Optimizing Electric Vehicle Infrastructure

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The market share of electric vehicles (EVs) is rapidly growing around the world, from less than 1% in 2016 to nearly 20% of global new vehicle sales (Virta, 2024). One major challenge to EV adoption is the need for investment in dedicated charging infrastructure. Indeed, the fear of not being able to charge an EV, sometimes called "range anxiety," is often described as a crucial deterrent preventing many new car buyers from even considering purchasing an EV. In response, there have been substantial government investments in charging infrastructure. For example, in the United States, the 2021 Bipartisan Infrastructure Law (BIL) allocated $5 billion for the building of a more comprehensive fast charging network. Yet, the spatial allocation of charging infrastructure can be very difficult and the stakes are high, as a single Level 3 (DC fast) charging station can cost as much as $200,000 (Sparkcharge, 2024). Thus, it may not be surprising that only 7 chargers were installed in the first two years of the BIL program (Shepardson, 2024).

This paper examines the consumer welfare impacts of increasing access to EV charging infrastructure. We develop a model of EV route choice and optimal charging locations, and estimate it with rich data from Connecticut on vehicle registrations, road segments, cell phone tracks, and charging locations and characteristics. At the core of the analysis is a model of EV driver decisions about where to travel and when to charge, and we complement this with a model of vehicle demand that shows how improved charging infrastructure can increase EV market share. We use the model to explore a "proof of concept" counterfactual that optimally adds Level 3 (L3) chargers in the set of nodes in Connecticut. A key result is that there are consumer welfare gains possible from optimally increasing the number of L3 charging stations in Connecticut, but that the gains primarily accrue to existing EV drivers.

In this paper, the economy is composed of many locations and drivers in each location who need to plan trips to different destination-locations. They minimize an objective function that depends on the cost of using different road segments, and the available battery capacity that can be replenished by costly stops at EV chargers. To solve this NP-hard problem we formulate it as a Mixed Integer Linear Programming (MILP) problem where additional inequalities characterize battery constraints. The optimal charger location problem is a global maximization problem where we maximize the weighted average of driver welfare across all routes. To solve this problem, we use a 'greedy algorithm' which iteratively allocates an additional L3 charger to the nodes that yield the greatest marginal improvement in welfare, accounting for charger demand, the existing charging network, and installation costs.

This work contributes to a growing literature on EVs and charging. Earlier work lays the groundwork by noting that there is a two-sided market for EVs, and that EV charging has potentially large network effects (Li et al., 2017). Springel (2021) quantifies these network externalities and show how they affect optimal subsidies. Ours is the first paper in the economics literature to model the social planner's optimal charger location choice given the road network and the potential effect on EV market share in the new vehicle market.

We also contribute to a broader economic literature on transportation infrastructure, where general equilibrium spatial models have become popular. For example, Allen and Arkolakis (2014) and Donaldson (2018) use gravity models to look at the welfare improvements from the U.S. interstate highway system and India's historic railroad network. Fajgelbaum and Schaal (2020) develop a general equilibrium trade network and explore the optimal transport problem with traffic congestion from a social planner's perspective using data from road networks in Europe. Allen and Arkolakis (2022) use a gravity spatial model with traffic to estimate the welfare effects of U.S. transportation infrastructure. Alder (2025) proposes a heuristic algorithm for road construction to maximize aggregate real income net of construction costs. Our work differs in being an analysis of EV charging and the social planner's optimal placement of chargers.

I. Data and Descriptives

Our first data source is vehicle registrations at the zip code x month level covering the period from 2018 to 2022. We have counts of vehicles of each model, model year, drivetype (e.g., electric vehicle), and trim. Our second data source is data on cell phone tracks, from Advan Neighborhood Patterns for 2022. These data are at the Census Block Group level, providing us the number of trips by origin and destination. For this study, we focus on average trips, but future work could look at different days and times. The cell track data allow us to calculate the median dwell time and median distance from home for trips. These data allow us to populate our origin-destination (OD) matrix. Our third data source consists of the location (latitude/longitude) and detailed information about all of the charging stations in Connecticut through 2024, from the National Renewable Energy Laboratory. Our final data source is the price of gasoline from the U.S. Energy Information Administration.

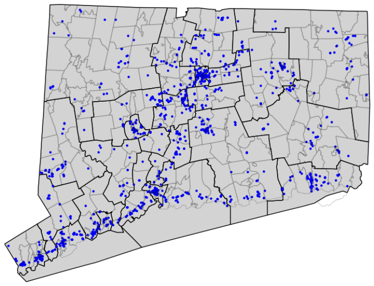
We aggregate our data to the Public Use Microdata Area (PUMA) level for computational tractability. There are 25 PUMAs in Connecticut. Figure 1 displays the locations of all Level 2 (L2) and L3 charging stations for 2024. We observe that many are along the shoreline and in the most populated areas of Connecticut, including the Interstate 91 corridor up the middle of the state. There are many more L2 chargers than L3 chargers in the state (Appendix Table A1). For creating our OD matrix, we use a seven nearest-neighbors approach to define links as the top seven origin-destination pairs.

II. Model

A. EV Charging Network Model

We consider a variation of the Electric Vehicle Routing Problem (EVRP), as laid out in Schneider et al. (2014). EVRP is an adaptation of the Traveling Salesman Problem to allow for the incorporation of limited battery capacity and recharging. We define the set of nodes $\mathcal{S}$ that the driver can visit that include the origin and the destination and $\mathcal{C}$ the set of charging nodes. Without confusion these nodes could be considered to be in the same geographic location, e.g., New Haven is a location that the driver can visit or a location that the driver can use to charge. We use a formulation where each driver minimizes the total road and charging costs, $\sum_{i,j\in\mathcal{S}} \bar{c}^D_{ij} x_{ij} + \sum_{i,j\in\mathcal{C}} \bar{c}^C_i z_i$, where x_{ij} is an indicator function that takes the value 1 if a driver uses a specific link in a certain direction from node i to j, and z_i is an indicator that takes the value 1 if a charger in a location is used. In addition b_i is the battery charging state at arrival at node i that is also optimally chosen by the driver to minimize the objective function. This is constrained to be always above zero such that each trip does not run out of battery. The $\bar{c}^D_{ij}, \bar{c}^C_i$ are associated costs of using a certain road segment and a certain charger, respectively, if the driver chooses to do so. The $\bar{c}^D_{ij}$ could be related to the segment's distance, while $\bar{c}^C_i$ to the kWh rate at the specific charging station or the time delay to charge, which could be a function of traffic in the charger and whether the chargers employed are of L2 or L3 type.

The EVRP is formulated as a MILP problem subject to inequality constraints (see e.g., Conforti et al. (2014)). We adapt a set of constraints that codify the traditional vehicle routing problem and add additional constraints that codify the battery charging problem. For the first, we define the



(a) Charger Locations

	Baseline	Counterfactual
Number of L3 Chargers	166	266
Mean Wait Time (year, Mil hours)	20.2	8.6
Mean EV share (%)	1.876	1.877
Total Charger Install Cost (Mil $)	-	1.0
Change in Net Welfare (year, Mil $)	-	229.1

(b) Counterfactual Welfare Effects

Figure 1. : (a) Charger Locations in Connecticut and (b) Welfare Gains from Adding Charging Infrastructure

start and end nodes, the must-visit nodes, and consistency constraints for x_{ij}, y_j, and z_i. We also constrain that start and end nodes are the same, i.e., the driver starts from home, visits a location, and returns to home. The constraints also codify the (optimally chosen) visited transient nodes and un-visited ones. In this work we assume that each node can only be visited once, following the standard EVRP formulation. We plan to relax this in future work. Notice, however, that the same location can be visited twice if charging takes place in that location.

We model battery charging with inequality constraints. Consider B to be the battery load when the car is charged (e.g., 80%). We assume every time a driver visits a charger, it charges up to that level. While it is common for electric vehicle owners to charge up to a certain level and not above to avoid battery degradation, the exact level of charging may depend on factors such as the duration of the trip and trip idiosyncrasies. We leave such potential considerations for future work. Denote the distance of segment i, j as d_{ij}, and the percentage of battery lost for each additional kilometer traveled as r. The inequality constraints state that the charge in the destination equals the battery load at the starting node, b_i, minus the battery lost in transit to j: $0 \leq b_j \leq b_i - r d_{ij} x_{ij}$. If node i is a node where charging took place, then $b_i = B$. Otherwise, b_i is the charge left when the driver arrived at that node. This constraint effectively acts as a recursive formulation of the charge level.

The EVRP is computationally NP-hard. We solve it using the GUROBI solver. We specify $\bar{c}_{ij}^D$ as the Euclidean distance between any two nodes to be and take $\bar{c}_i^C = \frac{1}{L2+L3^2}$, where L2 and L3 denote L2 and L3 charging stations respectively. We adapt the M/M/K queueing model to characterize the waiting time at each charger. The model assumes that charger arrivals (Q) are Poisson-distributed, with service times (T) exponentially distributed.[1] Q represents the aggregated charger visits, derived from solving the EVRP for each combination of OD trips (i, j). For every trip, we determine the optimal charging solution, repeating this process for all OD combinations. The entries in the OD matrix, which represent the number of drivers taking each trip, are then used to scale the results. The resulting z_i values are summed across all trips to calculate Q, the aggregated charger demand in each PUMA. The charger capacity, K, is defined as the sum of L2 and L3 charger in each PUMA (i.e., K = L2 + 5 · L3). The baseline expected waiting time at a charger located in each PUMA is then $\mathbf{1}_{\{Q \geq K\}}(Q - K + 1) \cdot \frac{T}{K}$.

[1]The average service time T is based on L2 and L3 service times in hours ($T = \frac{20 \cdot L2 + 4 \cdot L3}{L2 + L3}$).

B. Vehicle Demand

We model vehicle demand following Berry et al. (1995). The utility from agent i from choosing vehicle model j in market t is given by: $u_{ijt} = \boldsymbol{X}^1_{jt}\boldsymbol{\beta}_1 + \boldsymbol{X}^2_{ijt}\boldsymbol{\beta}_2 + \xi_j + \epsilon_{ijt}$. In this specification, $\boldsymbol{X}^1_{jt}$ is a vector of vehicle characteristics, $\boldsymbol{X}^2_{ijt}$ is a vector of charging variables, ξ_j are model fixed effects, and ϵ_{ijt} is an ideosyncratic error term. Vehicle characteristics include dummy variables for EVs, plug-in hybrid vheicles (PHEVs), conventional hybrids, and diesel vehicles. We include random coefficients for the parameters on the constant and the EV dummy to relax independence of irrelevant alternatives and allow for more flexible substitution patterns. We have microdata, so we directly include model fixed effects rather than solve a nested fixed point problem.

With the assumption of Type I independent and identically distributed errors, we can then follow Berry et al. (1995) and model market shares using the standard logit form. Identification in this setting requires instruments for price. We use the standard BLP instruments, which consist of the average vehicle characteristics of competitor firms in the same market. These should affect prices only by shifting markups in equilibrium. We perform a standard random coefficients logit estimation (with instruments) and estimate a separate demand model for each of the eight counties in Connecticut. We also explore estimations with Bartik instruments for charging variables and with second-choice moments, but these are less stable, so we focus on the above approach for this paper. Future work could include demographics and additional random coefficients.

III. Demand Estimation and Counterfactual Results

The goal of the demand model is to provide sensible own-price and cross-price elasticities to quantify the effects of additional charging stations on the market share of EVs. Appendix Table A2 presents the full demand estimation results. As expected, we observe a negative coefficient on price and the dollar cost per mile driven (price of gasoline divided by fuel economy). We also observe a negative coefficient on EVs, which is expected in order to rationalize the small EV market share. Other coefficients are largely expected in sign, with the exception of the range of the electric vehicles, which is not statistically significant. These coefficients largely align with the existing literature and seem to capture key determinants of demand. As an example, Appendix Table A3 shows sensible cross-price elasticities between common electric vehicles and similar gasoline vehicles for New Haven County in 2021.

We also estimate coefficients on charging station density variables (which are interacted with electric vehicle dummies for interpretation), which are calculated based on the density of charging stations in the county that the vehicle is registered in. We see positive, although not highly significant, coefficients for all charging stations, only L2 charging stations, and only L3 charging stations. The most notable finding here is that the effect of L3 chargers is much larger than L2 chargers.

We run our counterfactual scenario where we add L3 chargers to nodes on the network based on the marginal net benefits of adding an additional charger. To calculate the net benefits, we convert the total waiting time to dollars using a \$19.73 per hour value of time (Dorsey et al., 2025). We assume that L3 chargers cost \$100,000 to install and we assume a 10% annualization per year.

The counterfactual simulation results are shown in Panel (b) of Figure 1. The number of L3 chargers increases from 166 to 266, a very large increase. This reduces the average waiting time across all EVs from 20.2 million hours to 8.6 million hours. The market share of EVs only very modestly increases and nearly stays constant under our specification. In total, we observe a large welfare gain of \$229 million per year from increasing the number of chargers, and because these gains are almost entirely coming from reducing the waiting time, it is clear that the welfare gains are largely on the intensive margin, i.e., from existing EV drivers.

IV. Conclusions

In this paper, we develop a new model of optimal charger infrastructure locations given the transportation network, trips EV drivers take, and the effect of EV chargers on the market share of electric vehicles. Our work is a proof of concept showing that a very challenging computational problem can be solved in a feasible way to generate insights about optimal charging locations in a real empirical setting. There are many pathways for future research, including internalizing waiting time, creating a shortest-time origin-destination matrix, performing additional robustness checks, increasing the number of nodes, modeling home charging, and running further counterfactuals. But the current work already points to the potential for welfare gains from more charging infrastructure for EV drivers, and provides a tractable methodology for choosing charging station locations.

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Supplemental Appendix

Paper Title: Optimizing Electric Vehicle Infrastructure

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This short online appendix presents several additional tables.

Table A1—: Summary Statistics by PUMA (Connecticut, 2024)

PUMA (2020)	**L2 CS**	**L3 CS**	**Waiting time**
Northwest Hills	35	9	444.7
Hartford Town	95	4	1639.4
Connecticut River North	36	5	163.3
Capitol East	51	4	1910.8
Northeastern Planning Region & Stafford Town	30	5	148.5
East Hartford, Manchester & Vernon Towns	72	13	1881.7
Glastonbury, Wethersfield, Rocky Hill & Newington Towns	18	4	17806.1
New Britain, Southington, Berlin & Plainville Towns	64	1	18920.7
Capitol West	48	6	1036.4
Shoreline Southeastern	90	9	128.2
Inland Southeastern	43	3	2494.6
Lower Connecticut River Valley	71	6	2509.8
New Haven Town	91	6	1412.1
South Central West	37	9	5077.3
South Central North	52	5	8007.6
South Central East	43	14	3503.9
Waterbury Town	44	2	6310.7
Naugatuck Valley North	62	17	2138.2
Naugatuck Valley South	20	1	21039.0
Bridgeport Town	15	2	5516.2
Bridgeport Suburban	33	12	2626.7
Stamford & Greenwich Towns	55	10	0.0
Western Central	29	8	2065.9
Norwalk & Westport Towns	53	2	695.8
Western North	30	9	595.4

Note: CS stands for charging stations. Waiting time is in hours for any given day (We use a daily average number of visits in the OD matrix. We may scale it in different ways to make the number more realistic. For example, we may infer the number of charging trips from the number of EVs in the area).

Table A2—: Demand Estimation Coefficient Results

	Model 1		Model 2		Model 3	
Variables	**Coef.**	**S.E.**	**Coef.**	**S.E.**	**Coef.**	**S.E.**
Prices	-0.0321	0.026	-0.0318	0.026	-0.0317	0.026
Dollar per mile	-0.1565	0.047	-0.1572	0.048	-0.1567	0.046
Electric	-7.1711	15.889	-6.0906	15.121	-6.1462	14.764
PHEV	-6.0409	14.707	-6.5426	14.734	-6.6234	14.425
Hybrid	-1.6373	0.286	-1.6417	0.290	-1.6399	0.278
Diesel	-2.2449	0.423	-2.2481	0.423	-2.2510	0.423
Wheelbase	0.0425	0.022	0.0423	0.022	0.0420	0.022
Log HP / Weight	0.874	0.685	0.8662	0.686	0.8525	0.685
Doors	0.2055	0.144	0.2027	0.146	0.2024	0.142
Electric Range	-0.005	0.004	-0.0050	0.004	-0.0051	0.004
All chargers / km^2 x Electric	0.030	0.022	-	-	-	-
L2 chargers / km^2 x Electric	-	-	0.0326	0.023	-	-
DC chargers / km^2 x Electric	-	-	-	-	0.223	0.191
Sigma: Constant	3.793	2.386	3.835	2.420	3.801	2.285
Sigma: Broad EV	3.643	7.164	3.661	7.175	3.701	6.991
Model FE	Yes		Yes		Yes	
Drive Type FE	Yes		Yes		Yes	

Table A3—: Cross-Price Elasticities for New Haven 2021

Model	Tesla Model-3 LR	Tesla Model-Y LR	Tesla Model-Y Perf	Honda CR-V EX	Toyota Rav4 XLE	Subaru Forester Prem	Nissan Rogue S	Jeep Grand-Cher Lim
Tesla Model-3 Long Range	-1.3792	0.0040	0.0038	0.0020	0.0007	0.0016	0.0002	0.0023
Tesla Model-Y Long Range	0.0021	-2.0462	0.0038	0.0020	0.0007	0.0016	0.0002	0.0023
Tesla Model-Y Performance	0.0021	0.0040	-1.2868	0.0020	0.0007	0.0016	0.0002	0.0023
Honda CR-V EX	0.0021	0.0040	0.0038	-1.3056	0.0007	0.0016	0.0002	0.0023
Toyota Rav4 XLE	0.0020	0.0039	0.0037	0.0019	-2.1990	0.0254	0.0039	0.0022
Subaru Forester Premium	0.0020	0.0039	0.0037	0.0019	0.0115	-2.3264	0.0039	0.0022
Nissan Rogue S	0.0020	0.0039	0.0037	0.0019	0.0115	0.0254	-2.8183	0.0022
Jeep Grand-Cherokee Limited	0.0021	0.0040	0.0038	0.0020	0.0007	0.0016	0.0002	-1.3634