Optimal Placement of Electric Vehicle Charging Stations

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Abstract

Electric vehicles (EV) have been gaining popularity in recent years with sales growing in double digits in the US. This is partly due to concerns with limited fossil fuels, climate change and partly due to cost reduction and battery efficiencies leading to long term gains. However, charging station availability, long charging time and range anxiety is still a major concern for EV adoption and has been a significant driver for charging infrastructure studies. In this research, we try to understand the current infrastructure limitations and provide an optimal charging placement plan given a budget that satisfies most of the demand using an evolutionary algorithm. The aim is to consider multiple facets such as charging demand, coverage across a network, travel time, charging time and waiting time for a given network configuration.

1. Introduction

Global transportation industry is a major contributor to green house gas emissions leading to climate change as well as is also one of the biggest consumer of fossil fuels. The rate at which the industry has been draining fossil fuel resources is exponential and limited supply of fossil fuels is a cause of concern for such dependency (Moriarty and Honnery, 2016). This has encouraged many governments across the world including The United States to allocate resources and introduce new policies to help make the transition from diesel/petroleum vehicles to electric vehicles as well as provide incentives to make electricity greener and less dependent on fossil fuels. This transition is a viable way to mitigate the serious concerns regarding energy crisis and climate change. The consumers of electric vehicles (EVs) not only benefit from these government promotions for EV adoption but also see long-term benefits in terms of operation and maintenance costs.

The increase in EV demand brings with it new challenges related to electric mobility infrastructure such as vehicle charging and management of the related resources such as energy grid, transformers, power supply etc. In United States, in particular, EV sales have increased dramatically in recent years, going from 100,000 vehicles in 2014 to over 350,000 vehicles in 2018 (AFDC, 2020). This popularity of EVs in the US has also led to a sharp increase in the demand for EV charging stations. The concerns about the accessibility and convenience of charging stations for consumers are well founded (Bonges and Lusk, 2016). There are only limited number of charging stations available across the US with only few cities providing enough supply to meet the demand. EVs also take much longer to charge compared to traditional internal combustion engine (ICE) vehicles. Long charging time coupled with few charging stations lead to an anxiety among EV owners that they will run out of charge and would not be able to get enough charge to get to their destinations at times. This range anxiety has been the major bottleneck in the adoption of EVs. Hence, for a significant growth in EV adoption, tackling the EV charging infrastructure is vital.

The issues with the EV infrastructure become more grave due to different type of connectors i.e; not all vehicles are supported by all charging points. Furthermore, most of the charging stations are equipped with level 2 chargers, which in general provides 25-30 miles of range with one hour of charging. There is a significant shortage of level3 charging which provides 125 miles in 30 min and would be most beneficial in addressing the range anxiety among EV adopters. In this paper, we employ a model that results in an infrastructure which takes into account the demand as well as capacity of a charging station which takes into account the power supplied by level 2 and level 3 chargers separately while suggesting the optimal configuration.

In the U.S, the number of currently installed Level 2 charging stations is only 12.0 % of the total number of Level 2 stations needed to meet the projected charging demand in 2030 (Brown et al.). Furthermore, there are many charging network distributors with their own network of stations, making a unification of charging station deployment rather complex. Hence, if the current charging infrastructure is not persistently developed to meet demand or does not account for shifting demand patterns such as increase in population and EV ownership, the nation will have an inadequate charging network.

Furthermore, there are many charging network distributors with their own network of stations, making a unification of charging station deployment rather complex. Hence, if the current charging infrastructure is not persistently developed to meet demand or does not account for shifting demand patterns such as increase in population and EV ownership, the nation will have an inadequate charging network. A lack of available charging stations has been shown to be directly related to the consumers' decisions to buy EVs (Bonges and Lusk, 2016). Therefore, there is an urgent need to maximize the coverage and efficiency of charging stations to effectively meet the increasing charging demand.

To help city policy-makers allocate public resources efficiently to support the deployment of charging stations, a systematic approach is needed to quantify the benefit of placing public charging stations as well as to determine the adequate positions for these as many factors such as the range of the vehicles, waiting time and travel time affects the usability and usefulness of a charging infrastructure. In this paper, we employ a model that results in an infrastructure which takes into account the demand as well as capacity of a charging station while suggesting the optimal configuration.

In section 2, we first discuss recent studies in this area which helped guide our methodology. We then discuss a list of open data sources related to EV demand and charging that can be used for policy-making. Companies have an added advantage of consumer-trip or journey data. However, using generic datasets mean that a plan can be generated at places with less EV penetration as well, in order to increase the rate of adoption. We also discuss a pipeline used to setup the data for placement optimization in this section. In section 4, we discuss business insights from the data and provide access to number of visualizations as an interactive dashboard for the state of California. However, this is easily replicable to most states in the US. Here, we deep dive into Los Angeles county and city as well. In section 5, we discuss a detailed cost analysis to help understand various facets of charging station setup and in section 6, we provide details on an evolutionary model that can be used to identify optimal locations for charging station placement.

2. Literature Review

Battery cost efficiency (i.e, decline in battery prices due to more efficient batteries making the EVs cheaper with time) and improved charging technologies along with climate change concerns are tipping the scales towards Electric Vehicles. As stated in Kizhakkan et al. (2019) there can be multiple factors that come at play when determining the location of Electric Vehicle Charging Stations (EVCS) such as cost, demand coverage, vehicle movement pattern, user behavior, constraints related to road network and distribution grid. Many researchers have attempted to solve this problem with optimisation techniques like linear programming, genetic algorithms, greedy algorithms, game theory, machine learning techniques like Clustering and most recently deep reinforcement learning. Some of them used real world data while others used simulated data.

(He et al., 2013) provided a mathematical framework that takes into account the equilibrium between the supply and demand for energy when deploying charging stations on a macro-scale. Time, cost, and charger accessibility all played a role in how users decided where to go. The cost of supplying electricity was the basis for supply-side economics. Their approach focused on the deployment of large-scale charging stations (CS) which only provided the number of charging stations to be deployed without any indication of their location. (ipek et al., 2011) implemented a similar approach to (He et al., 2013) but provided the location of the charging stations. They determine which segments of the roads are utilized the most and divide them into x-y grids. They proceed to cluster the squares in the grid based on the intensity of the road utilisation and apply an optimisation algorithm to decide the most suitable cluster for charging stations deployment. Not only is this method limited by the fact that they used sensors generated data which would not be available in all areas, it also aggregate all stations to one particular area leaving other areas unsatisfied.

(Mehar and Senouci) suggested a genetic algorithm that accounts for factors such as the amount of traffic in a given region, the cost of land and infrastructure, the cost of investments, the cost of getting to the CS, the number of charging stations that can be used, and the efficiency of the energy grid. The authors suggest minimizing the goal cost and the transit cost in order to position charging stations in the best possible location. The algorithm quickly tested on a simulation of the traffic in Cologne, German. Although the method is quick, some context is missing. The proximity of charging stations to shops or public transportation is not taken into account. Even if traffic is dense in a certain area, the population of cars in that area does not have to be comprised of EVs. (Pevec et al., 2018) has created a data-driven, practical strategy for expanding the infrastructure for EV charging. One of the largest Dutch providers of charging infrastructure, ELaadNL, provided the data used in that framework. The information includes all transactions for a period of four years (i.e., 2013–2016). The hierarchical clustering method is used in the framework's initial section to group existing charging stations into clusters based on their distance from one another. Following the clustering of charging stations into zones, the usage of charging stations within each zone was determined and used as the dependent variable in the machine learning method. The framework predicts usage by altering the parameters of the XGBoost model. Places of interest, EV penetration, time of day,the quantity of charging stations in the designated zone, the number of competitors' charging stations and whether it is a weekend or weekday were all taken into account because they have a significant impact on charging patterns. The third component of the framework determines the ideal location for a new charging station based on the specified optimization function. The framework's accuracy (i.e., the location where a new charging station should be installed) depends on the distance at which clusters are based.

(Padmanabhan et al., 2021) accounts for potential changes in charging demand over time and solve this problem in two steps. The first step is a supervised regression approach to forecast the charging demand using traffic data , points of interest data and energy consumption data from the current charging stations in place. The second step build a reinforcement learning agent using Deep Q-Networks (DQN) on the Albany County, New York divided into a grid where each grid would represent the assigned demand from the regression model. The DQN model trains to place ten charging stations within this grid and is rewarded based on the demand alleviated and area covered with each placement.

3. Data

In this section we present an overview of the data set used and the pipeline used to address charging station deployment.

3.1. Data Sources

For an in-depth study of Electric Vehicle demand, cost of installing a charging station and optimizing the placement of new charging stations, data from multiple open sources were collated. Following are the various datasets considered:

- Alternative Fuel Data Center (AFDC) which has consolidated data for all electric vehicle charging stations available in the US along with details on their geographic co-ordinates, their number of chargers available, type of connectors, pricing, whether they are public or private among other details is used to study the current availability of charging infrastructure.
- US Census Bureau data Bureau data was used to understand the population distribution. High population density areas would require better infrastructure availability as the transition from ICE to EVs speed up. There is also higher profitability potential at high population density areas.
- Atlas Public Policy provided the EV registration data. It has data on all the electric vehicles registered from 2011 along with the model of the vehicle for 16 states in the US and it is updated annually.
- Finally, road network for Los Angeles was extracted from OpenStreetNetwork OSM using a python library OSMnx. The network consists of intersection of roads as nodes and the roads connecting them as edges which are directional depending on whether the road is one-way or two-way. Specifically, the road network is given by a graph G = (V,E) where V are the vertices representing the junctions of the roads and E are the edges connecting these junctions. It also provides mapping of the nodes to geographic co-ordinates as well as points of interest around each node in terms of restaurants, schools, parking areas, garages, offices etc within a certain distance from the node.

3.2. Data Processing

Setting up the data pipeline to extract and transform the data from multiple sources was a vital part of this project as it allows for a centralized way to study electric vehicle charging infrastructure using only open source datasets. The data sources from Section 4.1 was consolidated to perform exploratory analysis to generate insights as discussed in Section 5 and create a model to predict most beneficial charging station locations after adjusting for cost per the demand in the network with a given budget to build new charging stations. The availability of data sets at multiple geographic levels was a major challenge at this step and we provide a pipeline to integrate them. A simplified process of our data collection can be viewed below in figure 1.

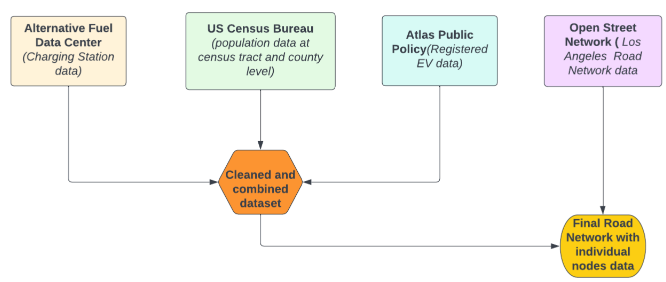

Figure 1. Data collection

AFDC API was called using a key and the data was processed to keep fields related to charging stations location data, and information related to number of each type of charger connectors. This data has a latitude and longitude which is mapped to the nodes in the road network from OSM by getting the nearest node using haversine distance calculated using the geographic co-ordinates between the two locations. The census population data was obtained for each census tract (a polygon represented by multiple points which form the boundary of the tract area) in the Los Angeles County and was filtered by age to retain the population that could drive legally. Using the registered number of EVs in the Los Angeles County, the charging demand was mapped to each census tract as the product of the number of EVs for every 1000 people in the county and the population at that census tract. Attributes at the census tract level such as number of EVs per tract are mapped to the network by first mapping each node to a tract. A node is mapped to a census tract if the node is within the polygon that describes the census tract. After mapping the nodes to the tract, all demand from the tract was equally distributed to all nodes in the tract. This results in a network map of nodes with the desired dataset for model creation.

In Section 6, we use population estimate, number of EVs present around the node or amenities to estimate the demand for a node which is used to get the benefit function for any charging plan. Already present charging stations are used, along with predicted charging stations to cater to the demand. Distances between two locations are used to represent various cost parameters such as travel time. We further simulate the cost parameters for Level 2 chargers as well as level 3 chargers. However, the extensive cost analysis can be incorporated in future works.

4. Data Analysis

Having aggregated data from several valuable sources, we were interested in understanding more about the placement of charging stations and how they are affected by the current charging demand. As stated previously, we assumed the charging demand to be modelled after the current number of EVs in circulation and the current population. With the goal of transcribing this data into insights that could be useful to urban planners, we built an Interactive dashboard backed by the data for displaying several key metrics as a contribution to the project. The dashboard can be accessed here

4.1. Charging Ports and Charging Infrastructures

The first part of the dashboard is an analysis of the charging stations. Figure 2 below shows the placement of different charging stations on the map filtered by the charging port available at that stations.

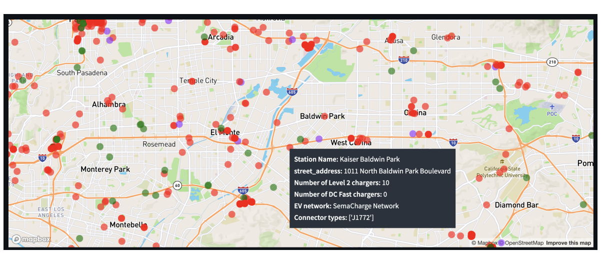

Figure 2. snippet of Charging stations on the map of California. Red designates Level 2 chargers available, Green designates DC Fast chargers available and Purple designates both

From figure 2 we can see that more stations have access to level 2 chargers only. This idea is better reinforced in the figure 3 that shows the huge disparity between the amount of stations having level 2 chargers only and the other types of chargers in the state of California. As we will see in the next section, part of this can be attributed to cost of installation of level 2 chargers which act as a huge deterrent for opting for DC fast chargers. The networking infrastructures need more capital to perhaps build optimal chargers like DC fast chargers and EV consumers look for fast charging because of the limited range of their cars. This problem can be analogous to the chicken and egg problem which shows hows detrimental it is for urban planners to take the matters in their hand.

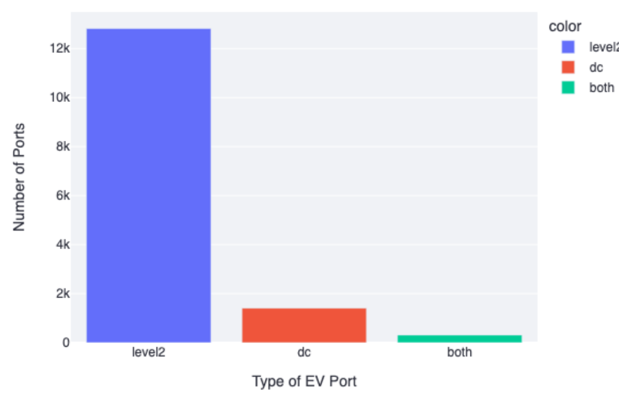

Figure 3. Distribution of stations with Level 2 , Fast DC and Both types of Chargers

Another interesting point to look at is the distribution of the network infrastructures that provide the charging stations in figure 4. Most of the charging stations do not belong to any network i.e Non-Networked. Before selecting an EV charging solution, It is important to note the distinctions between networked and non-networked stations. Both types of network deliver the energy required to power EVs, but their initial expenses, ongoing costs, accessibility and maintenance vary differently. Non-networked stations are standalone unit which means they are not connected to an EVSE network. As such they are not as accessible to EV drivers since their data has to be manually added to third-party applications like google maps.

4.2. Counties and Census Tract

In the dashboard we also present data at the County and Tract level mainly the EVs charging station density which displays which county or census tract has the most charging stations and the EVs density which shows which county or census tract has the most amount of EVs in circulation. For

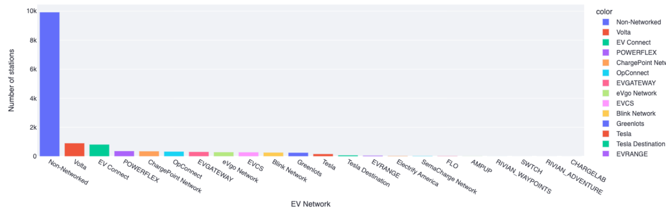

Figure 4. Distribution of Charging Station Network Infrastructures

the census tract data we only displayed the Los Angeles County due to performance constraints. We visualise both maps as choropleth maps as shown below in figure 5 and 6.

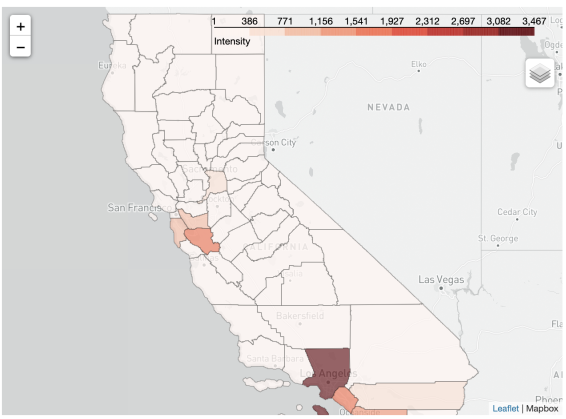

Figure 5. Choropleth map of all Counties in the state of California showing EVs charging station density

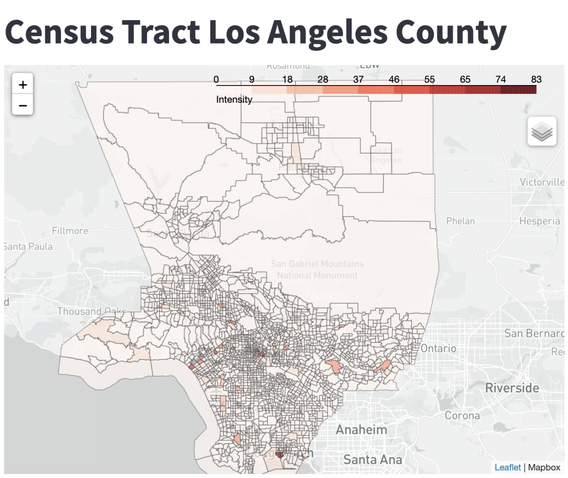

Figure 6. Choropleth map of all census tract in the Los Angeles County showing EVs charging station density

From these figures, we clearly see the huge gap in the density of charging stations in the counties and the census tracts. In figure 5 most counties have between 1 to 386 charging stations. Among the most densely populated by charging stations include the Los Angeles County, Santa Clara County and San Mateo County. Intuitively, it would make sense that the most populated counties will have the most amount of charging stations because of the incurring demand. Nevertheless when considering the amount of EVs that are registered in each of these counties, the amount of charging stations are simply not enough to satisfy the demand as seen in 7, for over 600,000 EVs in a county, there are only approximately 3500 charging stations which is not enough.

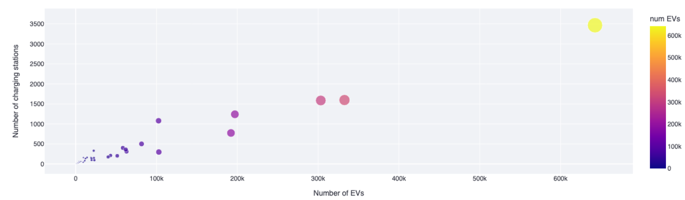

Figure 7. Pairwise plot Between number of EVs and charging stations in all Counties

5. Cost Analysis

To maximise the charging infrastructure available to the public, it becomes very important to understand the cost of building a charging station with even the most intricate costs accounted for. Such an analysis will play a very important role in determining the number of charging stations which can be built and the overall budget such a task would require, if undertaken. In the past year the U.S government has allocated $7.5 billion for the deployment of EV charging stations throughout the country as a part of the Infrastructure Investment and Jobs Act (IIJA). For the EV targets U.S is aiming, funding would be a major constraint. For an efficient EV infrastructure planning, it is pivotal to have a very good understanding of the actual cost of building an EV charging station. In the past few years numerous organizations such as the National Renewable Energy Laboratory (NREL), Environmental Defense Fund (EDF) and International Council on Clean Transportation (ICCT) have conducted cost analysis of EV charging stations. However, the novelty of the infrastructure, nascent stage of the technology and fluctuating cost of electricity and grid infrastructures has led to a wide range of variability in the estimates. We attempted a cost analysis of our own to try and determine the lower and upper-level cost of level 2 and level 3 charging stations which has been employed into the cost function of our model. Level 1 charger was not considered as the cost is very direct and unrelated to the scope of this study (Sam

Pournazeri, 2022).

There are various types of costs involved in the successful implementation of this project. The two main types of costs are Direct costs and Indirect costs. The bracket of direct cost consists of cost of equipment i.e., the charger cost, transformer cost, and other hardware components needed for the charger and indirect costs consists of all other costs like operation and management cost, construction costs and maintenance costs. The cost can also be divided into infrastructural costs which is the cost of charger, hardware, construction etc. and installation costs such as cost for qualified electricians and transmission costs (Peter Landau, 2021). In our analysis the main emphasis is on accounting for all the components and nuances that goes into the deployment of an EV charging station rather than to qualify the costs under a particular heading. The method followed was to identify all costs, big and small needed for a charging station from the conception of the project till its completion and further operation. The cost and a brief description of the cost is discussed in this section of the report.

First, a site assessment by a qualified engineer must be conducted to determine if the site is suitable for an EV charging station to be constructed which is expected to cost around 600$. The design and engineering cost is for the architect and electrical engineer to draft construction drawings containing all the components of the station drawn to scale in compliance with standards and building codes and cost for relevant permits which would be \$1500 to \$5000. The minimum area of a charging station is expected to be 500sq ft and the cost for leasing this land is expected to be \$3000 to \$5000 per month. The materials and construction costs such as cost for construction of pavements, shelters other structures is between \$300 to \$1200 for level 2 charger and between \$5000 to \$15000 for level 3 charger (Darya Oreizi, 2021).

The cost of installing the chargers indoors would be \$800 to \$1500 and for outdoors would be \$800 to \$2500 for both the level of chargers. The cost of installation of the station would mainly comprise of labor costs for the electrician and other associated installation costs such as wiring, trenching and appropriate permits (Robert Wortrich, 2022). We assume that it would take three months for the installation process with every month having 23 working days and 8 hours of work each working day. This gives us a total of 184 hrs. of electrician labor which when multiplied with 40$, the hourly labor cost assumed would result in labor costs of \$7360 to \$18400 for both the chargers. \$300 to \$800 for 50-Amp Outlet and 240-Volt Circuit required for installation. The wiring costs 6$ per foot, assuming 200-foot worth of wiring, the total wiring costs would be 1200$ to 1600$. If we consider there is a necessity for 100-foot worth of trenching work required, at the cost of 4$ per foot the total trenching cost would be 400$ to 1200$. 200-Amp Electrical Panel is necessary in majority of cases which amounts to 1800$ to 2500$ / (HomeGuide, 2022).

The equipment/material or actual charger cost varies considerably based on the manufacturer. With numerous players in the area such as Webasto, ClipperCreek, Bosch, Tesla, Siemens, JuiceBox and ChargePoint it is difficult to even narrow down on a broad range of values. Hence for this analysis we consider an equipment price of 3500$ for level 2 charger and 38000$ for level 3 charger of 50kW capacity based on NREL study in 2020 (Sam Pournazeri, 2022) . We are assuming a plugged-in connector type for the charger as they are easy to repair, portable and would need a 240-volt wall outlet to be installed which we have already considered in our analysis (Robert Wortrich, 2022). The Charging equipment has advanced communication capabilities where they communicate with the user through different apps and portals which would require additional accessories for the station such as Wi-Fi signal boosters and cable organizers which costs 190$ to 965$ (HomeGuide, 2022).

The station requires electricity connection from the grid or from any other electricity generating source which would in turn require a transformer which would be provided by the utility for a one-time cost payment. The transformer is used for the control of voltage of the electricity flowing from the grid to the charging station. It would be advisable to use a three-phase isolation transformer as it provides additional benefits such as electrical separation which helps in system earthing to prevent accidents and disasters due to unforeseen circumstances. The equipment cost of this transformer would be 2125$ for level 2 charger and 23500$ for level 3 charger as obtained from the electric vehicle transportation center. The installation of the transformer costs 4875$ for level 2 and 13,125$ for level 3 (Richard Raustad, 2016).

The costs listed till now were those required for the installation and construction of the charging station. Once this stage is completed the operation and maintenance cost of the station come into effect. This includes a wide variety of costs such as networking, maintenance, electricity cost and transmission and distribution costs from the grid. Modern charging stations have advanced capabilities such as access control, online payment processing, session time tracking and much more which requires networking, like our cell phones. There are many major players in this field such as Enel X, Amp Up and Chargepoint. This cost of network operation and maintenance is approximated to be \$400 per year per port (Darya Oreizi, 2021).

An important but most often forgotten cost of an EV charging station is usually the maintenance cost which becomes more prominent with time. These costs will include cleaning the station, servicing faulty equipment and replacement of parts which undergo wear and tear such as the charging plug. The maintenance cost is approximated to be 250$ for level 2 and 1500$ for level 3 charging stations (Darya Oreizi, 2021). The transmission and distribution of electricity from the grid also incurs charges of 1700$ to 5800$ for both the types of stations. The cost of electricity for a charging station per day would be 250$ to 322$ for level 2 and 500$ to 644$ for level 3 charging stations which can be offset depending on the consumption at that station /ref 19. It would also be very important for charging stations to have proper insurance policies for the benefit of the owner and consumers for which an average premium cost of 12400$ is considered (IdeaFight, 2022).

According to our analysis the total cost of installing, constructing and operating and maintaining a level 2 charging station would be between 46500$ to 70837$. For level 3 charging station it would be between 134325$ to 167834$. In this analysis we consider a level 2 or level 3 charging station to have a single charging equipment of each kind. The cost of charging station is highly variable and depends on the number of chargers used under a single station. The cost could vary tremendously based on the number of each type of charger used as well, since the difference in equipment price for level 2 and level 3 charger is considerably huge. Hence the reason for conducting this cost analysis was to approximate the cost of a single station having a particular level of charger.

6. Model

Genetic algorithm is a powerful tool to address combinatorial optimization problems. Genetic algorithms are derived from natural evolution and is comprised of components such as natural selection of strong individuals on the basis of an evaluation function, mutation and crossovers. In our case, individuals are initial configurations with x number of charging stations from k number of considered nodes, and each charging station having a [m, n] chargers set-up where m represents the number of level 2 chargers available and n represents the number of level 3 or DC fast chargers available at a single node. The initial population consists of many such configurations or individuals. The offsprings are then created from the population by either mutation (some modification to an individual in the population) or using crossover (merging of 2 parents; i.e, taking some part of one configuration from the population and complementary part of a second configuration from the population). There are many generations of population that are built like this and each generation should result in better configurations as the selection is on the basis of fitness/ how a configuration performs on the evaluation function.

Below we describe in detail the evaluation function used for EV charging placement and then present a case study for Los Angeles. The evaluation function is largely inspired from (von Wahl et al., 2022). The authors state a reduction of upto 97% in waiting time and increase in coverage by 400% using a similar evaluation function in Germany. Here, we extend the case study to Los Angeles county in California.

6.1. Evaluation function

There are majorly 3 components in our configuration evaluation function. The budget constraint is used to apply a constraint on the total expenditure required for the charging station placement plan. The fitness of any individual configuration that exceeds this budget is very poor. There is a benefit and cost of the configuration determined by the coverage of all the charging stations and the travel time, waiting time and charging time required depending on demand. All three components are described in more details below:

Budget constraint: For any charging station configuration given by $S : [[m_1, n_1], [m_2, n_2], ...[m_K, n_K]]$, m_i denotes the number of level 2 charger points at station represented by node of i, n_i represents the number of level 3 charge points at station and K is the total number of nodes considered. A set of points with $m_i + n_i > 0$ gives the actual nodes where the charging station needs to be built and is denoted by S_{cs}. On this set, a configuration expenditure $config\_spend(S_{cs})$ is determined by summing up the cost required to build all the stations in S_{cs}. Cost per level 2 charger and per level 3 charger is simulated using a gaussian distribution for set of all considered nodes k and the number of charging points at each station is used to get the total $config\_spend(S_{cs})$. If the $config\_spend(S_c s)$ is higher than a pre-defined budget, then the evaluation function immediately returns a very bad fitness for the configuration.

$$config\_spend(S_{cs}) = \sum_{s \in S_{cs}} (m_s * per\_lvl2\_cost_s + n_s * per\_lvl3\_cost_s)$$

Benefit: Benefit is calculated on the basis of charging station capacity in terms of power supplied (charging stations with higher capacity will be able to service larger number of vehicles) and coverage of a charging station in terms of area serviced by the station to avoiding close placement of stations. For any charging station s the capacity for the charging station given $capacity_s$ is as defined below:

$$capacity_s = m_s * per\_lvl2\_capacity + n_s * per\_lvl3\_capacity$$

Influential radius i.e, the radius in which the charging station influences demand is given by a sigmoid function of capacity multiplied by the maximal influential radius (r_{max}). This radius is used to determine whether a node is covered by a charging station.

$$r_i = r_{max} * \frac{1}{1 + exp(-capacity_i)}$$

The coverage for any node k, $cov(k)$ is then given by the total number of charging stations where the node k lies within the influential radius of the charging station. If a node k is serviced by more than one charging station, the additional benefit from the second charging station is lower and hence we use the following benefit function. The total benefit of the configuration is given by:

$$benefit(S_{cs}) = \frac{1}{|K|} \sum_{k \in K} \sum_{i=1}^{cov(k)} \frac{1}{i}$$

Cost: The cost function is formulated on the basis of expected travel time to the nearest station and charging as well as waiting time at the station depending on power required. Firstly, a demand is estimated at each node given by the EVs demand, discussed in the data processing section. This demand is normalised for the modeling purpose.

Now all the nodes from the graph k are mapped to a given charging station s on the basis of smallest haversine distance $dist(k, s)$. Then, the travel time from all the nodes is summed up using a weighted demand function. A constant velocity parameter representing the average travel speed in the area is defined as ν, used to convert the distance to time. The travel time of a charger configuration is given by:

$$travel(S_{cs}) = \sum_{k \in K} \sum_{s \in S_{cs}} \frac{dist(k,s)}{\nu} * demand_k$$

The charging time is estimated by the ratio of number of vehicles approaching a charging station D_s and the service rate μ_s, the rate at which the station serves the vehicles.

$D_s = \sum_{k \in K} \frac{demand_k}{dist(k,s)}$ where s is the nearest charging and

$\mu_s = \frac{capacity_s}{E}$ where E is the average energy demand per vehicle.

Then, the charging time is given by:

$$charging(S_{cs}) = \sum_{s \in S_{cs}} \frac{D_s}{\mu_s}$$

Finally the waiting time is modeled using the Pollaczek-Khintchine formula (Liu et al., 2019):

$$waiting(S_{cs}) = \sum_{s \in S_{cs}} (W_s * D_s)$$

where $W_s = \frac{\rho_s}{2 * \mu_s * (1 - \rho_s)}$ and $\rho s = \frac{D_s}{\mu_s}$ and $\rho_s < 1$

A weighting parameter α is used to combine the all the cost parameters to give the final cost as follows:

$$cost = \alpha * travel(S_{cs}) + (1 - \alpha) * (charging(S_{cs}) + waiting(S_{cs}))$$

Value: The overall value of a charging configuration is given by a weighted combination of benefit and cost and takes into account the demand coverage, budget constraint as well as the travel and charging time required by any configuration. This value is used to determine the fittest individuals from any population.

$$value(S_{cs}) = \lambda * benefit(S_{cs}) - (1 - \lambda) * cost(S_{cs})$$

6.2. Case Study: Los Angeles City

Because of the computational limitations, we restrict our study to Los Angeles; however the approach is flexible enough to be applied to other parts of the US. We use the following set of parameters for our model. The scripts for the case_study can be accessed at Code Repo

Maximum influential radius in km, r_{max} = 35
Average velocity in town in km/hr, V = 60
Energy required to charge a single vehicle, E = 25
Weight parameter for cost, $\alpha = 0.5$
Weight parameter for value, $\lambda = 0.7$
Number of nodes with non zero charging points in initial configuration, non_zero_stations = 100
Total budget of the charging plan, budget = 5000000

Initial size of the population, config_size = 100
Number of generations to be considered in Genetic Algorithm, num_evolutions = 50
Maximum number of lvl2 chargers per node, max_l2_chargers = 15
Maximum number of lvl3 chargers per node, max_l3_chargers = 15
Minimum number of lvl2 chargers per node, min_l2_chargers = 2
Minimum number of lvl3 chargers per node, min_l3_chargers = 2
Power supplied by each lvl3 charger in KWh, dc = 150
Power supplied by each lvl2 charger in KWh, lv2 = 15

The results for the above case for Los Angeles city can be visualised below:

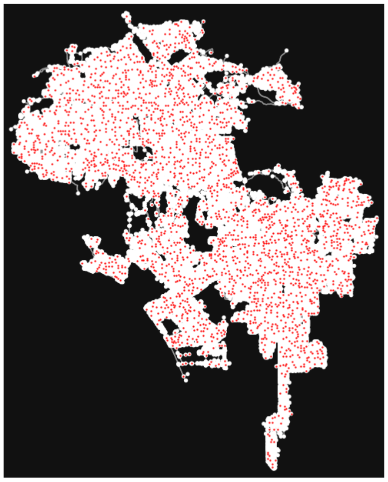

Figure 8. Predicted charging station locations in LA

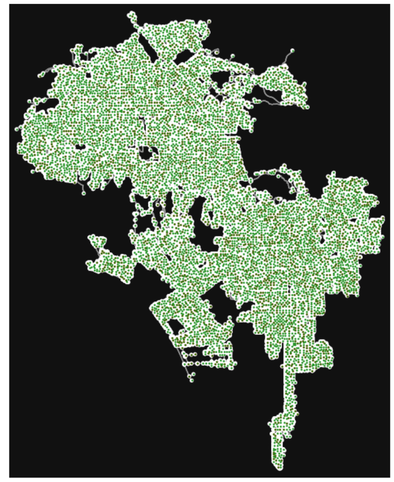

Figure 10. Existing and predicted charging stations in LA

In Figure 8 above, the predicted set of charging stations can be viewed. Figure 9 provides the existing locations of charging stations. Figure 10 further gives a combination of both the sets. We see that not a lot of charging stations are suggested in the LA region by the model as the current infrastructure is quite equipped to handle the demand. It would be interesting to see how this changes for an extrapolated demand 5 years from now.

Figure 9. Existing charging station locations in LA

6.3. Suggested future directions

On the basis of our research, we feel that following areas would further add on to the current study and can be built on top of it.

1. In current scenario, the $non\_zero\_stations$ consider non zero configuration separately for level 2 and level 3 chargers. However, a consolidated configuration with $non\_zero\_stations$ new charging stations should be considered. Furthermore, the configuration currently does not take into account already built charging infrastructure in a sense that it would consider a node mapped to a charging station and a node not mapped to a charging station equally for new construction. Similarly, right now we consider separate number of maximum chargers per station for level 2 chargers and level 3 chargers. However a combined configuration should be considered.

2. A simulated and very high level cost is used in the current optimization function. This would lead to a better budget utilisation as the expenditures become more accurate. To this purpose, we conducted a detailed cost analysis which can be leveraged in future work. Furthermore, some locations such as parking area and garages are more suitable to host charging stations and that can be a part of the budget optimization or can be used as a benefit component.

3. Haversine distance has been used to map everything such as charging stations to nodes, as well as attribute demand from a node to a charging station. However, the availability of road network can be utilised to get actual distances on road for any two points. Adding on to it, the road network

can also be utilised in the travel time to avoid busy roads, incorporate dynamic velocity across the road network in order to calculate travel time.

4. EVs per the sales is considered for demand, but driving pattern or parking behaviour would be a more accurate representation of the demand in a location. We could incorporate the demand if we had access to that data. Furthermore, the model is flexible enough to make predictions based on future demand predictions. Here amenities or POIs data can be utilized to adjust demand accordingly.

5. Incorporating availability of green energy sources and pricing of green energy can also be incorporated in the benefit-cost modeling to further prioritize the construction of green energy stations and maximize the leverage of transitioning to EVs from ICEs.

7. Environmental impact of Charging stations

7.1. Carbon Intensity Study

In 2020 the total generation of 4.01 trillion kilowatthours (kWh) of electricity from all sources in the US resulted in an emission of 1.55 billion metric tons of Carbon dioxide (CO2) (EIA, 2022). This is the emission from just one activity which is the energy generation. One of the main reasons EVs are being adopted at such a rapid rate is that they help reduce the carbon footprint in the environment. Studies have shown that there is a reduction of 60% to 68% carbon emissions from an electric vehicle in the US as compared to a conventional petrol/diesel vehicle (Grace Kay, 2021). With raising environmental awareness, everyone wants to contribute to the reduction in greenhouse gas emissions on their part and think using EVs instead of conventional diesel/petrol vehicles will make all the difference. While this is true to a certain extent it does not mean that EVs and EV charging does not affect or pollute the environment in any way. There is still quite a significant amount of greenhouse gas emissions associated with EV and EV charging. In this project we attempted a Carbon Intensity (CI) study of our own to try and identify the different sources and factors associated with EV charging stations and EVs which contribute to Green House Gas (GHG) emissions. While almost all the types of GHG emissions are emitted during the life cycle of an EV and EV charging station installation, we will be concentrating only on Carbon related emissions (CO2, CO etc) as they make up the majority of the emissions and have a much drastic and critical impact on the environment.

There are numerous methods to conduct a carbon intensity study for a project. It can be through a life cycle analysis, a global warming potential analysis or a carbon footprint analysis. In this paper we choose to analyze the carbon footprint of the project through the Green House Gas Emissions analysis. According to the guidelines of the United States Environmental Protection Agency (EPA), the GHG emissions and hence the carbon intensity associated with a specific project is measured in terms of Scope 1, 2, and 3 emissions (EPA, 2020a). Though Scope 1,2, and 3 emissions account for all the type of GHG emissions, we will be only considering the carbon emissions for the scopes in this study.

Direct GHG emissions due to activities such as combustion of fuel in furnaces, boilers, or vehicles from sources used directly for the project falls under scope 1 emissions. The emissions related to energy that is purchased or brought by an organization (electricity, heat, steam, etc) are accounted for under scope 2 emissions. Scope 3 emissions consist of all indirect emissions (apart from those reported in scope 2) which occur in the value chain or the life cycle of the project. These emissions do not arise from assets owned or controlled by the project owner, but rather from indirect sources such as the purchase of products, transportation of purchased products, production of the purchased products, etc (EPA, 2020b). Sope 3 emissions are rather exhaustive and very complex to determine. Hence, EPA mandates organizations, facilities and projects to report their Scope 1 and 2 emissions only and allows for scope 3 emissions to be excluded. Figure 11 below shows a high-level description of scope emissions (EPA, 2020c).

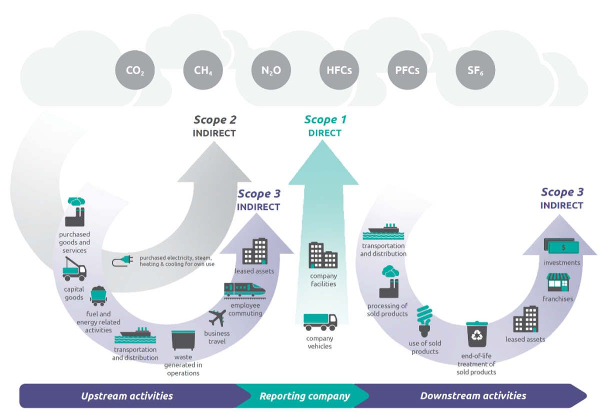

Figure 11.

Electrical Vehicles themselves contribute a considerable amount of emissions which arises from their manufacturing process but with respect to the scope of our Carbon Intensity study we will be considering it as scope 3 emissions for an EV charging station. Our aim with this study is to identify the potential sources of carbon emissions associated with deployment of a single EV charging station. We note that the type of charger uses (level 2 or level 3) does not affect the emission study and hence will not be mentioned explicitly in this study. Scope 1 emissions are direct and of the most relevance for this study. However, we will be looking into scope 2 and 3 as well. Scope 1, 2, and 3 emissions for an EV charging station is described below.

7.2. Scope 1 emissions

Grid Mix

The carbon emissions associated with the electricity used for a project will contribute directly to scope 1 emissions. Carbon intensity of electricity is the number of grams of carbon or carbon related compounds released during the production of a single unit of electrical energy (ie, a kWh or MWh) (national grid, 2022). Conventional sources of energy such as the burning of oil gas, or coal result in the generation of carbon dioxide (CO2) as a part of the power generation process, leading to high carbon intensity. Renewable sources of energy have very low carbon intensity and hence their scope 1 emissions are considered to be zero. In the US, the grid mix of a source of electricity is the best way to estimate the carbon emissions. Grid mix is the combination of different sources of energy used to generate the said electrical energy. These can be a single source such as coal or natural gas or a mix comprising of nuclear, coal, natural gas, hydroelectric, wind, solar, hydrogen, geothermal etc. This is also called Distributed Energy Resources (DER) feeding the grid. Each method of electricity generation has a separate carbon intensity associated with it which will be combined to determine the emissions for a mixed grid from which energy is drawn.

The geographical area we have considered for our project is the state of California in the US. Hence the study was carried out for California which can be easily extended or adopted for other states or countries. As of 2020 California generates a total of 300,000 GWh of electricity. The figure – shows the Total System Electric Mix in California in Gigawatt Hours (GWh) as of 2020 (California Air Resource Board, 2022). Approximately 97,350 GWh, 31,614 GWh and 25,000 GWh of the electricity comes from Natural gas, solar PV and unspecified sources respectively (California energy comission, 2022). Figure 12 below demonstrate this.

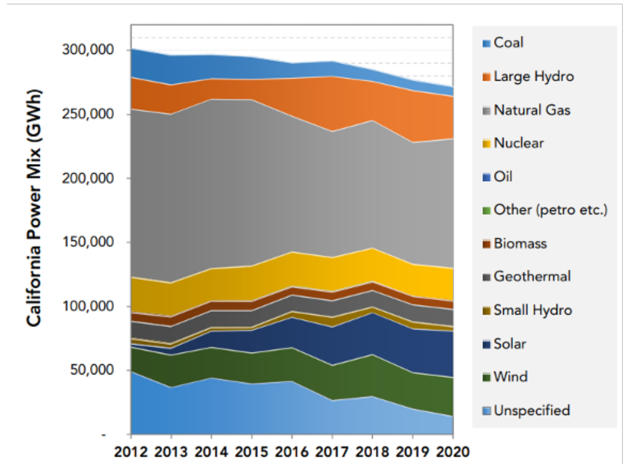

Figure 12. Total system Electric Mix in California in Gigawatt Hour (GWh)

The carbon emission factor for natural gas is 1.1 lb CO2/kWh, for other unspecifies sources it is 2.1 lb CO2/kWh and it is zero for renewables and hence for solar PV source based on the study by National Renewable Energy Laboratory (NREL) (Joyce McLaren, John Miller, Eric O'Shaughnessy, Eric Wood, Evan Shapiro, 2016). Using the carbon emission factor and total electricity generated by the sources under consideration, the carbon intensity of the grid of California can be approximated. 1 kWh of electricity production by natural gas results in an emission of 0.49 kg of CO2. This means for the 97,350 GWh of electricity produced 52.58×10^7 tons of CO2 is emitted. Similarly, 1kWh of electricity produced by the unspecified sources results in 0.953 Kg of CO2 emissions which would be 2.6×10^7 tons of CO2 for the 25,000 GWh electricity produced. This gives us a staggering 55.18 10^7 tons of CO2 emissions for the grid mix of California just for the energy generated from natural gas and unspecified sources. Therefore, an appropriate amount of Carbon intensity gets associated with projects or processes using this electricity. We can deduce from this analysis that 4.17 g of Carbon related emissions occurs for 1kWh of electricity used from such a grid.

In the US, California is one of the states where a sizeable amount of electricity generation is from renewable sources. In many other states coal or natural gas is still the major source of energy which means a proportional rise in these emission values calculated above as coal has a very high carbon emission factor. These numbers show us that electric transportation is only as green as the grid which feeds it energy. Hence there is dire need for replacing our energy source with more renewables and having a good grid mix balance. Figure 13 below shows modeled grid profiles representing varying levels of carbon intensity and its correlation to the grid mix (Bureau of Transport Statistics, 2020). As witnessed, the greener the grid gets the lesser the carbon intensity associated with the electricity produced.

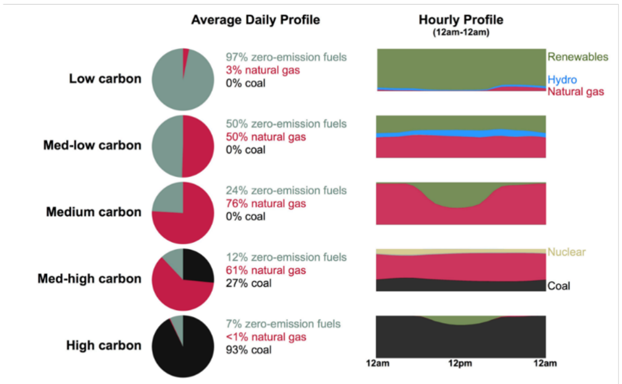

Figure 13. Modeled grid profiles representing varying levels of carbon intensity

Transportation

Another factor that directly contributes to scope 1 emissions is the non-electric sources of transportation used for the project. Construction and installation of an EV charging station will need the use of heavy duty pick-up trucks for transporting construction material, chargers, installation material and other equipment. We should also consider transportation such as cars and vehicles used for transportation of workers. For the purpose of this analysis, we assume that two Gasoline heavy duty pickup trucks are used which together run a total of 1000 miles for the purpose of charging station deployment. From the data compiled in the Bureau of Transportation Statistics, the Carbon emissions for heavy duty gasoline pickup truck is 17.14 g/mile which would lead to emissions of 34Kg of CO_2 from both the trucks in total (Bureau of Transport Statistics, 2020). We also assume ten gasoline cars are used for employee transportation and all the employees together travel a total of 500 miles for the purpose of a single charging station deployment. Carbon emissions from a single gasoline car is 2.81 g/mile (Bureau of Transport Statistics, 2020). This would give 14Kg of CO_2 emissions for employee transportation. The total Carbon intensity for transportation associated with the deployment of a single charging station would then be 48Kg. If in the long-term governments plan to install thousands of charging station, the carbon emissions will proportionally scale up to tons, just from associated transportation.

7.3. Scope 2 emissions

Any form of energy purchased for the operation and maintenance of a charging station would contribute to scope 2 emissions. Energy for cleaning the station, ventilation, HVAC systems, heat etc. all fall under this bracket. The carbon intensity for this scope again depends on the electricity from the grid. Hence the greener the grid the lesser will be the associated scope 2 emissions for a project. If the owner has a renewable power purchase agreement for the facility, then scope 2 emissions will be zero. A power purchase agreement (PPA) is the agreement between an owner of a facility or organization and an energy provider who uses only renewable sources for the generation of electricity (GE Renewable Energy, 2022). This provision of EPA acts as an incentive for utilities and owners to look towards renewable energy as their source and hence helps curtail scope 2 emissions effectively. Increasingly, utilities which have many forms of energy sources are also benefiting from this incentive and looking to move towards a much cleaner grid.

7.4. Scope 3 emissions

Scope 3 emissions comprise of almost all the indirect emissions which can be associated with a project. The EPA does not mandate the reporting of this scope emissions, but it would still be in the best interest of environmental impact for projects to carry out this scope study (EPA, 2020c). This list is extremely subjective and exhaustive and would not be very beneficial for this analysis. Hence, we have identified only a few critical sources of this type of emission and will not be diving into it in detail. Emissions from manufacturing of battery charger and its components such as cathodes, electrolytes anodes, separator plates, cell cases, electrolytes, and inverters fall under this scope. All the batteries and their components need to be recycled at the end of their lifetime. The energy and emissions associated with their recycling also contribute to this scope. The emissions associated with the energy needed for battery pack assembly, installation of battery enclosure containers and mining and refining of battery material (Lithium, cobalt, Nickel, etc.) are scope 3 emissions. Electric vehicle manufacture, painting, raw material procurement, mining for metals used in the vehicles, manufacturing of interior parts of the car, all has quite a significant carbon intensity. Once the cars are manufactured, they would have to be transported to locations all over the world using various means of transport which all have their own emissions. The cars need maintenance, repairs, and recycling at the end of their lifetime which would all add to this scope. To sum it up all the secondary and tertiary means of emissions associated with a project can be listed and studied under this scope. This is a very complex study and hence would need the support of a large database of information and resources to accurately determine the CI from this type of scope emissions.

The main takeaway from this Carbon Intensity study is that the source of energy feeding the grid from which the electricity is drawn determines the emissions associated with that electricity usage. The energy is only as green as the grid is. Therefore, for EVs to make any significant impact in reducing environmental damage, it is of paramount importance to clean up our grids. Responsible authorities and policy makers must also push for PPAs to be mandated for EV charging stations which can help reduce a great deal of carbon emissions. It would also be beneficial for charging stations to be directly integrated with renewable energy sources such as solar or green hydrogen. A great amount of emission results from all the manufacturing, fabrication, and raw material extraction processes of any product. While many of these are unavoidable in the value chain of a product, efforts still need to be made to reduce their carbon impact.

8. Conclusion

In this study, we discussed the importance of having a good charging infrastructure to promote EV adoption. Consumers are hesitant to go for electric vehicles if they cannot get it charged as it reverts the purpose of getting a car. We provide a framework to study electric vehicle demand and infrastructure on the basis of open source datasets which is replicable to other parts of the US. We further deep-dived into the datasets and provided insights specifically for the Los Angeles county as an interactive dashboard. Genetic algorithm was used to demonstrate the applicability of our model in the case of Los Angeles. Further, an extensive cost analysis was conducted to provide a sense of costs associated with building a charging station and which can be incorporated into our model. A carbon intensity study was carried out to evaluate the environmental impact of deploying a charging station in terms of scope 1, 2 and 3 emissions.

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