions reductions that could be achieved in 2026.

Table 37. Maximum Possible 2026 EV Emissions Reductions in DFW for Three Scenarios

Electric Passenger Cars and Truck Inventory Parameter	2026 EV Population Scenario for 12-County DFW		
	Baseline	High Oil Price	Low Oil Price
EV population projection	178,561	261,485	159,361
Total EV miles traveled	8,243,527	12,072,777	7,358,002
Daily accumulation (miles per vehicle)	46.2	46.2	46.2
NO_X exhaust (tons per day)	0.18	0.26	0.16
Nitric oxide (NO) exhaust (tons per day)	0.15	0.22	0.13
NO_2 exhaust (tons per day)	0.02	0.04	0.02
Nitrous acid exhaust (tons per day)	0.001	0.002	0.001
VOC exhaust and evaporative (tons per day)	0.39	0.57	0.35
VOC refueling (tons per day)	0.08	0.11	0.07
CO exhaust (tons per day)	10.38	15.20	9.26
SO_2 exhaust (tons per day)	0.02	0.03	0.02
NH_3 exhaust (tons per day)	0.16	0.24	0.15
$PM_{2.5}$ exhaust (tons per day)	0.01	0.02	0.01
PM_{10} exhaust (tons per day)	0.02	0.02	0.01
CO_2 exhaust (tons per day)	2,796.47	4,097.85	2,497.41
CH_4 exhaust (tons per day)	0.05	0.07	0.04
N_2O exhaust (tons per day)	0.04	0.06	0.03
Fuel consumption (gallons)	296,636	434,679	264,913

Most pollutants from on-road vehicles are emitted as tailpipe exhaust, so most of the emissions estimates reported in Table 37 reflect this. NO_X is composed of NO, NO_2, and nitrous acid. MOVES3 reports emissions for each of these NO_X components, so they are included here. VOC emissions occur as tailpipe exhaust, from evaporation, and during refueling at the gas pump. The VOC exhaust and evaporative emissions are combined for reporting, while the VOC refueling emissions are separated. While MOVES3 does estimate PM emissions for brake and tire wear, MOVES3 currently assigns the same brake and tire wear emission rates to EVs and non-EVs. So only PM exhaust impacts are included here. Lastly, while the MOVES3 model does not directly report fuel consumption for gasoline, diesel, or other fuels, it can be derived from the total energy consumption that is reported by MOVES3. The fuel consumption results in Table 37 should be viewed as the maximum possible fuel savings (i.e., gasoline and diesel not consumed) from EV sales for each scenario.

For a given EV population, the results in Table 37 may appear to be lower than what would be expected based on the methodology employed by some other studies. An incorrect approach taken by some of these studies is to assume that the net emissions reductions from EVs are simply based on the fraction of EVs in the local fleet. This incorrect approach ignores the impacts of emissions standards becoming more stringent over time and effectively assumes that all ICE vehicles in the local fleet have the same emission rates.

As Figure 60 shows, this is not the case since there is a wide variation in emission rates as a function of the model year. To illustrate this point more clearly, Table 38 presents calculations of passenger car NO_X emissions for Dallas County in 2026. The weighted average NO_X emissions rate (across the 1996–2026 model years) of 0.0358 gpm is multiplied by the total passenger car VMT to obtain a total NO_X emissions estimate of 2.73 tpd (which matches Table 32). The projected passenger car EV population of 34,235 (which matches Table 34) is 2.01 percent of the total within the county. The incorrect approach would assume that passenger car NO_X emissions should simply be reduced by 2.01 percent to estimate the impact of the EVs in the fleet, and the results are presented in units of grams, pounds, and tons. However, a more suitable approach accounts for how emission rates and VMT vary as a function of model year, and these emission results are 45 percent lower. As shown, an analysis is highly likely to overestimate EV emissions impacts if it does not take into account the variation in emission rates and activity as a function of model year.

Table 38. Sample 2026 NO_X Emissions Calculations for Passenger Cars in Dallas County

2026 Dallas County Passenger Car Parameter	Value
Projected passenger car population (EVs and ICE vehicles)	1,702,546
Projected passenger car total VMT (EVs and ICE vehicles)	69,119,519
Weighted average NO_X emission rate for 1996–2026 model years (grams per mile)	0.0358
Total passenger car NO_X emissions (grams)	2,474,479
Total passenger car NO_X emissions (pounds)	5,455
Total passenger car NO_X emissions (tons)	2.73
Projected passenger car EV population	34,235
Projected passenger car EV population relative to passenger car total	2.01%
Incorrect allocation that assigns 2.01% EV population fraction to total NO_X emissions (grams)	49,757
Incorrect allocation that assigns 2.01% EV population fraction to total NO_X emissions (pounds)	109.70
Incorrect allocation that assigns 2.01% EV population fraction to total NO_X emissions (tons)	0.05
Correct allocation that uses model year population, VMT, and NO_X emission rates (grams)	27,550
Correct allocation that uses model year population, VMT, and NO_X emission rates (pounds)	60.74
Correct allocation that uses model year population, VMT, and NO_X emission rates (tons)	0.03

Comparison of EGU Charging Emissions to Maximum Possible Emissions Reductions from EV Operation

Table 39 summarizes the final results from the sections "EGU Impacts" and "Estimating Maximum Possible Additional Emissions Reductions for EV Population Scenarios." The table includes the net emissions increase for EV charging from Table 31 and the maximum possible emissions reductions due to EV operation from Table 37 for the three EV population scenarios of baseline, high oil price, and low oil price.

Table 39. Comparison of EV Charging Emissions Increase versus EV Operation Emissions Decrease

EV Scenario	Net Emissions Increase from EGU Charging versus Reduction from EV Operation (Tons per Day)								
	NO_X	VOC	CO	SO_2	$PM_{2.5}$	PM_{10}	CO_2	CH_4	N_2O
EV: EGU generation	0.67	0.02	0.27	1.01	0.06	0.06	1,206	0.07	0.01
EV: Baseline population	0.18	0.47	10.38	0.02	0.01	0.02	2,796	0.05	0.04
EV: High-oil-price population	0.26	0.68	15.20	0.03	0.02	0.02	4,098	0.07	0.06
EV: Low-oil-price population	0.16	0.42	19.26	0.02	0.01	0.01	2,497	0.04	0.03

The net increase in EGU generation emissions should be compared directly with the maximum possible emissions reductions from the EV baseline population scenario. For reference, the maximum possible emissions reductions are included for the high- and low-oil-price EV population scenarios. For the primary ozone precursor of NO_X, the net increase of 0.67 tpd for EV charging is higher than the maximum possible reductions from EV operation, such as 0.18 tpd of NO_X for the baseline population scenario.

For this study, the maximum possible on-road emissions reductions for EV operation are confined to the DFW area with the bulk occurring during daytime hours, while the emissions for the net increase in generation for EV charging are dispersed throughout the ERCOT grid with the bulk occurring during nighttime hours. In a photochemical modeling analysis, lowering DFW on-road emissions by 0.18 tpd of NO_X would have a minimal impact on modeled local ozone formation, as would increasing power plant NO_X emissions throughout Texas by 0.67 tpd.

The increase in EGU NO_X emissions (and all other pollutants) depends on the specific plants that will increase generation in response to higher demand from EV charging. As explained in the section "EGU Impacts," cost-optimized dispatch is used to allocate additional generation to minimize the overall cost of electricity to end-use consumers. In other words, the next MWh of generation needed to maintain the balance between supply and demand on the grid will be met by the plant(s) that provides (or bids) the lowest cost per MWh rather than the plant(s) that has the lowest emission rate of NO_X, SO_2, CO_2, etc. per MWh.

As shown in the section "Clean Air Markets Program Data," the emission rates for Texas power plants operating in 2022 ranged from:

- 0.03 to 15.67 pounds per MWh of NO_X with an average of 0.53 (Table 17).
- 0.01 to 8.55 pounds per MWh of SO_2 with an average of 0.72 (Table 18).
- 756 to 5,139 pounds per MWh of CO_2 with an average of 1,278 (Table 19).

If only the plants with the lowest NO_X emission rates provided the additional increase in generation needed for EV charging, then the net increase in EGU emissions would be lower than 0.67 tpd of NO_X. Conversely, if only the plants with the highest NO_X emission rates provided the additional increase in generation needed for EV charging, then the net increase in EGU emissions would be higher than 0.67 tpd of NO_X. The pollutant of NO_X is used to explain this concept here, but it applies to all pollutants emitted by fossil fuel power plants.

In contrast to NO_X, Table 39 shows that the VOC and CO emission increases from generation for EV charging are lower than the maximum possible emission reductions from EV operation. This is primarily because the combustion temperature of burning natural gas and coal for power plant operation is much higher than for ICE operation with gasoline and diesel fuel. In general, the very high temperatures for power plant operation result in more oxidation in the combustion process, which lowers the amount of VOC and CO emitted as by-products.

However, the same high temperature in power plant combustion that leads to lower VOC and CO results in higher NO_X, which increases as a function of peak combustion temperature.

For SO_2, Table 39 shows that the net increase in emissions from EV generation at 1.01 tpd is much higher than the maximum possible emissions reductions that could be achieved from EV operation at 0.02 tpd. In Table 18 and Table 26, the SO_2 emission rates for coal plants are much higher than for natural gas plants. If all increased generation needed for charging EVs was allocated to natural gas plants, the net SO_2 emissions increase in generation would be lower than 1.01 tpd. The maximum possible SO_2 emissions reductions from EV operation is low because the current sulfur content of gasoline under the Tier 3 regulations cannot exceed an average of 10 parts per million (ppm), compared to an unregulated average of roughly 300 ppm in the 1990s and earlier before gasoline sulfur regulations were promulgated. In other words, the SO_2 emission rates for modern gasoline vehicles are already so low that the net SO_2 emissions reduction for operating an EV instead of an ICE vehicle is minimal.

For most of the pollutants reported in Table 39, the net difference is relatively low between the increase in EGU emissions to charge EVs and the maximum possible emissions reductions that can be achieved from operating an EV. The notable exception is CO_2 emissions where significant overall emissions reductions can occur, but it is highly dependent on the mix of fuel types (e.g., coal, natural gas, nuclear, wind, and solar) that account for the net increase in generation needed for charging EVs. Table 19 shows that the CO_2 emission rate in pounds per MWh for a coal plant can be roughly double that for a natural gas plant. If all increased generation for charging EVs was allocated to natural gas plants, the net CO_2 emissions increased for generation would be lower than the 1,206 tons per day in Table 39. Conversely, if all increased generation for charging EVs was allocated to coal plants, the net CO_2 emissions increased for generation would be higher than the 1,206 tpd in Table 39.

If all net increase in generation needed for charging EVs came from zero-emission electricity sources such as wind, solar, nuclear, and hydro, then the net increase in CO_2 emissions for generation to provide EV charging would be zero. However, these zero-emission sources are not typically available to provide the net increase in generation needed on short notice (i.e., the marginal power) to ensure that the overall supply and demand for electricity remains in balance at all times. Even though total generation from non-dispatchable wind and solar sources is likely to increase over the span of several years, the increased generation needed at a specific point in time will usually be provided by dispatchable fossil fuel power plants. When electricity demand momentarily increases to charge EVs or for any other purpose, additional wind and solar radiation are not momentarily provided to existing wind turbines and solar panels.

For gasoline and diesel fuel used to power ICE vehicles, the amount of CO_2 emitted per gallon of fuel consumed is roughly constant at:

- 8,526 grams per gallon (or 18.8 pounds per gallon) for gasoline with 10 percent ethanol.
- 10,198 grams per gallon (or 22.5 pounds per gallon) for diesel fuel.

Due to this direct correlation, the CO_2 emission rate in units of gpm decreases as fuel economy in units of miles per gallon (mpg) increases. As an example, Table 40 shows how CO_2 emissions decrease for a gasoline ICE vehicle accumulating 100 miles in fuel economy increments of 10 mpg from 10 to 50 mpg.

Table 40. 100-Mile CO_2 Emissions for Gasoline Vehicles from Fuel Economy of 10–50 mpg

Fuel Economy of Gasoline ICE Vehicle (mpg)	CO_2 Emission Rate of Gasoline ICE Vehicle (gpm)	CO_2 Emissions per 100 Miles (Grams)	CO_2 Emissions per 100 Miles (Pounds)
10	852.60	85,260	187.97
20	426.30	42,630	93.98
30	284.20	28,420	62.66
40	213.15	21,315	46.99
50	170.52	17,052	37.59

As shown, doubling the fuel economy of an ICE vehicle will reduce CO_2 emissions by half. For example, operating a 20-mpg gasoline vehicle for 100 miles will emit 94 pounds of CO_2, while operating a 40-mpg gasoline vehicle for 100 miles will emit 47 pounds of CO_2 instead. As discussed in the section "Overview of EV and Light-Duty Emissions Standards," auto manufacturers use the sale of both EVs and ICE vehicles when meeting fleet average emission standards, and this EV/ICE averaging applies to both fuel economy and CO_2 emission rate regulations. The 2,796 tpd of CO_2 reduced for the baseline population scenario in Table 37 presents the maximum possible on-road reductions that can occur assuming that EVs are not used by auto manufacturers for fleet averaging to meet standards for fuel economy and CO_2 emission rates.

Conclusion

The overall conclusions from this analysis are:

- We estimated the maximum possible on-road reductions that can occur assuming that EVs are not used by auto manufacturers for fleet averaging to meet standards for fuel economy and emission rates, which is likely to be the case. Our estimates are therefore optimistic.

- For many pollutants such as NO_X and SO_2, there is no a significant increase or decrease in total emissions between the increases from operating fossil fuel power plants to charge EVs and the maximum possible reductions that can be achieved from operating EVs versus ICE vehicles. This is due in large part to the relatively low emission rates that are required of modern ICE vehicles.

- CO_2 is the pollutant for which the largest potential emissions reductions can be achieved from EV operation, but CO_2 is highly dependent on the average fuel economy of the ICE vehicles displaced and the fuel mix of the power plants needed to provide the net increase in generation needed for charging EVs.
- Unless and until zero-emission electricity sources (e.g., wind, solar, nuclear, and hydro) can provide 100 percent of the electricity needed to power the grid, dispatchable fossil fuel sources such as coal and natural gas will be used to provide much of the net increase in generation that will be needed for charging EVs and other activities that require the use of electricity.

Primary ways in which this study differed from others are:

- When estimating the potential emissions reductions from EVs, some other studies have incorrectly assumed that the EV population fraction within a calendar year should simply be multiplied by the total NO_X, SO_2, CO_2, etc. emissions for that year. This approach ignores how emissions standards have become more stringent over time, and often leads to a significant overestimation of possible emissions reductions from EVs.
- The approach outlined here is consistent with current regulations by recognizing that auto manufacturers use sales of zero-emitting EVs to offset sales of higher-emitting ICE vehicles when meeting fleet average emission standards. In most cases, there is no net reduction in emissions from EVs due to this fleet averaging. By modeling the what-if scenario under the optimistic assumption that EVs not being used for fleet averaging, the maximum possible emission reductions for a given EV population were estimated for multiple criteria and GHG pollutants.
- Some other studies have estimated the increased generation by power plants needed to charge EVs but then applied average EGU emission rates by fuel type (e.g., coal and natural gas) to all plants equally. This study used the latest available plant-specific emission rates by pollutant from the 2021 eGRID dataset from EPA. Such an approach provides improved spatial and temporal resolution of the emissions needed to charge EVs throughout Texas. This type of high spatial and temporal resolution is essential for photochemical modeling applications that estimate hourly ozone in various local areas.

Recommendations

We recommend the following for further study:

- At the time this analysis was performed, MOVES3 was the latest available version of the MOVES model from EPA. In late August 2023, EPA released the MOVES4 version of the model, which explicitly models energy consumption for EVs as a function of temperature and also accounts for charging losses as a function of age. This more refined approach in MOVES4 will produce better estimates of the total generation needed for charging EVs under specific scenarios.

- This analysis was confined to light-duty EVs since they represent the large majority of the current EV population. As better data become available for medium-duty and heavy-duty EVs, these types of analyses can be included.
- The eGRID dataset from EPA typically contains the most suitable rates for estimating emissions impacts from increased generation at power plants. However, there is typically a lag time of one year or more in obtaining the eGRID data. For example, the 2022 eGRID results may not be available until sometime in 2024. Whenever future work is performed, the latest available eGRID emission rates should be used.
- When estimating the net increase in generation needed to charge EVs, multiple scenarios should be considered. The highest ozone days that drive the level of the eight-hour ozone design values tend to occur on the most stagnant days when wind power generation is at its lowest. Therefore, ozone modeling should include generation scenarios for low-wind-power days. Alternate days can also be included for average-wind-power and high-wind-power scenarios. Further work can utilize the improved spatial and temporal resolution of the emissions needed to charge EVs throughout Texas and investigate environmental justice and public health impacts in relation to EVs adaptation.

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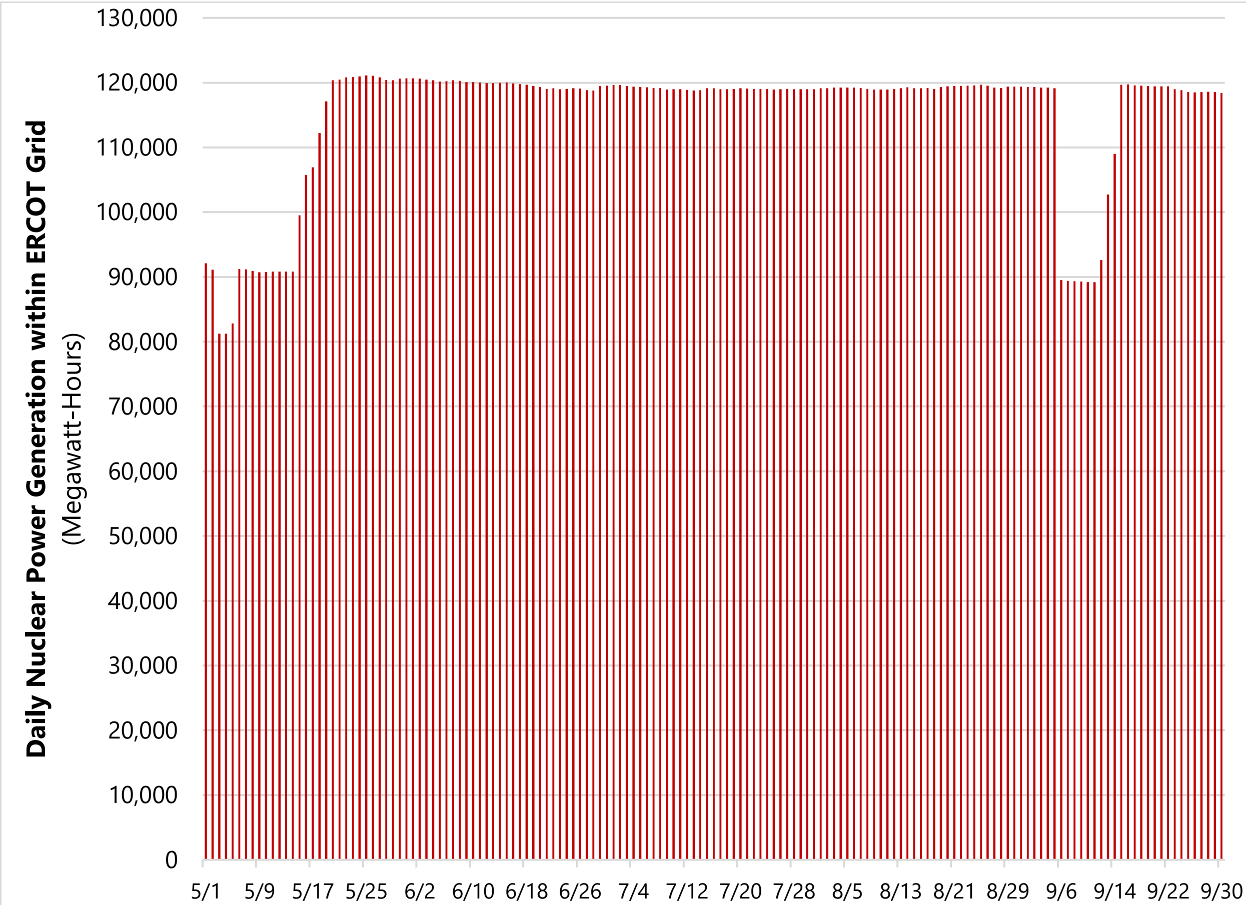
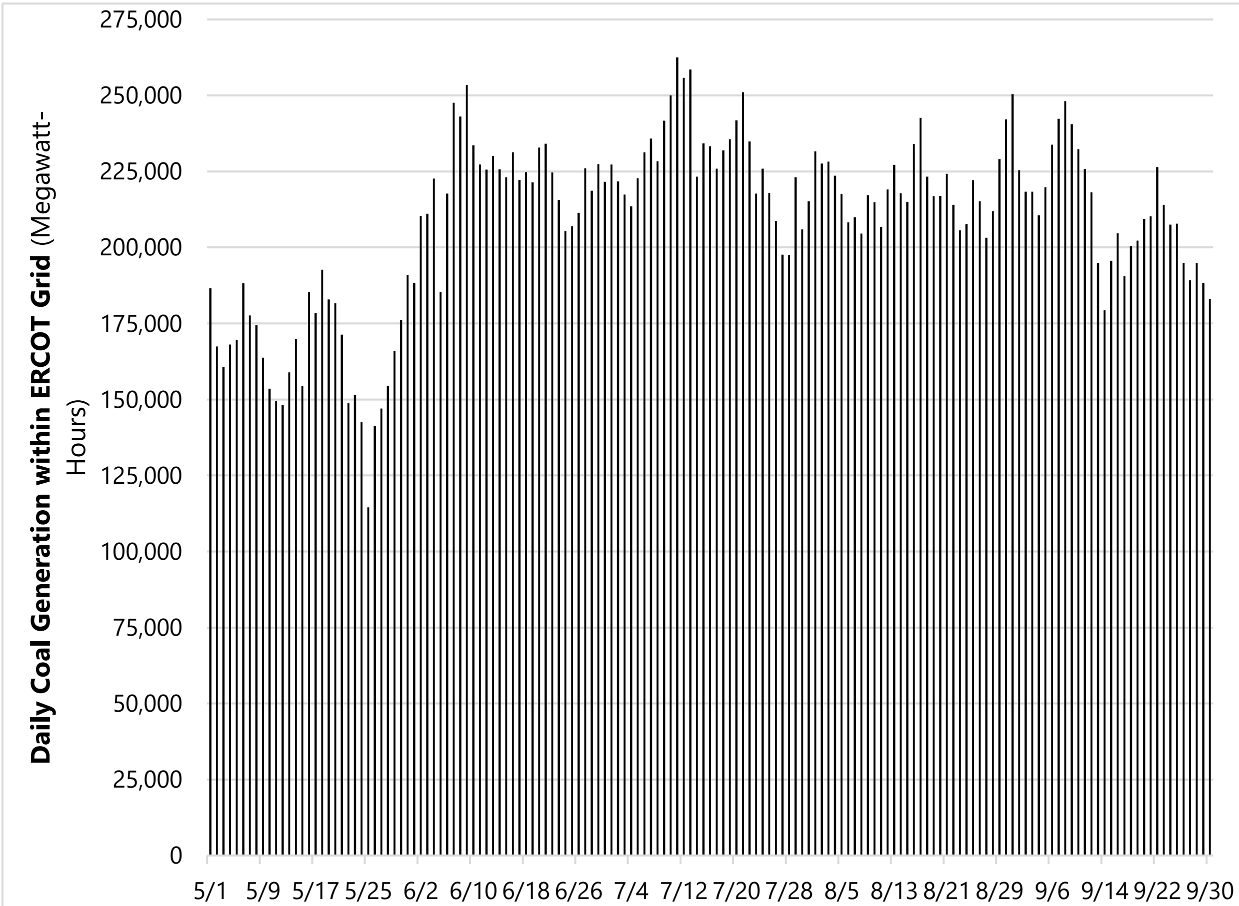
Appendix A: ERCOT Grid Daily Electricity Generation by Source Type

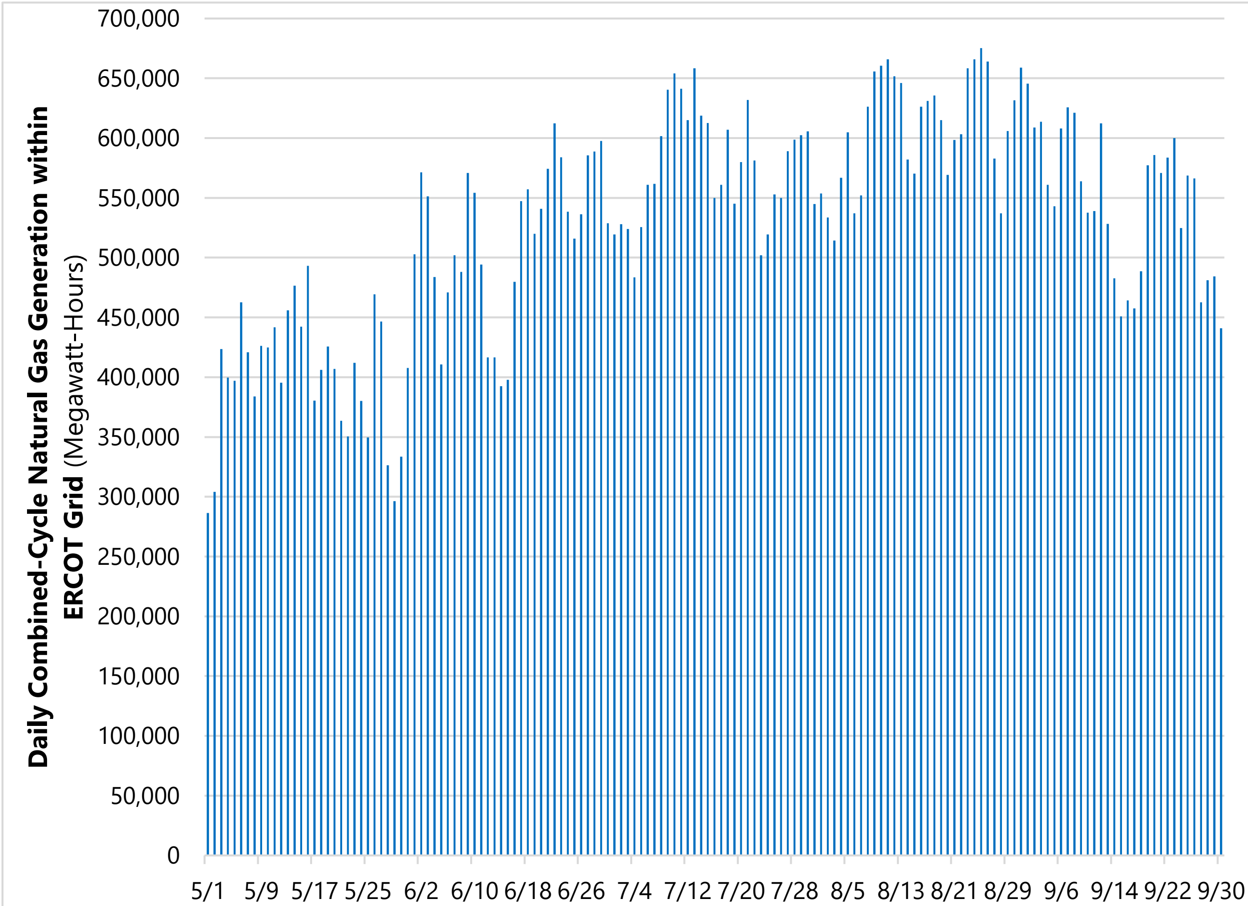
This appendix covers the daily electricity generation by source type within the ERCOT grid for May to September 2022, previously discussed in "Electricity Generation in the ERCOT Grid in 2022."



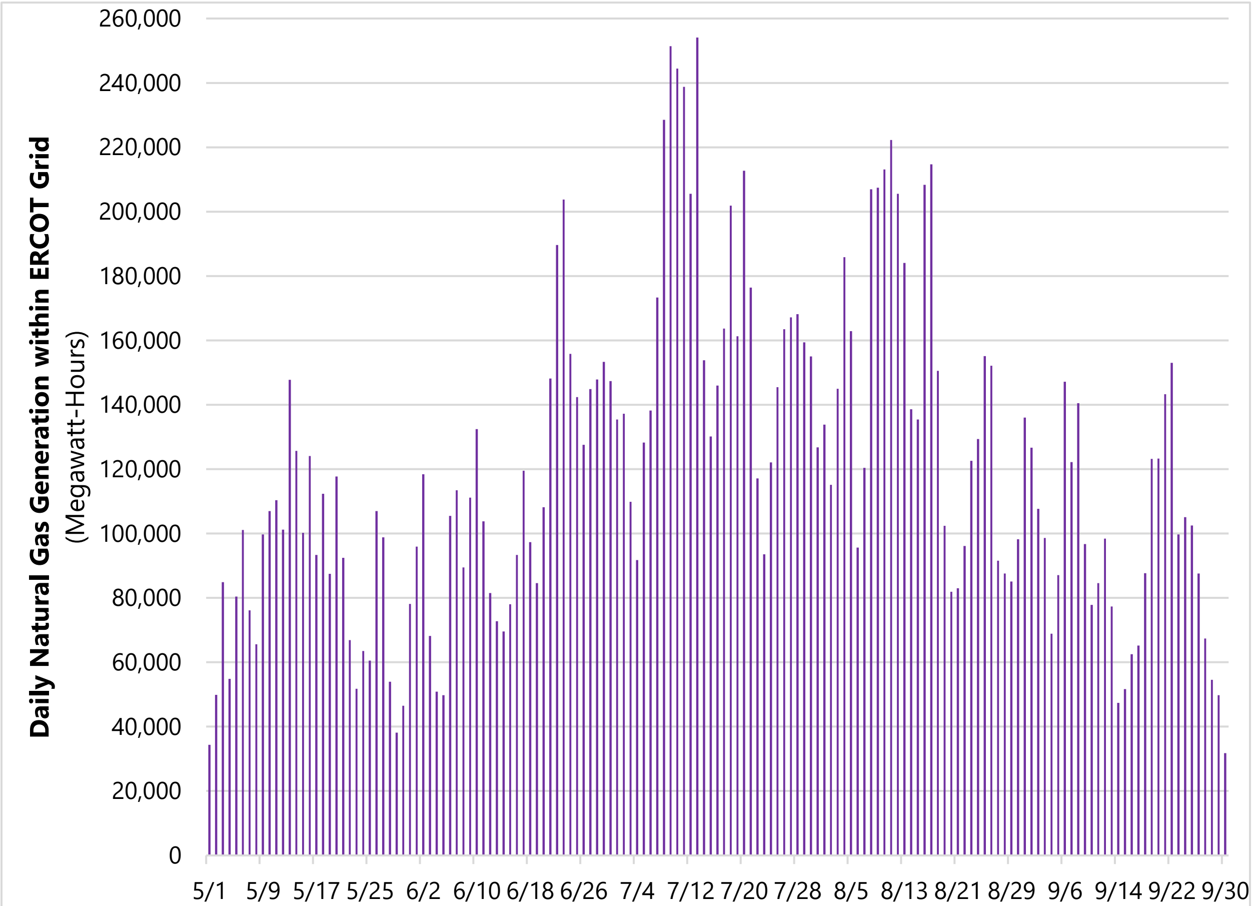
Daily nuclear generation, May to September 2022.



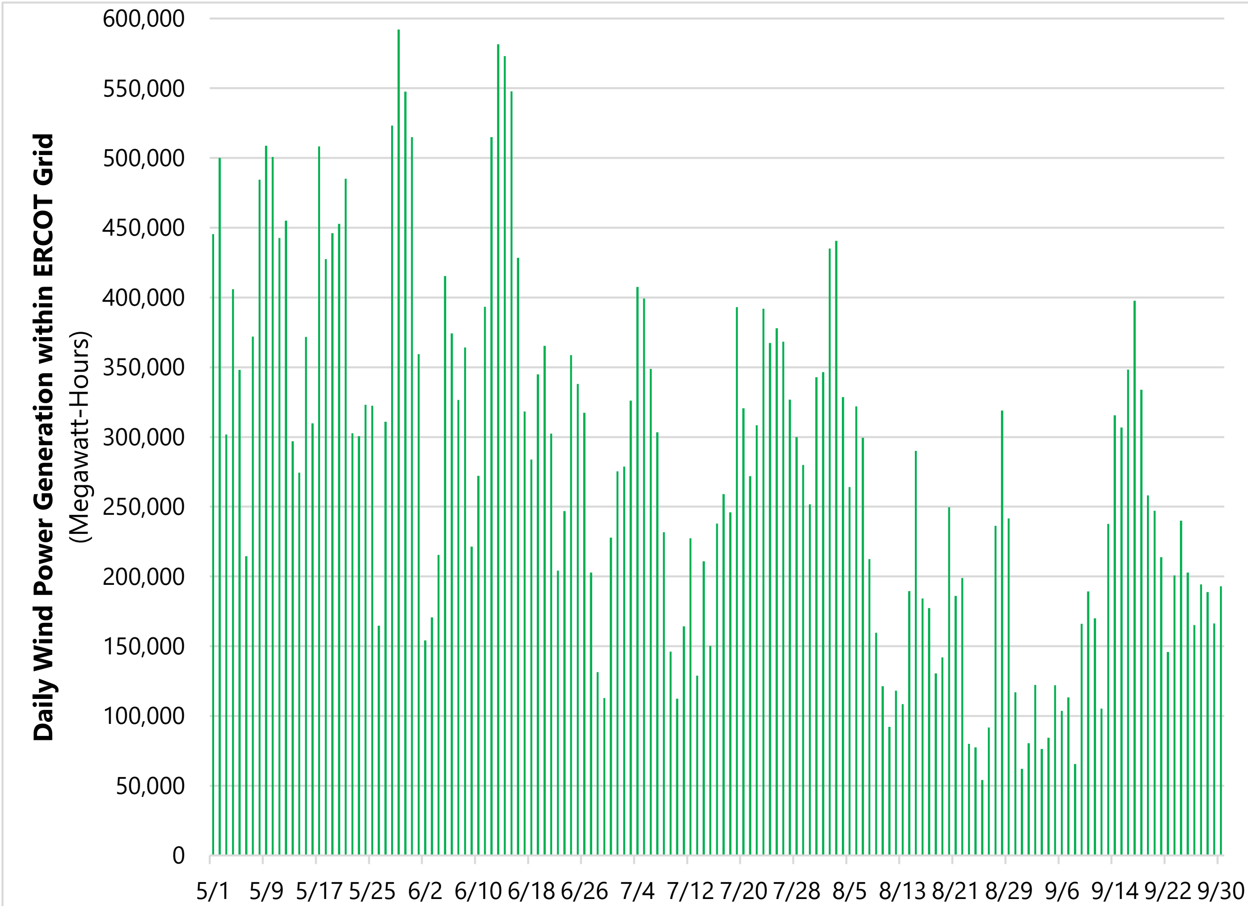
Daily coal generation, May to September 2022.



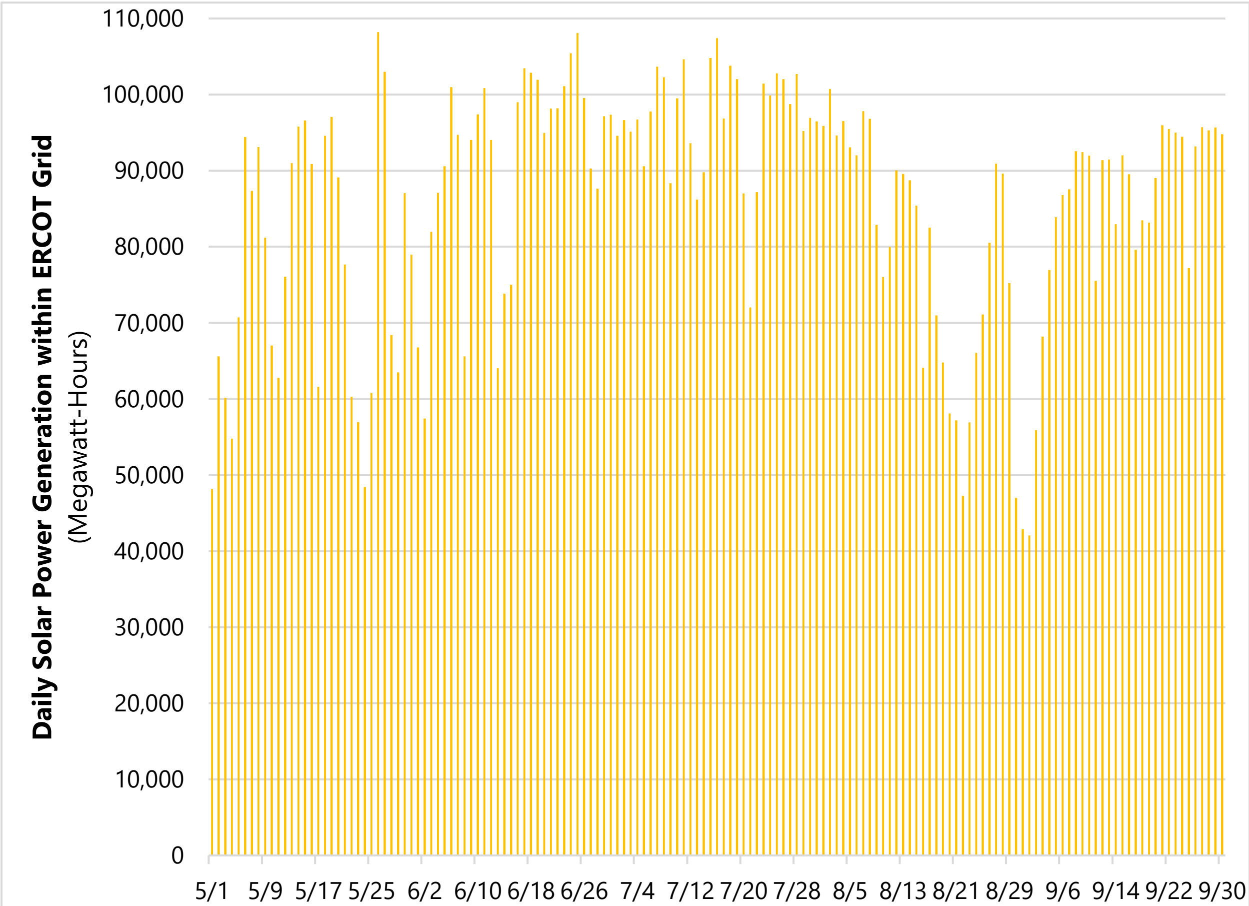
Daily combined-cycle natural gas generation, May to September 2022.



Daily natural gas turbine generation, May to September 2022.



Daily wind generation, May to September 2022.

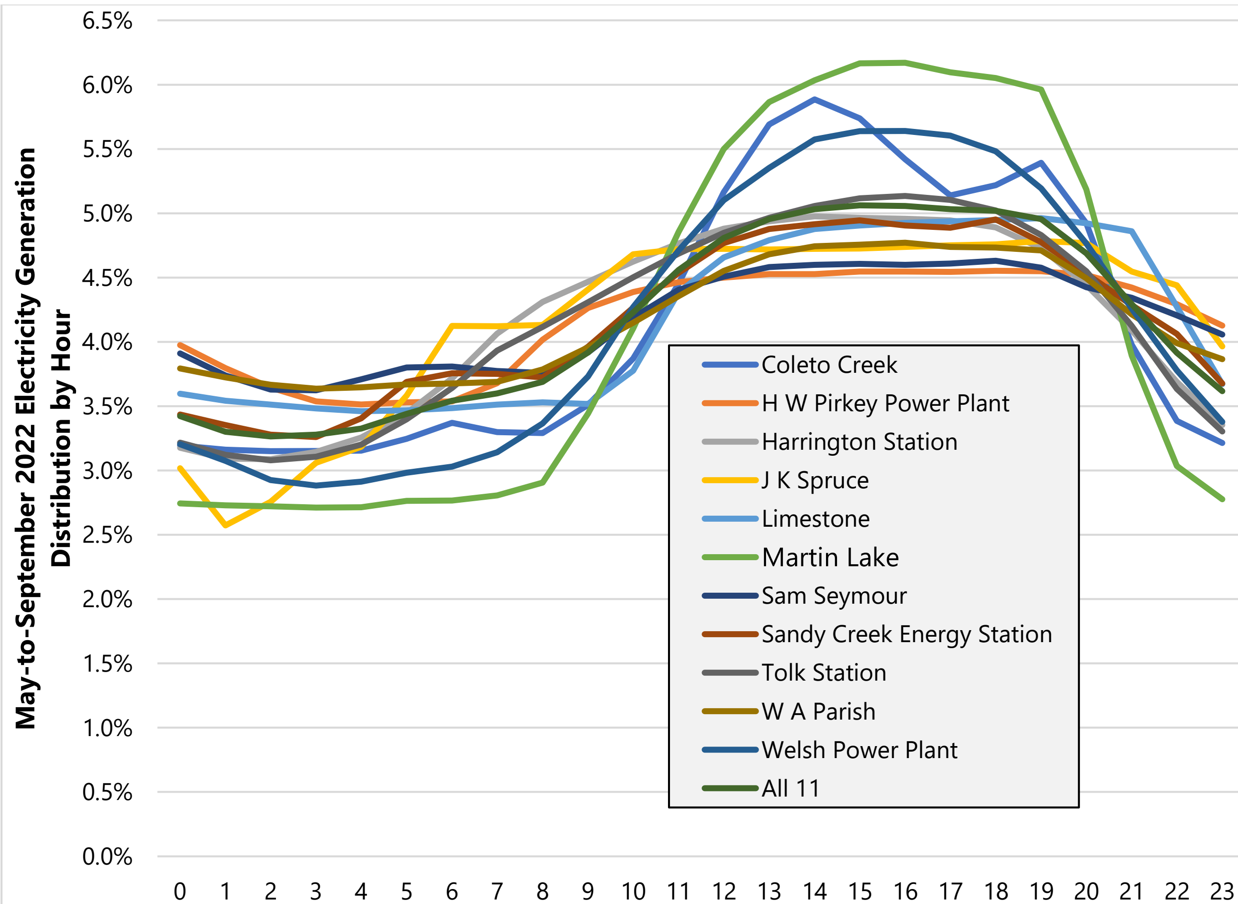


Daily solar generation, May to September 2022.

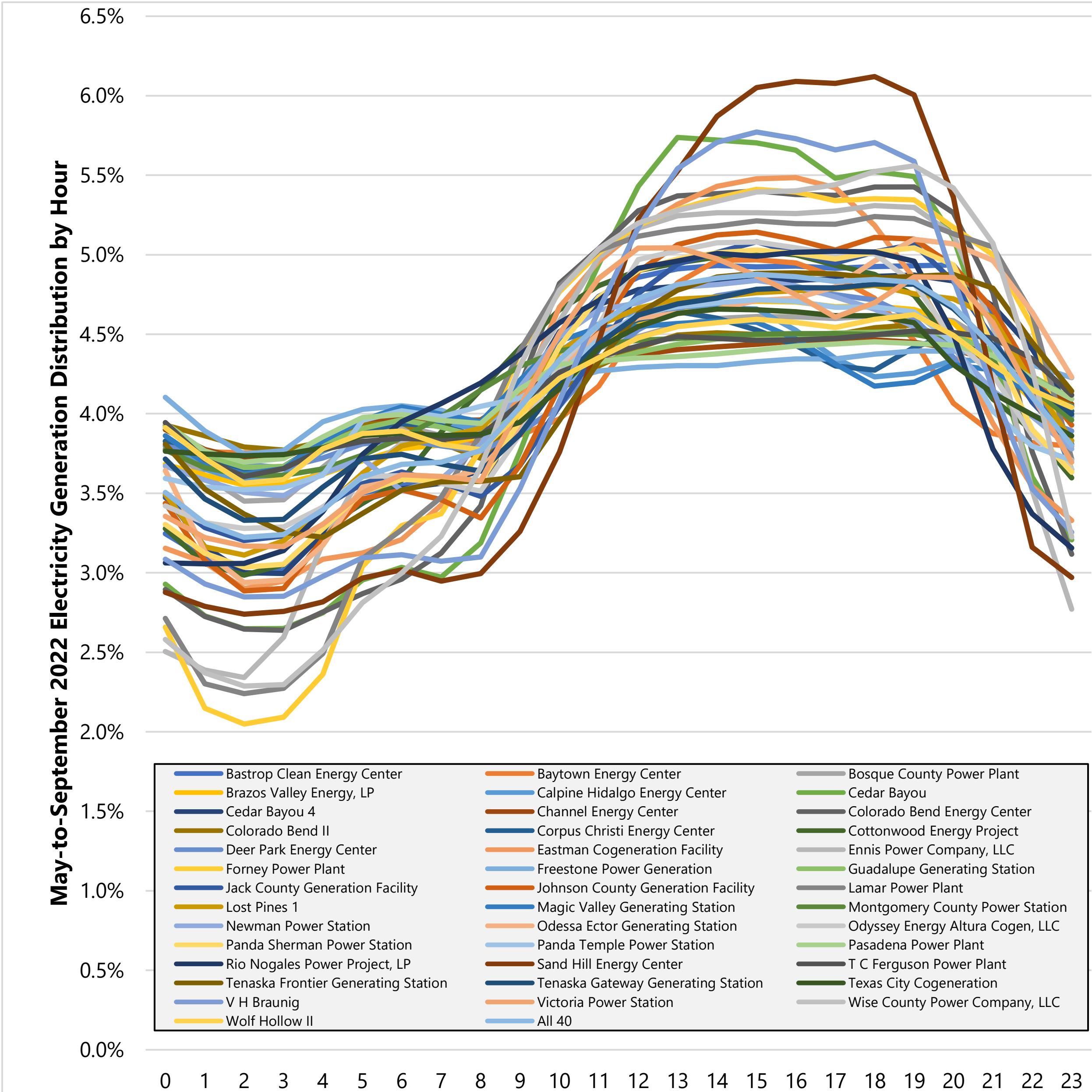
Appendix B: Operating Profiles and Plant Names as Listed in the CAMPD

This appendix provides the operating profiles and plant names as listed in the CAMPD for the following groups, as discussed in the section "Clean Air Markets Program Data":

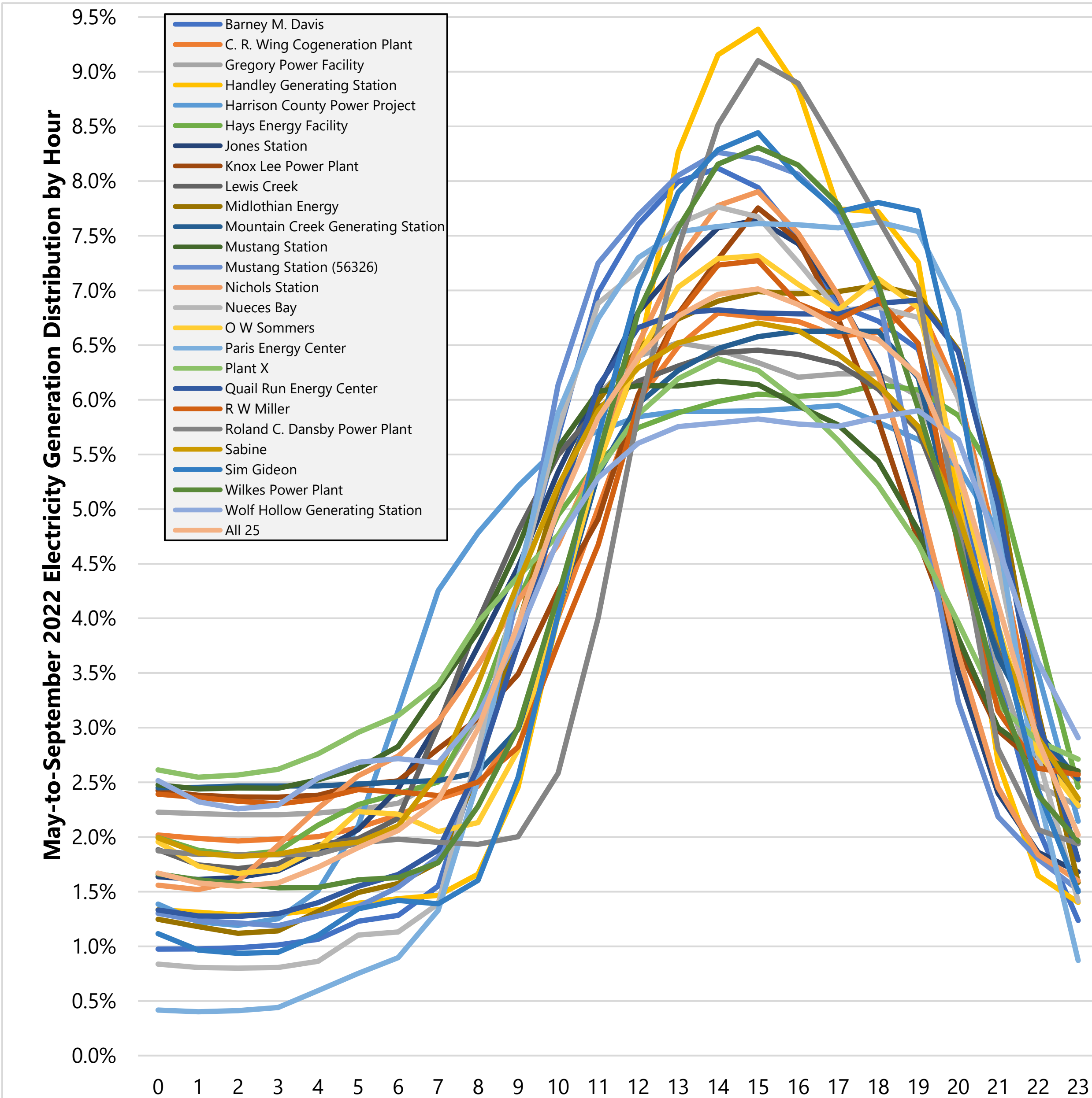
- 11 base-load coal plants with spare capacity, mostly overnight.
- 40 base-load natural gas plants with spare capacity, mostly overnight.
- 25 intermediate or load-following natural gas plants with a generation that fluctuates between day and night.
- 36 peaking plants that typically have zero or minimal overnight generation and are run primarily to meet the highest demand during some afternoons.



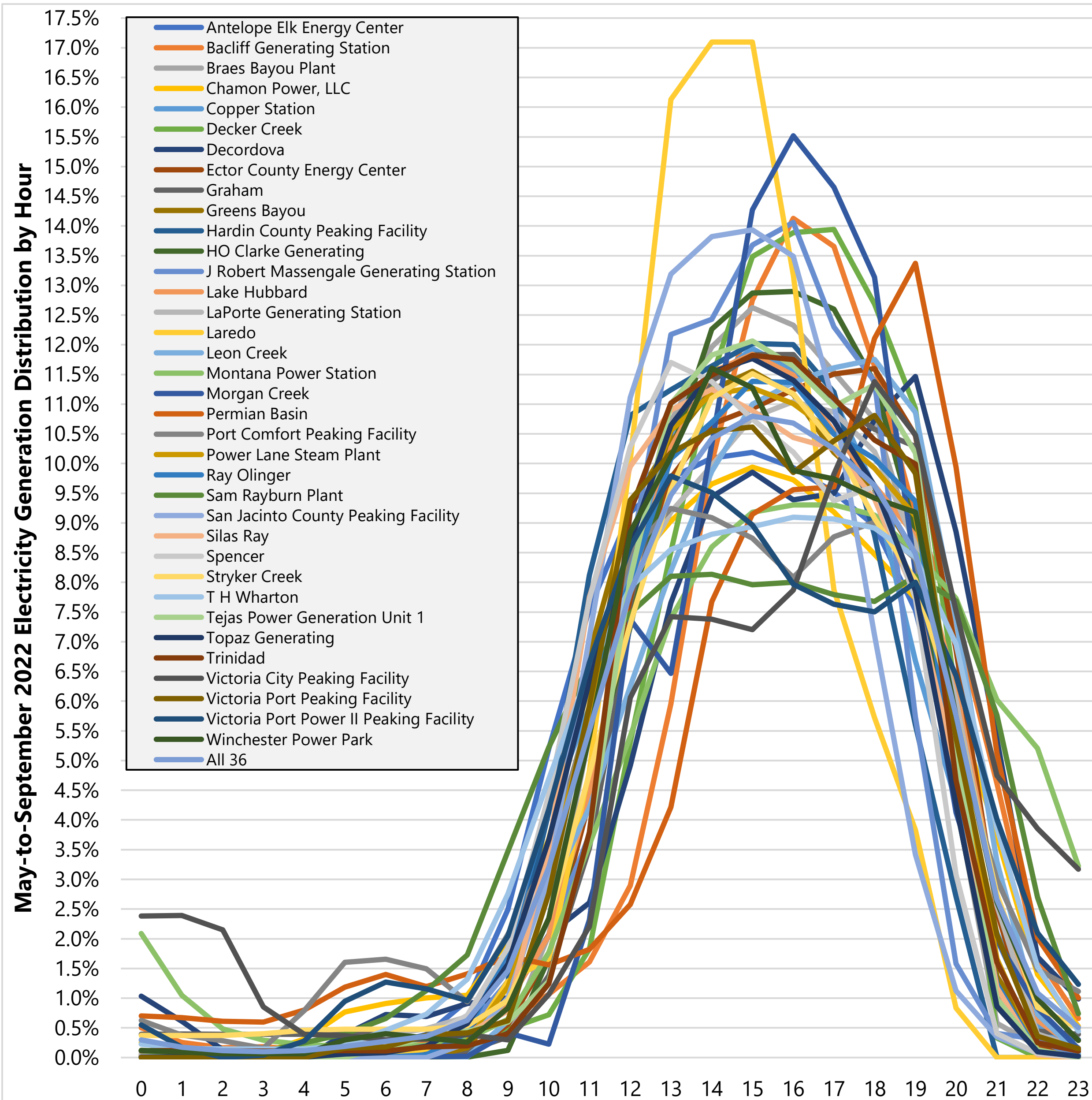
11 coal plants with spare capacity, May to September 2022.



40 natural gas plants with spare capacity, May to September 2022.



25 intermediate natural gas plants, May to September 2022.



36 natural gas plants with peaking profiles, May to September 2022.