

Article

Contributions of Extended-Range Electric Vehicles (EREVs) to Electrified Miles, Emissions and Transportation Cost Reduction

Hritik Vivek Patil ¹, Akhilesh Arunkumar Kumbhar ¹, and Erick C. Jones, Jr. ^{2,*} 

¹ Department of Computer Science and Engineering, College of Engineering, University of Texas at Arlington, 701 S Nedderman Dr. Arlington, TX 76019, USA; hxp4075@mavs.uta.edu

² Department of Industrial, Manufacturing, and Systems Engineering, College of Engineering, University of Texas at Arlington, 701 S Nedderman Dr., Arlington, TX 76019, USA

* Correspondence: erick.jones@uta.edu

Abstract

Transportation is the highest emitting sector in the US, and electrifying transportation is an effective way to reduce emissions. However, electrification efforts have typically focused on battery electric vehicles (BEVs); but extended-range EVs (EREVs), EVs with a backup gasoline generator, could play a major role. Nonetheless, reducing transportation-related costs and carbon emissions hinges on understanding how an EREV's range and charging profile affect electric miles driven and, by extension, emission savings. This study evaluates the distribution of vehicle miles traveled (VMT) between electric and gasoline modes for EREVs across electric range (25–150 miles) and charging frequency scenarios. Using 2023 U.S. trip data by distance and monthly VMT benchmarks, we apply a dynamic mean-distance estimation method to match observed totals and allocate VMT to EV or gasoline power based on trip length. We explore different charging, efficiency, and cost scenarios. Our results show, at current average efficiencies, that EREVs with a 50-mile range (13.7 kWh battery) could electrify 73.3% of national VMT, while 150-mile range EVs could electrify 86.8% illustrating that there are diminishing returns at higher ranges. We also compute corresponding carbon emissions savings using national fuel economy and emissions factors. Results highlight the nonlinear trade-offs between range and emissions reduction. Findings suggest that expanding the EREV range significantly boosts electrification potential up to 100 miles but offers marginal gains beyond. However, if users charge infrequently, larger range EVs are needed to maintain the benefits of vehicle electrification. Our results imply that policymakers and manufacturers should prioritize moderate range EREVs for households who frequently charge (e.g., homeowners) and long range BEVs for infrequent users (e.g., apartment dwellers).

Keywords: extended-range electric vehicles; EV battery size optimization; transportation electrification; trip distance analysis; energy policy; battery range trade-off



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1. Introduction

The transportation sector accounts for a substantial share of global emissions, with light-duty vehicles (LDVs) being the major contributor [1]. Electrifying vehicle miles traveled (VMT) is thus a critical goal in reducing greenhouse gas emissions and achieving net-zero targets [2]. Plug-in electric vehicles (PEVs), including battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and extended-range electric vehicles (EREVs), have emerged as viable solutions, yet their environmental benefits depend heavily

on how they are used in real-world driving [1,3,4]. Not all PEV miles are truly electric, particularly in extended-range models, and estimating this electric-to-gasoline split is essential for realistic policy assessments [3,4].

This study investigates how different battery sizes and corresponding ranges affect the percentage of VMT that are electrified, and how this, in turn, impacts costs, emissions, and installed battery capacity. While many models assume parity in usage between EVs and internal combustion engine vehicles (ICEVs), recent studies suggest that PEVs tend to be driven significantly less than gasoline cars [5,6]. Furthermore, trip assignment within multi-vehicle households often favors ICEVs for high-occupancy or longer trips due to range anxiety and charging infrastructure limitations [7,8]. These findings challenge earlier assumptions and demand updated, representative modeling of VMT distribution by powertrain and range [2,7].

Summary of key results. Our national model finds that, at national average efficiencies and costs, 50-mile range EREVs electrify 73.3% of VMT (2.391 T electric mi/yr), rising to 86.8% at 150 miles (2.83 T). The annual CO₂ savings increase from 574 Mt (50 mi) to 679 Mt (150 mi), while the battery-capex cost per ton CO₂ avoided rises from 0.072 USD/kg CO₂ (50 mile) to 1.82 USD/kg CO₂ (150 mile), indicating diminishing returns beyond 100 mi. However, if users charge less frequently, then longer-range EVs are needed to maintain the benefits of electrification. These findings imply that frequent charging households could balance cost and benefits with moderate range EVs, while infrequent charging households need larger range EVs to maintain electrification benefits.

2. Background

2.1. Effects of EVs on Emissions

A common assumption in electrification modeling is that each mile driven in an EV displaces one mile driven in a gasoline car. Recent research shows that this assumption is often unrealistic. Zhao et al. [6] quantified U.S. EV mileage and found that non-Tesla EVs were frequently driven less than comparable gasoline vehicles. Doshi and Metcalf [5] similarly highlighted large differences in usage across models. Early studies from the U.S. Department of Energy's EV Project also reinforce this point: Smart et al. [3,4] documented that Chevrolet Volt drivers often relied more heavily on gasoline than expected, with charging habits shaping the share of electric miles. Thus, environmental benefits depend on actual usage.

2.2. Balancing EV Costs with Their Benefits

Although EVs offer greater efficiency and lower emissions than gasoline vehicles, their higher upfront cost—driven largely by batteries—remains a significant barrier [1,9]. Li et al. [10] showed that subsidies and charging infrastructure investments create strong indirect network effects. Zaino et al. [2] reviewed global EV adoption research and found that cost, policy design, and charging availability consistently dominate as the most important adoption factors.

Governments' interest in electrification is not only environmental; it is also industrial and strategic. A recent cross-country review documents how purchase incentives, supply-chain localization, and charging-network investment are being combined with trade and industrial policies to capture value in batteries, power electronics, and software stacks [11]. Earlier work focused on developing economies shows similar policy bundles, emphasizing local content rules, tariff design, and public R&D to balance climate objectives with domestic competitiveness and job creation [12]. These studies motivate our cost-effectiveness framing: the relevant metric for policy is not battery capacity per se but electrified VMT and CO₂ avoided per dollar of public and private expenditure.

Implication for this study. When comparing ranges, we therefore evaluate outcomes in USD/tCO₂ and USD/mi (electric), aligning with the policy literature’s emphasis on value-for-money rather than hardware size [11,12].

2.3. Multi-Vehicle Household Dynamics and Range Anxiety

EV usage patterns are also shaped by household vehicle ownership. Chowdhury et al. [7] applied machine learning to U.S. households owning both EVs and ICEVs, showing that gasoline cars are often chosen for longer or higher-occupancy trips. In a companion study, the same authors [8] demonstrated that EV adoption preferences are strongly influenced by household composition and trip needs. Approximately 65% of U.S. households were owner-occupied in the last quarter of 2024. Owner-occupied households are more likely to have larger households, home charging, and more varied vehicle needs. These households, on average, have larger cars with more passenger capacity, higher towing capacity, and road trip capabilities (e.g., range and comfort). In contrast, renters generally have smaller, more efficient cars for mostly city driving and the occasional road trip.

2.4. The Role and Trade-offs of Extended-Range EVs (EREVs)

Extended-range EVs (EREVs) combine electric driving capability with gasoline backup, offering a compromise between BEVs and conventional vehicles. EREVs are often called series hybrids and have similar equipment to plug-in hybrid electric vehicles (PHEV) in that they have a battery (albeit a larger one) and a gas engine. However, unlike PHEVs, EREVs are propelled exclusively by the electric motors, which are powered by the battery; the gas engine serves only as a generator to recharge the battery. This means their operating profile is like that of a BEV, but with the ability to recharge on the go. However, to use both fuel systems, EREVs typically have much smaller batteries than BEVs (but much larger than PHEVs) and a much smaller engine than a typical ICE vehicle. This can reduce costs and material usage but could also reduce the positive impact of EV operations and the overall performance of the vehicle.

Nonetheless, Subramanyam et al. [13] showed that EREVs can replace a substantial share of gasoline trips if integrated well. Yet EV Project data indicate that extended-range models may underdeliver their full electric potential if charging is inconsistent [3,4,36,37]. Recent studies also highlight battery materials scale-up, circularity, and geopolitical considerations [9,14–16]—making it preferable to deploy *less* battery capacity where possible.

2.5. Control Strategy Matters for Realized Benefits

Beyond hardware, energy management strategy strongly affects fuel use and emissions of EREVs. Liu et al. propose adaptive controllers that blend meta-heuristics (RF-IGWO, MGO) to allocate traction demand between the engine-generator and the battery under varying road grades and traffic [17]. Compared with rule-based baselines, such strategies reduce fuel consumption and emissions across multiple drive cycles by exploiting preview information and learning-based calibration [17].

Implication for this study. Our scenario bands (Worst–Average–Best) capture hardware and energy price uncertainty; the Liu et al. evidence suggests an additional “operations” margin, pushing real-world outcomes toward the Average/Best cases when advanced control is used.

2.6. Wireless Power Transfer (WPT) Can Shift the Optimal Range.

Compact inductive power-transfer designs are reducing the size and materials cost of onboard receivers. Liang et al. demonstrate an integrated inductive–capacitive nanocrystalline core aimed at higher power density and footprint reduction for IPT systems, a

direction that can ease vehicle packaging constraints [18]. Complementing static IPT, Wang et al. propose a *dynamic* wireless-charging architecture—based on a flux-pipe supply rail and an H-type receiver—that targets more uniform output voltage as coupling changes during motion [19]. Together, these results indicate that as WPT matures (from stationary depots now to limited dynamic segments later), drivers can harvest more energy *en route*, reducing peak daily energy that must be carried onboard.

Implication for this study. If WPT availability expands, the cost-optimal range that maximizes electrified VMT per installed TWh would likely shift *downward*; hence, our fixed-infrastructure results should be interpreted as conservative with respect to future charging convenience [18,19].

2.7. EV Load Handling and Power-System Implications

2.7.1. Coordinated charging and residential peak shaving.

Beyond vehicle hardware, how EVs are scheduled to charge materially shapes grid impacts [35]. Malik, Mubashshir, and Lehtonen formulate a collaborative demand-response optimization that co-schedules EV charging with residential space-heating storage to shave evening peaks [20]. By jointly timing flexible thermal loads and EV charging, their framework reduces feeder peaks and shifts energy to lower-cost, lower-carbon hours—highlighting that operational coordination can deliver system benefits without new hardware.

Implication for this study. Scenario comparisons of EV range should be interpreted alongside operational practices. With coordinated charging, the system can accommodate higher electrified VMT at lower marginal grid cost and emissions than naïve “charge whenever” baselines [20].

2.7.2. Fast-charging congestion and queuing control.

At public DC fast-charging hubs, service discipline and power allocation determine driver wait times and station utilization. Malik and Lehtonen model fast-charging as a queuing/scheduling problem and propose control strategies that minimize expected waiting time by adapting charging-slot allocation and power sharing across plugs [21]. Such policies reduce congestion at peak periods and make better use of installed capacity.

Implication for this study. When fast-charging is coordinated (rather than first-come, fixed-power), realized travel electrification improves for a given station footprint. Our cost-effectiveness metrics (USD/tCO₂ and USD/electric miles) therefore reflect an operational upside that complements hardware-only comparisons [21].

2.8. Where This Work Fits in the Literature

We examine how smaller all-electric ranges—more amenable to near-term adoption given cost and charging constraints—can still deliver substantial environmental benefits by electrifying the majority of miles. Beyond total electrified VMT, we evaluate the cost-benefit ratio of adding range and identify the diminishing returns point. Methodologically, we contribute a validation framework that reconciles trip-bin estimates with official VMT, and a decision framework for policymakers and automakers that trades off battery cost (kWh/TWh installed) against the electric VMT generated by that range.

3. Methods

This study evaluates the share of electric versus gasoline VMT across varying EV ranges using U.S. data, using a least squares estimation method. We estimate electrified VMT and validate it against official 2023 records, then we project CO₂ emissions for multiple range scenarios.

3.1. Data Sources

We use two main datasets: (i) the Trips by Distance dataset from the U.S. Bureau of Transportation Statistics (BTS), which provides monthly counts of trips across distance categories [22]; and (ii) the official 2023 Monthly VMT data from the Federal Highway Administration (FHWA), used for validation [23].

3.2. VMT Calculations

We start by dividing the trip distances into 9 bins that align with our datasets, see Table 1. From the datasets, we know how many trips are made by each trip distance bin, so we calculated an average mileage for each bin using bounded least squares, in order to minimize the difference between the reported VMT and our calculated VMT, which is the optimized average multiplied by the number of trips. Therefore, for each EV range (50, 75, 100, 125, and 150 miles), we calculate the following:

- Electric VMT: All miles in bins where round-trip distance is less than or equal to EV range.
- Gasoline VMT: The difference between the trip distance and EV miles for trips that exceed EV range.

Table 1. Annual 2023 Trips by Trip Distance from [22] and modeled VMT by distance bin (VMT = Trips \times Avg miles).

Trip Distance Bin (mi)	Trips (B/yr)	Avg Bin Dist (mi)	Calculated VMT (B)
0–1	146.47	0.30	43.94
1–3	123.02	1.00	123.02
3–5	63.63	3.00	190.90
5–10	81.92	5.00	409.58
10–25	77.73	10.00	777.31
25–50	24.43	25.00	610.70
50–100	8.25	50.00	412.25
100–250	3.75	100.00	374.80
250–500	0.77	250.00	193.50
500+	0.51	500.00	256.50

Let $T_{m,i}$ be BTS trips in month m and distance bin i , and Y_m be FHWA total VMT for month m (miles). We estimate a single year-wide vector of bin-average distances $x = \{x_i\}$ by solving a bounded least squares problem:

$$\min_x \sum_{m=1}^{12} \left(\sum_i T_{m,i} x_i - Y_m \right)^2 \quad \text{s.t.} \quad \ell_i \leq x_i \leq u_i,$$

where $[\ell_i, u_i]$ are the bin bounds. The resulting x_i are used for all months.

3.3. General EREV Operating Assumptions

All vehicles are EREVs with the same range. EREVs start each trip with a full battery (except in the limited charging scenarios) and do not charge en route. Trips are round-trip with the same distance to and from, and for a round-trip that exceeds range R , the first R miles are electric and the remainder gasoline. After each trip, the vehicle recharges at home.

3.4. Charging Frequency Method

In order to explore how weekly charging frequency affects EV VMT and, by extension, costs and emissions, we explore four charging scenarios: 7-day, 5-day, 3-day, and 2-day per week charging. We assume all vehicles charge at night to maximum capacity. We believe

these cases align with people who could have EREVs in different housing scenarios, where people who own a single family home would charge every day when they get home (7-day), people who live in rented single family homes a little less often (5-day), people who live in smaller multifamily housing a little less often (3-day), and people who live in apartments the least often out of all groups (2-day).

3.5. Vehicle Count and Fleet Battery Capital Cost

3.5.1. Vehicle Count

Let Y_{year} be the annual U.S. VMT for 2023 (miles) and \bar{d}_{veh} the average miles per vehicle per year. Then

$$N_{\text{veh}} = \frac{Y_{\text{year}}}{\bar{d}_{\text{veh}}}. \quad (1)$$

We use $Y_{\text{year}} = \sum_{m=1}^{12} \text{FHWA}_m \cdot 10^9$ and \bar{d}_{veh} from national statistics.

3.5.2. Battery Size and Installed Capacity

For range R (miles) and on-road EV efficiency η (mi/kWh),

$$s_{\text{kWh}} = \frac{R}{\eta}, \quad \text{Installed}_{\text{TWh}} = \frac{N_{\text{veh}} s_{\text{kWh}}}{10^9}. \quad (2)$$

3.5.3. Battery Capital Cost

Let c_{bat} be the pack cost per kWh (115 USD/kWh [24]). Total fleet battery capital cost:

$$C_{\text{fleet}} = c_{\text{bat}} \times (N_{\text{veh}} \cdot s_{\text{kWh}}). \quad (3)$$

Unit metrics:

$$\frac{C_{\text{fleet}}}{\text{EV VMT}} \quad (\$/\text{electric mile}), \quad \frac{C_{\text{fleet}}}{\text{EV CO}_2 \text{ saved}} \quad (\$/\text{tCO}_2). \quad (4)$$

3.6. Electric VMT, Gasoline VMT, and Emissions

Trips are grouped into distance bins with midpoint d_i and trip count n_i . VMT in bin i is $v_i = n_i d_i$. Electric miles are $e_i(R) = n_i \min(d_i, R)$. Electric share $s(R) = \frac{\sum_i e_i(R)}{\sum_i v_i}$. Gasoline VMT is $\sum_i (v_i - e_i(R))$. Gasoline emissions intensity $g_{\text{gas}} = 8887/\text{MPG}$ (g/mi). Grid EV intensity $g_{\text{EV}} = (\text{kWh}/\text{mi}) \times (\text{gCO}_2/\text{kWh})$. Annual CO₂ saved:

$$\text{EV CO}_2 \text{ saved [t]} = \frac{(g_{\text{gas}} - g_{\text{EV}}) \cdot \text{EV VMT}_{\text{annual}}}{10^6}. \quad (5)$$

3.7. Operating Cost per Mile (Retail Electricity and Gasoline)

Let p_e be residential retail electricity price (USD/kWh) and n_{EV} the EV on-road efficiency (mi/kWh):

$$\text{Cost}_{\text{EV}} = \frac{p_e}{n_{\text{EV}}} \quad [\$/\text{mi}]. \quad (6)$$

Let p_g be the gasoline price (USD/gal) and MPG the average fuel economy:

$$\text{Cost}_{\text{gas}} = \frac{p_g}{\text{MPG}} \quad [\$/\text{mi}]. \quad (7)$$

4. Results and Discussion

4.1. Annual Trips and Modeled VMT by Distance Bin

In order to calculate how often an EREV runs on electricity, and by extension the ratio of electric to gas VMT, we had to disaggregate VMT by trip distance. Table 1 shows the

trip distance by bin and total number of trips provided by [22] and shows our estimated average bin distances that allowed us to calculate a VMT by trip distance.

Table 2 shows how our estimated VMT by month compares with the actual VMT by month provided by [23]. Our model goal was to minimize the sum of the squared error over the year, modifying one average bin distance for the year that was applied to every month.

Lastly, Table 3 illustrates how we calculated EV and Gas VMT based on EREV range. In this table, we assume that the 50-mile EV range EREV charges before each trip and calculate what percentage of the VMT in each trip distance bin would be met by electricity. We then multiplied that percentage by the total VMT in that bin to get the EV VMT. Gas VMT is simply the Total VMT subtracted by the EV VMT.

4.1.1. Validation Against FHWA Monthly VMT

When identifying an average bin distance, we evaluated the bin sizes monthly as well as yearly. While the monthly is more accurate for the year it is trained, it overfits for that given year. Fixed bin widths are more flexible for yearly variations and should be easier to reproduce. While seasonal distances are important as seasonality also affects range, the developed charging and efficiency scenarios will capture variation in electrified VMT more efficiently than overfitting the average bin distance would.

Table 2. FHWA vs. modeled monthly VMT in 2023 (billions); FHWA from [23].

Month	FHWA VMT (B)	Model VMT (B)	Error (%)
January	248.90	278.36	11.84
February	235.40	260.22	10.54
March	273.70	286.38	4.63
April	258.20	280.00	8.44
May	289.60	283.51	-2.10
June	285.60	274.95	-3.73
July	289.80	294.99	1.79
August	290.90	290.02	-0.30
September	278.00	284.65	2.39
October	284.00	288.69	1.65
November	265.10	279.08	5.27
December	263.60	284.07	7.77

Table 3. Annual trips, VMT, and allocation between EV and gasoline at 50-mile range. Trips in billions (B) from [22,23].

Trip Distance Bin (mi)	Avg Dist (mi)	Trips (B/yr)	Trips (B/wk)	Trips / HH /wk	VMT (B/yr)	EV VMT (B/yr)	Gas VMT (B/yr)	EV% in bin
0–1	0.30	146.47	2.817	21.437	35.30	35.30	0.00	100.00
1–3	1.00	123.02	2.366	18.004	118.61	118.61	0.00	100.00
3–5	3.00	63.63	1.224	9.313	184.06	184.06	0.00	100.00
5–10	5.00	81.91	1.575	11.989	394.94	394.94	0.00	100.00
10–25	10.00	77.73	1.495	11.376	749.50	749.50	0.00	100.00
25–50	25.00	24.42	0.470	3.575	588.76	588.76	0.00	100.00
50–100	50.00	8.24	0.159	1.207	397.24	198.62	198.62	50.00
100–250	100.00	3.74	0.072	0.549	361.08	90.27	270.81	25.00
250–500	250.00	0.77	0.015	0.113	186.41	18.64	167.76	10.00
500+	500.00	0.51	0.010	0.075	246.86	12.34	234.52	5.00

$s(50)$ EV share (round-trip) = 73.28% | EV VMT = 2391.07 B, Gas VMT = 871.73 B.

4.2. Factors, Assumptions, and Sources

In order to calculate emissions, battery size, capital cost, operating cost, and other metrics, we identified average values from various sources for key parameters. However, some of these parameters vary or could possibly vary in the future, so in order to explore a

broad range of future outcomes, we created three scenarios: worst, average, and best. The worst scenario explores cases where electric vehicles are, on average, inefficient, battery packs are expensive, and electricity is expensive, but ICEVs are efficient, and gas is cheap. The average scenario uses nationwide averages for all parameters. The best scenario assumes that electric vehicles are more efficient than average, electricity is relatively cheap, the grid has a low carbon intensity, ICEVs are inefficient, and gas is expensive. This is shown in Tables 4.

Table 4. Emission and cost factors used in CO₂ and cost calculations. Source column added per guidance.

Parameter	Value (Worst/Average/Best)	Source
Average Fuel Economy	18/26.4/36 mpg	[25]
CO ₂ per Gallon of Gasoline	8.887 kg/gal	[25,26]
CO ₂ per Gallon of Diesel	10.18 kg/gal	[26]
EV Energy Use per Mile	2.9/3.6/4.2 mi/kWh	[27–29]
U.S. Grid CO ₂ Intensity (2023)	125/348/714 g CO ₂ /kWh	[30]
Average Retail Electricity Price (U.S.)	USD 0.15/USD 0.25/USD 0.40/kWh	[31]
Average Gasoline Price (U.S.)	USD 2/USD 3/USD 5/gal	[32]
Average Miles per Vehicle per Year	11,408 mi/veh/yr	[33]
Average Miles per Driver per Year	13,476 mi/driver/yr	[34]
Households (2023)	131.4 M	[34]
Total VMT (2023)	3262.80 B mi	[23]
Vehicle Count	286.1 M	(Equation 1)

4.3. Emissions and Cost Calculation

Table 5 shows the calculations for emissions for each scenario and vehicle type. Table 6 shows the calculations for capital cost (CAPEX) and operating cost (OC) as well as cost ratios for each scenario and vehicle type. Three patterns emerge from these tables:

1. Small ranges account for the majority of VMT electrification. A 50-mile EREV yields an EV share of 73.3% and 2.39 trillion electric miles annually, with 573.9 Mt CO₂ avoided (national averages).
2. Diminishing Returns: More battery capacity is needed to electrify the next mile. Using national averages, Fleet Wh Battery Capacity per electric VMT increases from USD 1.097 (50 mi) to USD 3.291 (150 mi), i.e., each additional electric mile requires more battery as the range grows.
3. Costs escalate nonlinearly. Using national averages, fleet pack CAPEX per electric mile rises from USD 0.161/mi (50 mi) to USD 0.409/mi (150 mi), and the battery capex per ton of CO₂ saved rises from USD 712/t to USD 1802/t. Gains in electric miles flatten after ~100–125 miles (EV VMT increases by +320 B from 50→100, but only +121 B from 100→150), while battery requirements continue to climb (battery capacity from 3.6 [50 mi] to 10.7 TWh [150 mi]).

Table 5. Range–cost–emissions metrics (annual). Inputs per Table 4; EV/Gas VMT from model.

Scenario	Vehicle Type	Gas VMT (B)	MPG	Gallons (B)	Gas Emissions (Mt CO ₂)	Electric VMT (B)	mi /kWh	Electricity (TWh)	Electricity Emissions (Mt CO ₂)	Total Emissions (Mt CO ₂)	CO ₂ Saved (Mt CO ₂)
Worst	ICE LDV	3262.80	36.00	90.63	805.55	0.0	2.9	0.0	0.0	805.5	0.0
Worst	(25-mile EV range) LDV	1326.05	36.00	36.83	327.39	1936.7	2.9	667.8	476.8	804.2	1.3
Worst	(50-mile EV range) LDV	871.73	36.00	24.21	215.22	2391.1	2.9	824.5	588.7	803.9	1.6
Worst	(75-mile EV range) LDV	711.79	36.00	19.77	175.73	2551.0	2.9	879.7	628.1	803.8	1.7
Worst	(100-mile EV range) LDV	551.85	36.00	15.33	136.25	2710.9	2.9	934.8	667.5	803.7	1.8
Worst	(125-mile EV range) LDV	491.22	36.00	13.65	121.28	2771.6	2.9	955.7	682.4	803.7	1.9
Worst	(150-mile EV range) LDV	430.60	36.00	11.96	106.31	2832.2	2.9	976.6	697.3	803.6	1.9
Worst	EV ICE LDV	0.00	36.00	0.00	0.00	3262.8	2.9	1125.1	803.3	803.3	2.2
Average	(25-mile EV range) LDV	3262.80	26.40	123.59	1098.48	0.0	3.6	0.0	0.0	1098.5	0.0
Average	(50-mile EV range) LDV	1326.05	26.40	50.23	446.44	1936.7	3.6	538.0	187.2	633.7	464.8
Average	(75-mile EV range) LDV	871.73	26.40	33.02	293.48	2391.1	3.6	664.2	231.1	524.6	573.9
Average	(100-mile EV range) LDV	711.79	26.40	26.96	239.64	2551.0	3.6	708.6	246.6	486.2	612.2
Average	(125-mile EV range) LDV	551.85	26.40	20.90	185.79	2710.9	3.6	753.0	262.1	447.8	650.6
Average	(150-mile EV range) LDV	491.22	26.40	18.61	165.38	2771.6	3.6	769.9	267.9	433.3	665.2
Average	(150-mile EV range) LDV	430.60	26.40	16.31	144.97	2832.2	3.6	786.7	273.8	418.7	679.7
Average	EV ICE LDV	0.00	26.40	0.00	0.00	3262.8	3.6	906.3	315.4	315.4	783.1
Best	(25-mile EV range) LDV	3262.80	18.00	181.27	1611.10	0.0	4.2	0.0	0.0	1611.1	0.0
Best	(50-mile EV range) LDV	1326.05	18.00	73.67	654.77	1936.7	4.2	461.1	57.6	712.4	898.7
Best	(75-mile EV range) LDV	871.73	18.00	48.43	430.44	2391.1	4.2	569.3	71.2	501.6	1109.5
Best	(100-mile EV range) LDV	711.79	18.00	39.54	351.47	2551.0	4.2	607.4	75.9	427.4	1183.7
Best	(125-mile EV range) LDV	551.85	18.00	30.66	272.49	2710.9	4.2	645.5	80.7	353.2	1257.9
Best	(150-mile EV range) LDV	491.22	18.00	27.29	242.56	2771.6	4.2	659.9	82.5	325.0	1286.1
Best	(150-mile EV range) LDV	430.60	18.00	23.92	212.62	2832.2	4.2	674.3	84.3	296.9	1314.2
Best	EV	0.00	18.00	0.00	0.00	3262.8	4.2	776.9	97.1	97.1	1514.0

Table 6. Capital and Operating Cost by Battery Size. Comparison of VMT Electrification by Battery Size. Battery cost from [24]; inputs per Table 4.

Scenario	Vehicle Type	% EV VMT	% Increase	Battery Size Average (kWh)	Battery Capacity (TWh)	Battery (Wh) / VMT	Battery Cost \$/T	\$ CAPEX /kg CO ₂	\$ CAPEX /EV Mile	\$ OPEX	\$ OPEX /VMT	\$OPEX / kg CO ₂
Worst	ICE LDV	0.0%	N/A	0.0	0.0	0.000	\$ -	N/A	N/A	181.27	\$ 0.056	N/A
Worst	(25-mile EV range) LDV	59.4%	59.4%	8.6	2.2	0.681	\$ 0.33	\$ 25.23	\$ 0.017	340.81	\$ 0.104	\$ 258.02
Worst	(50-mile EV range) LDV	73.3%	13.9%	17.2	4.4	1.362	\$ 0.67	\$ 40.88	\$ 0.028	378.23	\$ 0.116	\$ 231.95
Worst	(75-mile EV range) LDV	78.2%	4.9%	25.9	6.7	2.043	\$ 1.00	\$ 57.47	\$ 0.039	391.41	\$ 0.120	\$ 224.98
Worst	(100-mile EV range) LDV	83.1%	4.9%	34.5	8.9	2.724	\$ 1.33	\$ 72.11	\$ 0.049	404.58	\$ 0.124	\$ 218.83
Worst	(125-mile EV range) LDV	84.9%	1.9%	43.1	11.1	3.405	\$ 1.67	\$ 88.16	\$ 0.060	409.58	\$ 0.126	\$ 216.69
Worst	(150-mile EV range) LDV	86.8%	1.9%	51.7	13.3	4.086	\$ 2.00	\$ 103.53	\$ 0.071	414.57	\$ 0.127	\$ 214.63
Average	EV	100.0%	13.2%	103.4	26.7	8.172	\$ 4.00	\$ 179.73	\$ 0.123	450.04	\$ 0.138	\$ 202.25
Average	ICE LDV	0.0%	N/A	0.0	0.0	0.000	\$ -	N/A	N/A	370.77	\$ 0.114	N/A
Average	(25-mile EV range) LDV	59.4%	59.4%	6.9	1.8	0.549	\$ 0.21	\$ 0.04	\$ 0.011	285.18	\$ 0.087	\$ 0.61
Average	(50-mile EV range) LDV	73.3%	13.9%	13.9	3.6	1.097	\$ 0.41	\$ 0.07	\$ 0.017	265.11	\$ 0.081	\$ 0.46
Average	(75-mile EV range) LDV	78.2%	4.9%	20.8	5.4	1.646	\$ 0.62	\$ 0.10	\$ 0.024	258.04	\$ 0.079	\$ 0.42
Average	(100-mile EV range) LDV	83.1%	4.9%	27.8	7.2	2.194	\$ 0.82	\$ 0.13	\$ 0.030	250.97	\$ 0.077	\$ 0.39
Average	(125-mile EV range) LDV	84.9%	1.9%	34.7	8.9	2.743	\$ 1.03	\$ 0.15	\$ 0.037	248.29	\$ 0.076	\$ 0.37
Average	(150-mile EV range) LDV	86.8%	1.9%	41.7	10.7	3.291	\$ 1.24	\$ 0.18	\$ 0.044	245.61	\$ 0.075	\$ 0.36
Average	EV	100.0%	13.2%	83.3	21.5	6.583	\$ 2.47	\$ 0.32	\$ 0.076	135.95	\$ 0.042	\$ 0.17
Best	ICE LDV	0.0%	N/A	0.0	0.0	0.000	\$ -	N/A	N/A	906.33	\$ 0.278	N/A
Best	(25-mile EV range) LDV	59.4%	59.4%	6.0	1.5	0.470	\$ 0.12	\$ 0.01	\$ 0.006	437.52	\$ 0.134	\$ 0.49
Best	(50-mile EV range) LDV	73.3%	13.9%	11.9	3.1	0.940	\$ 0.23	\$ 0.02	\$ 0.010	327.54	\$ 0.100	\$ 0.30
Best	(75-mile EV range) LDV	78.2%	4.9%	17.9	4.6	1.411	\$ 0.35	\$ 0.03	\$ 0.014	288.83	\$ 0.089	\$ 0.24
Best	(100-mile EV range) LDV	83.1%	4.9%	23.8	6.1	1.881	\$ 0.46	\$ 0.04	\$ 0.017	250.11	\$ 0.077	\$ 0.20
Best	(125-mile EV range) LDV	84.9%	1.9%	29.8	7.7	2.351	\$ 0.58	\$ 0.04	\$ 0.021	235.44	\$ 0.072	\$ 0.18
Best	(150-mile EV range) LDV	86.8%	1.9%	35.7	9.2	2.821	\$ 0.69	\$ 0.05	\$ 0.024	220.76	\$ 0.068	\$ 0.17
Best	EV	100.0%	13.2%	71.4	18.4	5.642	\$ 1.38	\$ 0.09	\$ 0.042	116.53	\$ 0.036	\$ 0.08

4.4. Transportation Emissions by Subsector

The inspiration of this work was to see how transportation emissions, the largest emitting sector (28%) in the US, can be reduced. LDVs account for about 57% of transportation emissions as illustrated by Figure 1 which shows all categories of emissions in transportation: rail, watercraft, aircraft, and ground transportation, with ground transportation being by far the largest.

Figure 1 illustrates how electrifying (or partially electrifying) light-duty vehicles could reduce LDV emissions by more than half, putting them in line with the emissions produced

by trucks and aircraft, which have orders of magnitude fewer vehicles and total VMT. Future work, can investigate how electrification (or partial electrification) of medium to heavy duty trucks, aircraft, watercraft, and rail could reduce those subsectors emissions in a similar way.

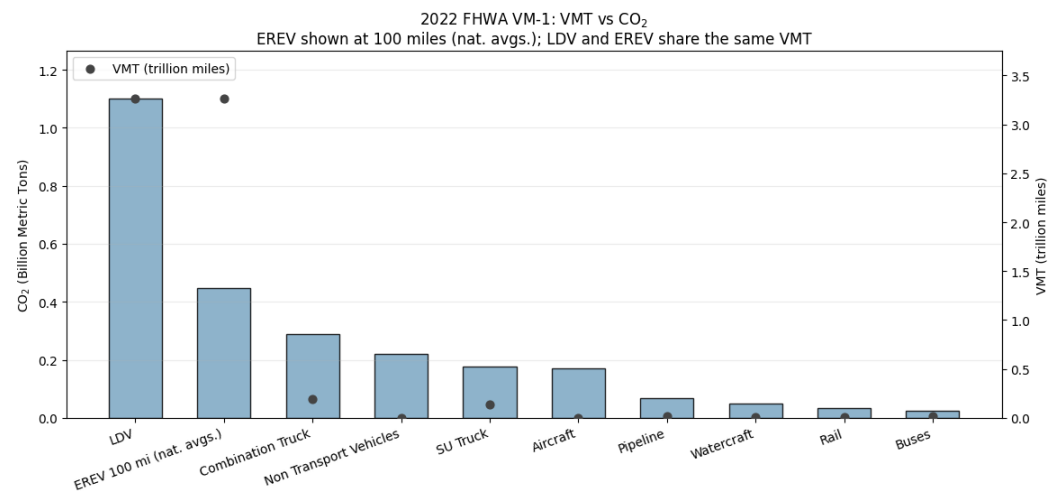


Figure 1. Emissions and VMT by Transportation Mode (2022).

4.5. Battery Capacity and Capital Cost

Figure 2 shows how many TWh of batteries would be required to transform all LDVs to an EREV with a given range. The scenarios—worst, average, and best—correspond to ranges for electric vehicle efficiency. These results show that efficiencies matter for battery size, and these effects magnify at higher vehicle ranges. All charging frequency cases will have an installed battery capacity equal to the average (blue) scenario because only efficiency and range affect battery size.

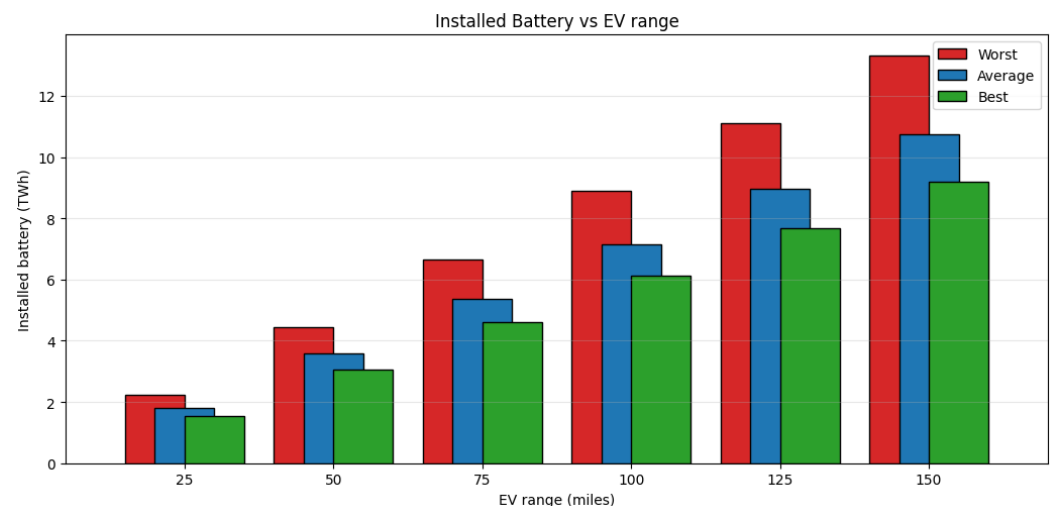


Figure 2. Installed battery capacity (TWh) vs. EV range by scenario.

Figure 3 illustrates the cost of electrifying the entire LDV fleet by EV range and scenario. Larger batteries are needed for lower efficiency, which increases the capital cost of EREVs. Again, all charging frequency cases will have a capital cost equal to the average (blue) scenario because only efficiency and range affect battery size and, by extension, capital cost.

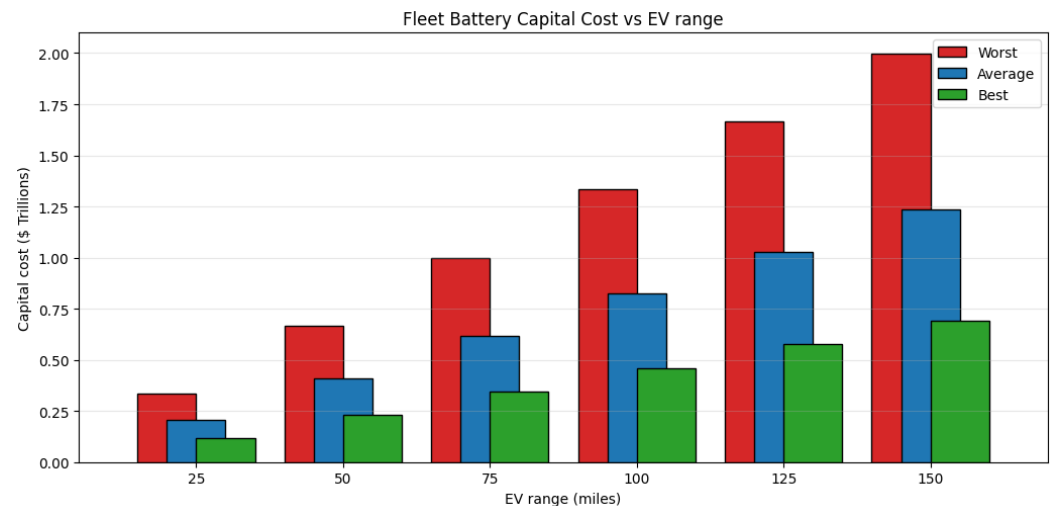


Figure 3. Fleet battery capital cost (\$T) vs. EV range by scenario.

4.6. Charging Pattern and VMT Shares

We calculated the electric and gas VMT by creating weekly driving profiles where we divided the total number of yearly trips in each trip distance bin by the number of drivers and then by the number of weeks for all trip distances less than 100 miles. These values are shown in Table 3. We distributed those trips across the week to realistically match the average household's weekly trip pattern. For instance, mid-range trips that resemble commute distances, we aligned with the weekdays. Shorter trips, which could be school pickups or grocery store trips, were spread through weekdays. Slightly longer short trips and slightly longer than commute distance trips were spread over the weekend. This distribution ended up with a relatively even distance traveled per day of about 75 miles.

We excluded trips over 100 miles from the weekly profile for two reasons. One, we calculated the trips over 100 miles to be relatively rare (less than 1 per week), and calculating the VMT for a partial trip would create an unrealistic profile. Two, it is reasonable to assume that if a driver knows they are going on a long trip, they would plan ahead and charge before the trip. Therefore, we assumed drivers would have a normal charging schedule during the week for shorter trips that would not be interrupted by the occasional long trip. We calculated the EV VMT for longer trips by only assuming that the first part of the round-trip started with a full battery and assigned the difference as Gas VMT. So if a driver took a 200-mile round-trip on the weekend and their EREV has a 50-mile range, then we assumed that 150 miles of that trip used gas.

Figure 4 shows the weekly charging scenarios. The rows are the weekly charging frequencies from 7 to 2 times a week, and the columns are the EV range of 50 to 150 miles. The green lines show which days the cars are charged at night, and the black lines show the charge in the car, in miles available, at the beginning of the day. Our results show that, as expected, more frequent charging results in more electric VMT, and the larger the capacity, the less frequently you need to charge.

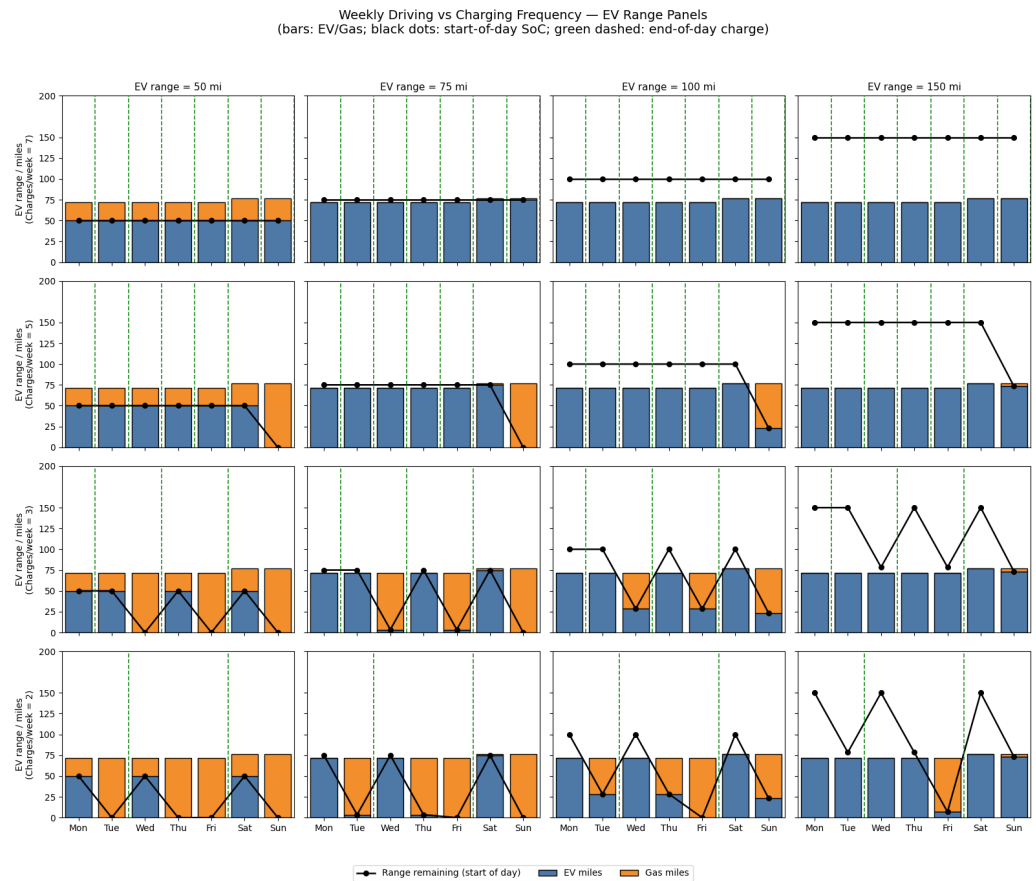


Figure 4. Daily VMT by EV range and charging frequency. Bars: EV/Gas miles; black dots: start-of-day SoC; green dashed: end-of-day charge.

Figure 5 shows how charging frequency changes the ratios of electric and gas VMT by charging range. It shows that lower charging frequencies, especially for lower-range vehicles, can have a dramatic effect on how much electric VMT is actually used compared with the theoretical maximums. The electric and gas VMT ratios for the worst, average, and best case scenarios will have the same distribution and be similar to the 7-day-a-week charging frequency VMT ratio (far left bars in each range section), but with slightly more electric VMT, because we assume that they charge before each trip.

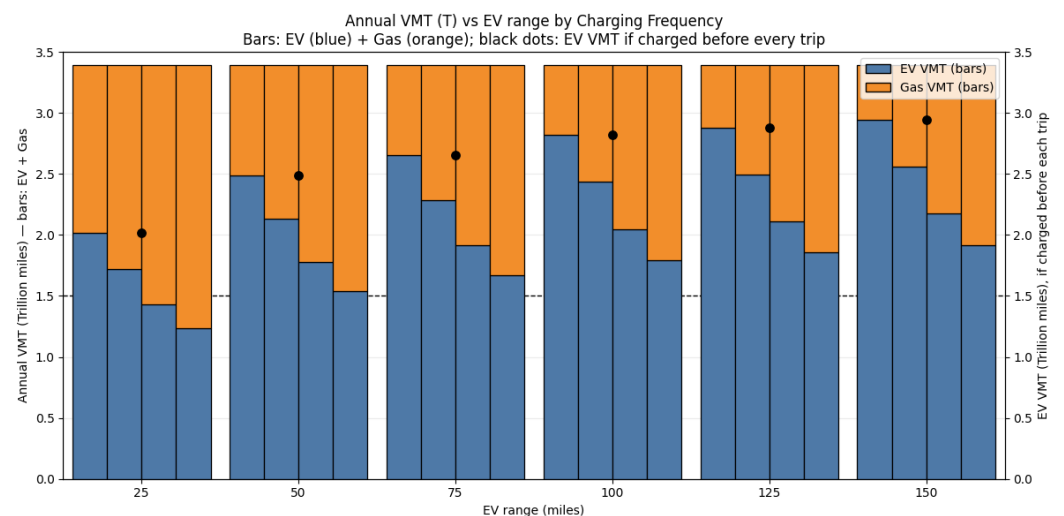


Figure 5. Annual VMT (B) vs. EV range by charging frequency. Bars: EV/Gas miles; black dots: EV VMT assuming full charge before every trip.

4.7. Emission Savings and Cost of Emission Savings

Figure 6 illustrates the CO₂ emissions for each range and scenario. The scenario assumptions relevant to this graph are the EV efficiency, the electricity grid carbon intensity, the miles per gallon for the gas VMT, and the emissions per gallon of gas, which is constant. The results illustrate that the CO₂ savings offered by EREVs are dependent on the efficiency of gas and electric vehicles as well as the grid carbon intensity. If the EREVs are of average efficiency and charged by an average grid (middle columns), then they provide massive CO₂ savings. However, if the ICE fleet becomes dramatically more efficient and the electricity grid becomes dirtier, for instance, because of increased coal electricity generation, then the CO₂ savings vanish (left columns). PHEVs or low-range EREVs (25-mile and 50-mile ranges) can see higher emissions even as EV efficiency and grid carbon intensity improve because more of their miles use inefficient gasoline; however, higher-range EREVs benefit from the improved efficiency of electric miles, and their emissions decrease (right columns).

Note that in the worst case, for all EREV ranges, the emissions are extremely close to the ICE emissions. However, our parameterization has electricity emissions just a little less than gasoline emissions, which means that any electrified emissions will be slightly better than ICE emissions for our defined worst case. However, if the national average grid intensity is raised to 800 g CO₂ / kWh, the electric vehicle efficiency is dropped to 2.8 mi/kWh, or the average ICE fleet mpg is raised above 37, then EREVs would emit more. While we believe this scenario is unlikely, it is important to point out that there are scientifically feasible scenarios where EREVs and EVs could emit more than ICEVs.

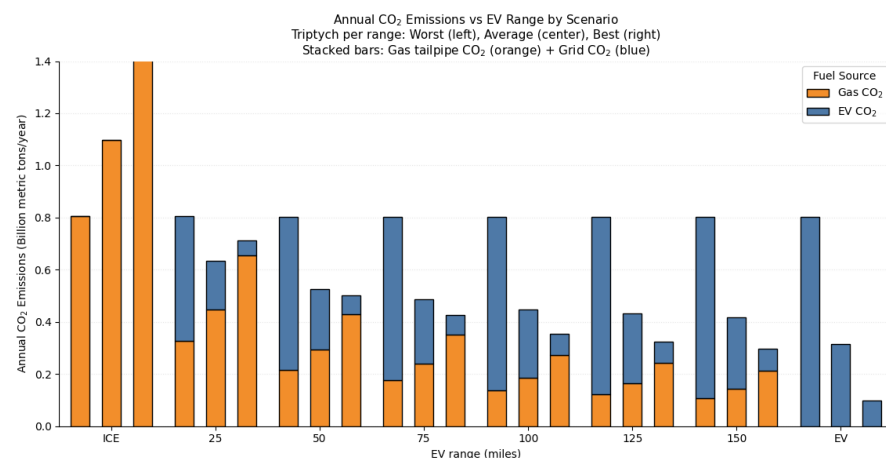


Figure 6. Annual CO₂ savings vs. EV range by scenario.

Figure 7 illustrates the CO₂ emissions for each range and charging frequency. We assume the average scenario that defines the electric and gas vehicle efficiency and the electric grid carbon intensity. The results show that the CO₂ savings offered by EREVs are dependent on how often they charge, which affects how many miles are electric versus gas. Less frequent charging results in more Gas VMT, which results in higher emissions. Higher-range EREVs mitigate or eliminate this impact, as shown by the small (or zero) increase in Gas VMT when the charging frequency drops from seven to five or five to three, in line with EREV ranges of 125 and 150. Therefore, for lower charging frequencies, a larger EREV range helps maintain the maximum number of electrified miles.

These results could be skewed one way or another by scenario, as shown in Figure 6. However, for all electrified charging frequencies, there are CO₂ savings, as any electrified mile, for all scenarios, will produce fewer emissions than a corresponding gas one.

Nonetheless, these results show that the CO₂ benefits of EREVs are heavily dependent on charging frequency, which is in turn influenced by charging infrastructure.

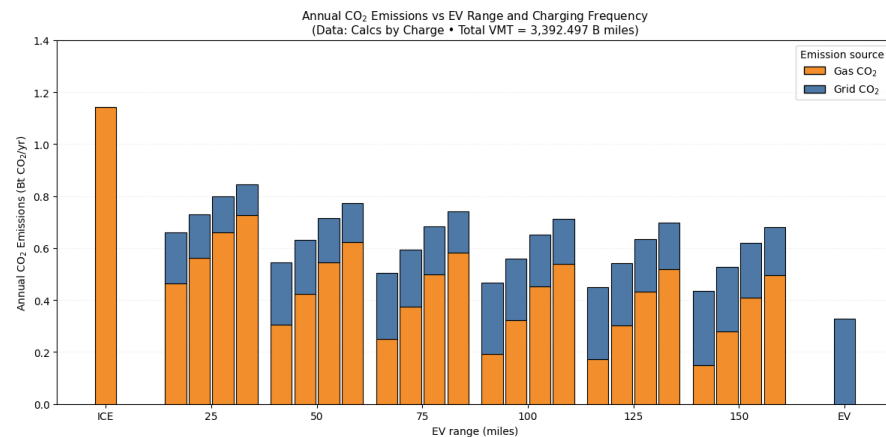


Figure 7. Annual CO₂ savings vs. EV range by charging frequency.

4.8. Cost of Electrification and Emission Mitigation

Figure 8 shows the capital cost per electric mile over a 10-year lifespan by scenario and range. The calculations assume that the vehicles charge before every trip. The EV VMT for a given range are the same for all scenarios (black dots), so the denominator (EV Miles) does not change. However, the scenario assumptions change the numerator (capital costs), highlighting that inefficient EVs and expensive batteries cost more than efficient EVs and inexpensive batteries. These results are expected but show that there are diminishing returns to battery size in relation to electric VMT.

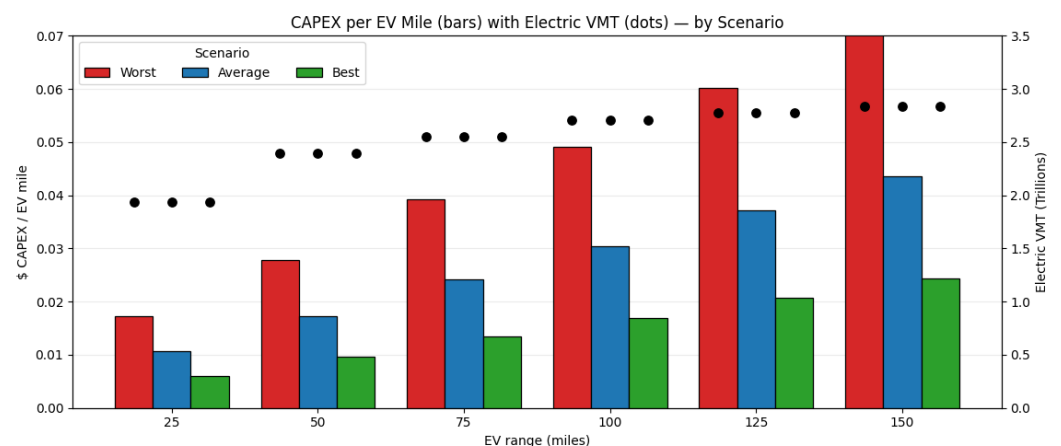


Figure 8. Cost per electric mile and EV VMT (Black Dots) vs. EV range by scenario.

Figure 9 shows capital cost divided by the electric VMT over a 10-year lifespan by charging frequency and range. The calculations assume that the vehicles charge before every trip. In contrast to the above figure, the EV VMT (black dots) changes by charging frequency, so the denominator (EV Miles) changes, but the scenario assumptions are the same, so the numerator (capital costs) stays the same. Thus, in this case, charging frequency drives EV VMT, which in turn drives cost. The cost per electric mile is higher for longer range vehicles since they have more electric miles, but the difference between electric VMT is similar across all charging scenarios.

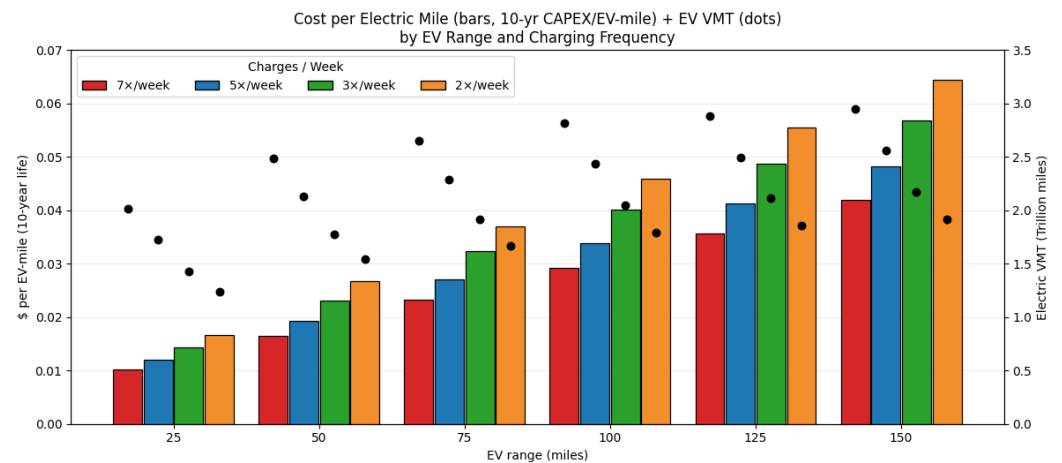


Figure 9. Cost per electric mile and EV VMT (Black Dots) vs. EV range by charging frequency.

Figure 10 shows the CAPEX per ton of CO₂ saved over a 10-year lifespan relative to the pure ICE case by scenario. Again, the scenario assumptions drive the increase in cost per CO₂ saved, as costly batteries raise the numerator, dirtier grids lower the denominator, and inefficient EVs both raise the numerator and lower the denominator. However, in all scenarios, there are CO₂ savings (black dots corresponding the secondary y-axis), which show that EVs do reduce CO₂, but the price of those savings can get expensive. This will hold even though in this case we assume vehicles charge at the beginning of every trip because any electric mile reduces CO₂ even if only by a little.

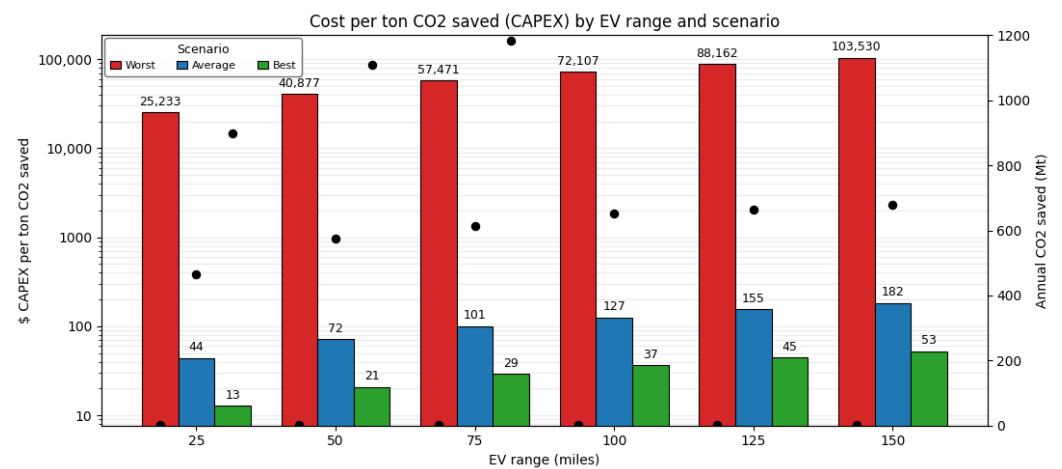


Figure 10. Cost per ton CO₂ saved and annual CO₂ Saved (Mt) (Black Dots) vs. EV range by scenario.

Figure 11 shows the CAPEX per ton of CO₂ saved over a 10-year lifespan relative to the pure ICE case by charging frequency. In contrast to the scenarios where the assumptions change both the numerator and the denominator, charging frequency only affects the percentage of electric VMT, which in turn only affects the kg of CO₂ saved (the denominator represented by black dots on the secondary y-axis). This shows the magnitude of the impact that less frequent charging has on CO₂ savings. Less frequent charging erodes the benefits of electrification for lower ranges, but bigger batteries mitigate this effect substantially.

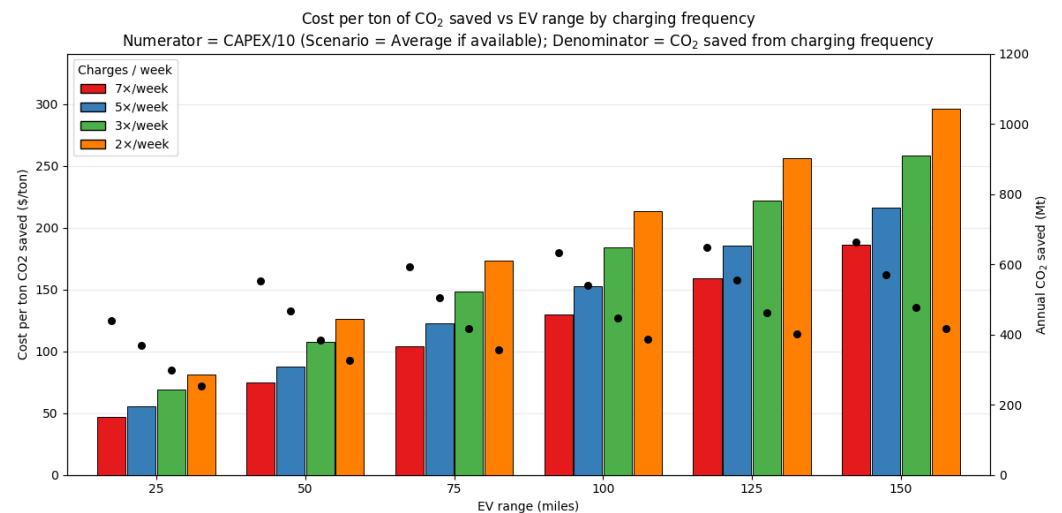


Figure 11. Cost per ton CO₂ saved and Annual CO₂ Saved (Mt) (Black Dots) vs. EV range by charging frequency.

Figure 12 shows the operating cost by scenario and range broken up by electric cost and gas cost. This illustrates that the scenario's assumption of electric and gas efficiency and electricity and gasoline costs drive operating costs. For almost all scenarios, the higher the range, the lower the operating cost with diminishing returns. However, in the worst case, the more electric VMT, the higher the operating costs, as that illustrates a scenario with unusually low gas cost (USD 2 a gallon) and unusually high average electricity cost (0.40 USD/kWh) as well as very efficient ICE vehicles (36 mpg) and very inefficient EV (2.9 mi/kWh, 97.7 mpge). Note, this figure assumes the EREVs charge before each trip, and these operating costs could shift as the electric to gas VMT ratio shifts by charging scenario.

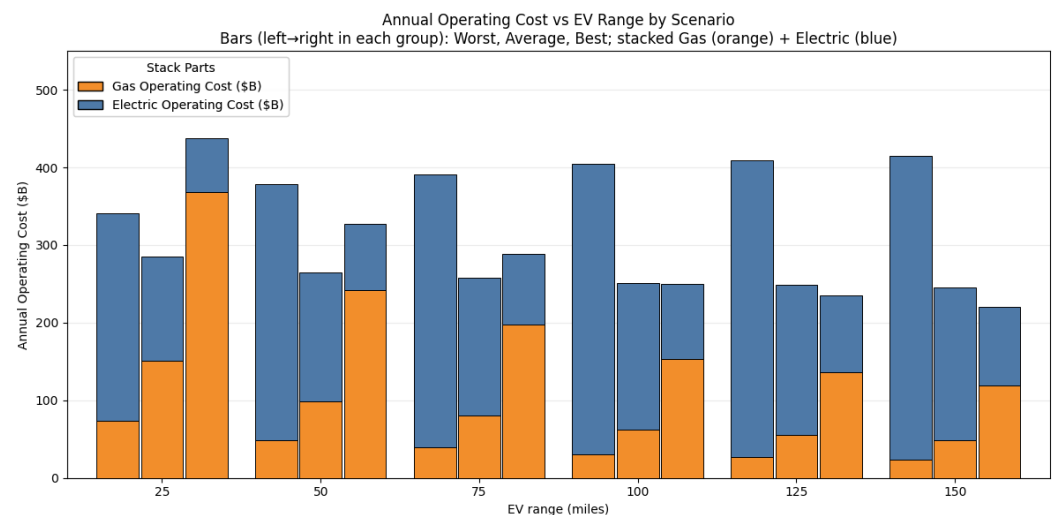


Figure 12. Annual Operating Cost vs. EV range by scenario.

Figure 13 shows the operating cost by charging frequency and range, broken up by electric cost and gas cost. This shows that less frequent charging increases operating cost at average prices. However, this is very sensitive to the price of electricity and gas and the efficiencies of the EV and gas engines, which is explored above.

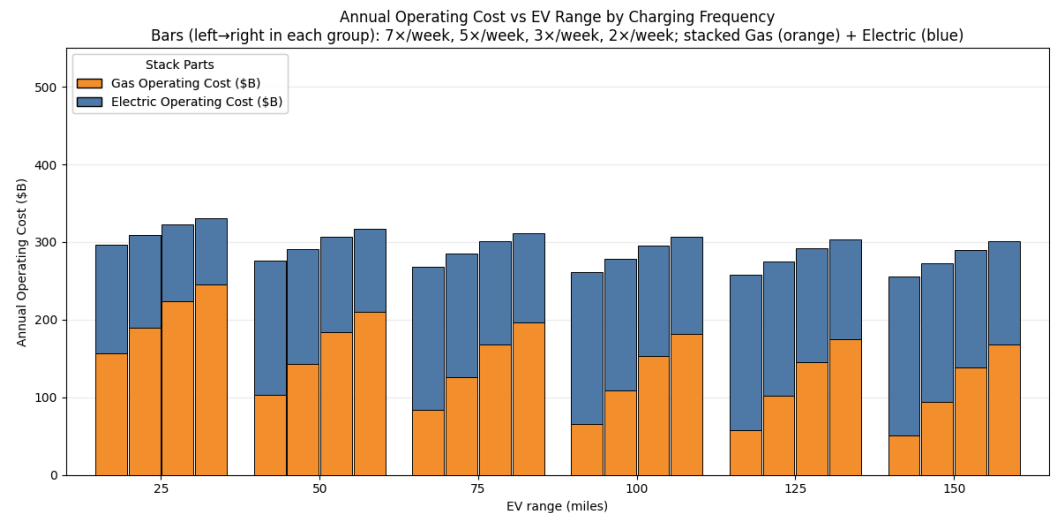


Figure 13. Annual Operating Cost vs. EV range by charging frequency.

5. Conclusions

Our results show that vehicle electrification always provides some carbon emission benefits under current conditions. Longer EV ranges increase both electric miles and CO₂ savings, but the most cost-effective benefits occur around 100 miles of range. From 50 to 150 miles, the electric share of U.S. light-duty VMT rises from 73.3 % to 86.8 %, and annual CO₂ savings increase from 574 to 680 Mt. However, the battery capital cost per ton of CO₂ avoided escalates from 0.072 USD/kg CO₂ at 50 mi to 0.182 USD/kg CO₂ at 150 mi, and installed battery capacity per electric mile more than doubles. Using national average electricity prices and efficiencies and assuming a charging frequency that maximizes electric VMT, the operating cost for electric miles averages 4–8 ¢/mi, compared with 11.4 ¢/mi for ICEVs. Therefore, for frequent chargers, moderate-range EREVs (100–125 mi) achieve the best balance between emissions reduction and total battery investment.

Nonetheless, charging frequency shapes real-world performance and experiences. Our results show that drivers who charge fewer than five times per week can lose up to 75% of potential electrified miles while increasing the unit cost per electric mile and ton of CO₂ saved. Longer range models temper these effects and provide a buffer against losing electrified benefits, but frequent, reliable charging access—at home and workplaces—is critical to maximizing CO₂ reductions.

Contrary to common assumptions, these results imply that less frequent chargers (e.g., renters, apartment dwellers) do not benefit from dual-fuel flexibility, as it is costlier and less efficient. Infrequent chargers either need more electric range to electrify the VMT between their charging sessions, or they will use more gas, which severely diminishes the efficiency and emission benefits of low-to moderate range EREVs. Therefore, BEVs provide more cost-effective benefits for infrequent chargers since they have more electric range, which allows for less frequent charging. However, in order to be attractive, these BEVs must be efficient and cost-effective, which implies smaller vehicles. Furthermore, because infrequent chargers will require more energy during each charge session, since they drive further between charges, the refuel rate (energy/time) must be fast enough to prevent long refuel times that drive down adoption.

In contrast, frequent chargers (e.g., homeowners with home chargers) can still achieve over 90% of the emissions reduction and efficiency benefits with moderate range (100–125 mile range) EREVs. Since these users charge more often, they need less battery capacity to electrify the VMT between charges. Furthermore, the flexibility of EREVs are more likely to align with homeowners' preferences, since they, on average, have larger

cars with more passenger capacity, greater towing capacity, and longer range for road trips; areas where pure BEVs currently lag. Therefore, policies and advertising strategies that encourage infrequent chargers to adopt pure BEVs and frequent chargers to consider mid-range EREVs in addition to pure BEVs could provide the appropriate balance between cost-effectiveness, efficiency, emissions benefits, and customer preference.

The different use cases for EREVs and BEVs also impact battery chemistry choices. EVs with Lithium Iron Phosphate (LFP) batteries have lower degradation rates and higher cycle rates at the expense of energy density and charging speed, which fits the moderate range, frequently charged EREV profile. On the other hand, EVs with Lithium Nickel Manganese Cobalt (NMC) batteries have more energy density and can charge faster, but are more expensive per unit of capacity, which fits the profile of longer range and infrequently but rapidly charged BEVs. However, high-performance EREVs could benefit from the increased power available to NMC batteries, and cheaper BEVs could benefit from the cost-effectiveness of LFP batteries, highlighting that there are still tradeoffs for every use case.

At the sector level, fully or partially electrifying light-duty vehicles could cut U.S. ground-transport emissions by more than half, bringing LDV emissions to parity with aviation and freight subsectors. At current national averages, electrifying the LDV fleet with moderate range batteries (100–125 mi) and frequent charging (5+ times/week) would require roughly 7–9 TWh of battery capacity and USD 0.8–1.0 trillion in capital, yet deliver near-optimal decarbonization efficiency without the material intensity of full BEV deployment.

Partial electrification via EREVs reduces power sector impacts compared with pure EVs because long-distance trips (where electric motors require more power at highway speeds) would use gasoline, which operates at the top of its efficiency curve at highway speeds. EREVs could also reduce the mining demand (and by extension the environmental impacts) for the critical minerals necessary to manufacture batteries, or allow those resources to be used in higher-impact EV use cases, like in fleet operations. However, if the charging infrastructure is inadequate and the charging frequency decreases, larger batteries will be needed to provide more range to keep the same electrified miles, which will limit some of the material-saving benefits. Future work could explore mineral intensity, power-system implications, and stochastic scenarios for more insights. This study is limited as it only aims to explore the effects of partial or full electrification across a wide yet realistic range, but does not attempt to prescribe what will happen. Customer preferences and behavior will influence the true adoption and charging frequency of these technologies. Nevertheless, our findings highlight that a “moderate range–high utilization” approach yields greater systemic benefit than pursuing ever-larger batteries for marginal impact gains.

Main Implications: Policymakers should prioritize incentives for material-efficient, higher-capability, moderate-range EVs for frequent chargers; longer range EVs for infrequent chargers, and invest in charging infrastructure to convert infrequent chargers into frequent chargers. Manufacturers should investigate expanding (or creating) two segments: a higher passenger capacity, more towing and road trip capable, moderate-range EREV segment for frequent chargers with larger households who prefer the flexibility of dual-fuel vehicles, and a BEV segment for infrequent chargers that provides efficient city driving, enough range for multiple days of driving, adequate road trip capabilities, and the ability to quickly replenish the battery.

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original draft preparation, H.P., A.K.; writing—review and editing, E.J.; visualization, H.P., A.K.; supervision, E.J. All authors have read and agreed to the published version of the manuscript.

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