EV Infrastructure Planning and Grid Impact Assessment: A Case for Mexico

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EV Infrastructure Planning and Grid Impact Assessment: A Case for Mexico

Apollo Jain

RESEARCH PROJECT

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Abstract

In much of the world, electric vehicle adoption is increasing. This is a welcome change for many of these countries, where gasoline-powered vehicles contribute to high levels of ozone and fine particulate matter ($PM_{2.5}$), which results in tens of thousands of deaths a year.

City planners can use this document to formulate plans regarding where to build charging stations to meet new demand, how much infrastructure to build at each location, and how to plan new electrical infrastructure to meet such demand. Herein, we provide a framework to address the aforementioned issues.

Projections on EV sampling and the input data are used to construct Monte Carlo based models on where these cars will be by the hour. It shows how to obtain the locations and sizes of these stations using clustering algorithms and convex optimization. Load profiles are generated given statistics regarding home and work charging, in addition to the newly found information about public charging. Guadalajara was used as a case study for this model due to the fact that it is one of the foremost technology hubs in Latin America and that there was data provided about the city through the Instituto Nacional de Ecología y Cambio Climático (INECC).

1 Acknowledgements

This thesis would not have been possible without the help of a number of individuals. First of all, I'd like to thank Dr. Sascha Von Meier. Her course was instrumental in cementing my interest in both power systems and renewable energy. Without her introductions, I likely would not have joined RAEL. She has also been an incredible help to me as both a professor and as a Graduate School Advisor.

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I'd also like to thank Dennis Wu for being a great help to me during this process. The data and trends that he has analyzed throughout this process have been instrumental to the creation of this work. I wish him the best of luck upon graduation and at UCLA.

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Lastly, I'd like to thank Dr. Daniel Kammen. The resources that his lab has provided have been incredibly helpful in the production of this document.

2 Introduction

Global emissions from the transport sector account for about 23 percent of total energy related emissions, and could grow as countries develop [4]. Deep decarbonization of our transportation options is needed if we are to meet the Paris Agreement goal of stabilizing GHG emissions concentrations below a 2^oC warming scenario, and to increase our mitigation efforts for a safer 1.5^oC temperature target. This will only be possible if climate action is taken at the scale and pace that is needed to mitigate this change. New policy approaches that leverage the power of innovative technologies are required to advance towards this goal.

In many countries, decarbonization is being achieved through the conversion from gasoline powered vehicles to plug-in electric vehicles (PEVs). While EV charging still generates carbon emissions and particulate expulsion due to modern grid reliance on fossil fuels, EV use would result in better air quality [6]. Furthermore, EVs themselves produce less than half of the global warming emissions of comparable gasoline-powered vehicles, meaning that adoption of such vehicles would result in lower regional particulate and carbon emissions [7].

One of the biggest factors holding EVs back, apart from cost and range, is the lack of available infrastructure for individuals to go about their charging needs [8]. If a consumer wants to go around the city to run a long list of errands, or they want to go on a road trip, he or she will inevitably be concerned with whether it is possible to recharge his or her car outside of home. Owners of gasoline-powered vehicles have the advantage of being able to quickly refill their vehicles at gas stations in a matter of minutes, whereas for EV owners, the closest analog to such infrastructure is Level III (High Power DC Chargers)and IV (Very High Power DC Chargers; the only such chargers on the market are Tesla Superchargers) charging stations, where even then, charging may take up to 30 minutes [9]. Thus, for governments wishing to increase EV ownership among their citizens, it is necessary to figure out how to place EV charging stations in a way that is economically feasible, meets consumer demand, and ensures continuous or near-continuous electrical service.

Several publications deal with determining the optimal sizing and placement of electrical charging stations. A capacitated-flow refueling based approach is presented in [10] to capture Plug-in Electric Vehicle (PEV) demand on the transportation network under driving range constraints. [1] looks at ensuring coordinated PEV charging at the transmission system, distribution system, and charging system level in order to ensure that load profile is optimized at the provincial, municipal, and station level while meeting consumer demand. [2] proposes a method for charging station planning to ensure that charging service is met while reducing power loss and voltage deviations of distribution systems. [3] looks at optimal station placement considering EV energy loss, electric grid loss, station development cost, and other factors. Lastly, [11] looks at optimal placement of stations in urban environments given spatial and temporal charging demands.

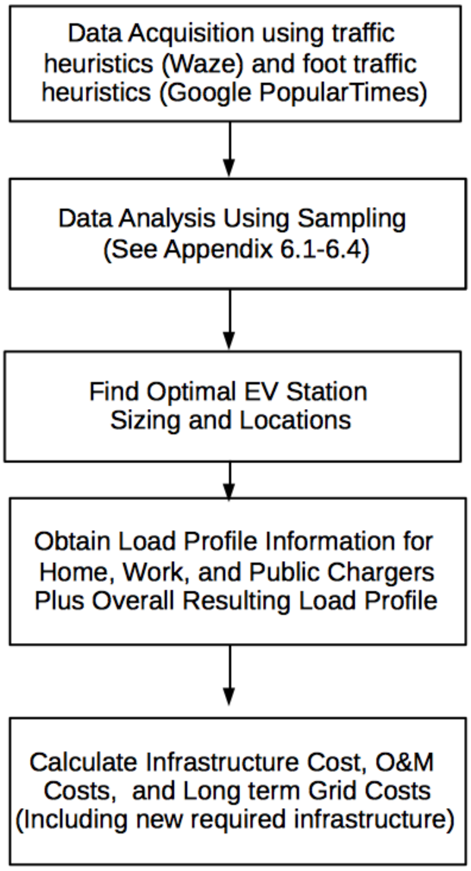
This document takes many of the insights from the aforementioned publications and combines them to create a comprehensive strategy to get charging station sizes and locations, and effects on the grid. The method also allows for city planners to look at building proposed charging infrastructure in phases, and figures out any distribution-level infrastructure that must be added to account for the increased electrical demand. Insights can be obtained in order to meet consumer demand and maximize profit.

The first stage of this process begins by talking about the process of obtaining the necessary data and how to process the data so as to obtain a particle distribution that resembles the true distribution of the municipality in question. The second stage discusses the method of determining the size and locations of charging stations. The third stage involves using the proposed charging station, along with EV users' home and work charging habits, load profile projections, and EV ownership projections to see what the impacts of this demand will be on the grid and what new infrastructure needs to be built. Suggestions are made on how to tune this method for multi-phase planning for EV charging station creation.

Mexico will experience explosive EV growth in the next decade; indeed, it has signed the International Energy Agency's pledge to reach 30% EV Penetration by 2030 [5]. Thus, this procedure has the potential be useful to Mexican city planners who need to address these projections. The city of Guadalajara is selected as a case study due to the fact that it is a tech hub in Mexico and Latin America (and thus is more likely to adopt EV technology) and the fact that data on the city was available through RAEL's institutional partner, INECC. Several planning scenarios are investigated for the city, including single phase examples for low, moderate, and high growth in EV ownership. The process of obtaining information, finding station locations and charger configurations, investigating the load increase, and observing the impact on the grid are all described for this scenario.

3 Procedure

Figure 1: The EV Station Analysis Procedure



The process of the flowchart begins with Data Acquisition, which involves getting representative samples for traffic, including EV traffic. The second step involves sampling data to show when all n EVs in a particular city for all 24 hours for each of the seven days of the week. Next, a linear program is used in order to get the optimal charger configuration for different brands and levels of chargers. Load Profile information is found for the city using various pieces of information regarding EV usage in that particular municipality, such as percentage of charges done at home, work, and at social chargers, the number of EVs in the city, the average size of the battery, etc. The last step is calculating the size and cost of grid updates using a capacity extension model called SWITCH.

3.1 Obtaining and Processing the Data

The first necessary item is some heuristic to define the spatio-temporal distribution of cars and/or people. The second necessary item is the current load profiles of the areas being surveyed, so that it is possible to quantify the strain on the grid for that area, especially as the population of an area, and the number of EVs that this population uses, grows over time. The last necessary item is a general breakdown of the charging habits of EV users.

In general, EV owners have two options when charging in public. The first, destination charging, includes placing a vehicle on a Level II charger. This strategy is useful if an individual has some level of charge, but would like to charge their vehicle enough to get them a longer general range [10]. On the other hand, urgent charging is a strategy employed when an EV has very low amounts of charge. In such a case, an EV must be charged quickly in order to get the owner home [10]. EV owners in need of urgent charging will either be in traffic and about to go about fast charging or will be in a commercial location with their car at a charging station. Thus, sample points that represent both of these situations can represent both above scenarios accurately.

The spatio-temporal distribution of cars and people can be obtained in a number of ways. An accurate way to measure congestion of certain areas over time is to use data from Inrix, which offers real-time traffic and parking availability in many cities. The specifics of this method are outlined further in the appendix.

Assuming that Waze and Google Places data have been obtained using the methods described in the appendix, it is now time to use Monte Carlo Sampling methods in order to create a representative population of electric vehicles. In our scenario, the Waze Traffic Jam data shows the popularity of certain road sections, and thus shows the density of cars (including EVs) going through a certain region at a certain point in time. The Google Places data describes the distribution over time of when individuals visit certain commercial establishments; such data generally indicates when and EV will be parked near such places, and thus when and where and individual would want Level II charging. The method has several limitations for several reasons. First of all, Google PopularTimes data is normalized, so any data that is used from it does not incorporate how many people go to different types of places (*i.e.* a large shopping mall will have more people in it than a small shop, but on Google PopularTimes the populations for any given hour of any day will be normalized to a height of 100). The issues with Waze, on the other hand, stem from the way the data is sampled. Since Waze is sampled for the size of traffic jams, there could be inaccuracies with how busy a place is, since traffic jams may simply be caused by lack of good infrastructure rather than the actual popularity of certain areas of a city. For both of these data sources, there is also bias in the data, since the data caters to smartphone users and users of the Waze app, so most of this data will from individuals who have enough money to afford smart phones. This may not be a problem, since many EV owners will share demographic similarities with those same power smartphone users [13]. After going through the Monte Carlo Sampling method described in the appendix, representative data points will now be available for input into the second step in the process: finding station location and size.

While there are ways to obtain information related to EV charging habits and the density of people in certain locations over time, it is more difficult to get information about load demand for entire municipalities. It may be necessary to get habits on charging from other areas of the world, and then assume that users in the current municipality follow similar habits. Environmental agencies at the national level (in our case, INECC) will likely have easier access to data related to the various load zones of a country, and thus, will be able to get access to the load profiles for a desired municipality more easily. The data should be formatted as a time series with hourly granularity so that it can be fed into the final step of this process, which is described in later sections.

3.2 Finding the Location of an EV Charging Station

City planners with to optimally find locations of new stations with the constraint that other charging stations may already exist. In this case, it is ideal to place new stations in locations that would best meet new demand, and expand stations that already exist. This process uses a modification of k-means clustering. The iterative process is similar to traditional k-means clustering, with the constraint that m stations were kept at the same place (i.e. at the same centroid), while n stations were placed in new locations. Thus, the n non-fixed station locations will change after a number of iterations, but the partitions of classified samples will differ for both fixed and non-fixed cluster centers. The pseudo-code, which is a modification of Lloyd's Algorithm, is as follows:

```
def station_locations(data_pts, current_stations, m):
    # m is the number of new stations you want to create
    n = len(current_stations)
    randomly initialize m stations − now have (n + m) total stations
    initialize voronoid diagrams for all (n + m) stations
    while stations have not converged and iterations < max_iterations:
        for each of the points, figure out the closest station
        find a new centroid for new station voronoid diagrams (m new)
    return all station locations and corresponding voronoid diagrams
```

We now we have our n old station locations and m new station, locations, as well as the relative popularity of each station.

There are a few things to note about the results of this algorithm. The first thing to note is that the algorithm can converge to different solutions on different runs given the way that clustering algorithms work. This, of course, is not necessarily the best situation if multiple planners are using different instances of the same software tool for this approach. A good rule of thumb is to generally see what configuration the algorithm converges to on multiple attempts in order to see if the solution is generally correct. The second thing to note is that the station "locations" do not necessarily have to be set in stone. As long as the station is generally close to the area that the algorithm converges to, it will properly serve the cars that are assigned to it effectively.

3.3 Determining Infrastructure to Meet Requirements

Upon getting the new station locations, it is necessary to figure out what infrastructure to allocate to each station. In other words, how many types of chargers, and what types of chargers, should we place at different EV charging stations to meet the following requirements:

(a) Need to minimize total building costs
(b) Must take into account infrastructure/building costs, O&M costs, electricity costs, and revenue from customers
(c) Must ensure that the new demand due to public charging stations do not cause overall municipal demand to exceed the load zone's capacity
(d) Each station must have enough charging infrastructure to meet car demand at all hours, including peak hours.
(e) Each station must have at least one charger and may also have a maximum number of chargers, since there could be land limitations, cost limitations, electrical limitations, etc.

Let us assume we have stations $i \in 1, ..., u$ and charger types $j \in 1, ..., v$. These requirements are met with the following Linear Program:

$min\ 1^T(C_{sta} + C_{ener} - C_{rev}) + \alpha|\hat{T}n|_2$ (i)
s.t. $C_{sta} = K_{setup} + (K_{infra} + \hat{\beta})n$ (ii)
$C_{ener} = \gamma p_{sc}(1^T \Psi \tau)\hat{E}n$ (iii)
$C_{rev} = 12\gamma r \delta_{station}$ (iv)
$\hat{W}n - (\phi - \eta v) \geq 0$ (v)
$\hat{S}n \geq 1$ (vi)
$\hat{S}n \leq c_{max}$ (vii)
$\theta\hat{M}n \geq p_{sc}\delta_{max}$ (viii)
$n \geq 0$ (ix)

The variables above are defined by the following:

- $C_{sta} \in R^u$ is the operating cost of building and operating each station i.
- $C_{ener} \in R^u$ is the energy cost for each station i.
- $C_{rev} \in R^u$ is the revenue at each station i. The unit is dollars
- $\hat{T} \in R^{u\ x\ uv}$ is a matrix of the average charging time of charger type j at station i. The unit is in hours per charger, and entries can be decimal values. *
- α is the L2 Regularization term that is weighed on the aforementioned variable corresponding to the time that a person has to wait - think of it as a penalty for "customer dissatisfaction with spending time at a station." This is not a regularization term in a traditional sense, since we already are minimizing, so the main purpose is to add extra weight to a new parameter. We would like to have a unique solution and do not necessarily care about sparsity, so the L2 norm is preferred. This is technically a unitless parameter, but can be thought of as inverse minutes.
- $n \in R^{uv}$ gives the number of chargers at each station. The units is number of chargers**

- $K_{setup} \in R^u$ is the setup cost (i.e. the cost to buy land, connect the station to the grid, etc.) of each station i. The unit is dollars.
- $\hat{K}_{infra} \in R^{u\ x\ uv}$ is the cost of connecting some charger type j at station i to the grid
- $\hat{\beta} \in R^{u\ x\ uv}$ is the cost of a each charger type, including both purchasing and O&M costs. The unit is dollars *
- p_{sc} is a constant that gives the proportion of the time that the charger is operating at peak capacity (i.e. the proportion of time a charger is using the values in $\hat{E}$ - otherwise, energy use is 0 for sake of simplicity). This is a unitless constant.
- $\hat{E} \in R^{u\ x\ uv}$ is a modified the matrix that contains a vector that corresponds to the amount of energy each charger type in an hour if a car is plugged into it. The unit is kWh *
- γ is a constant that determines the number of years a station will be in service. The unit is years.
- $\Psi \in R^{24\ x\ 6}$ is a matrix that corresponds to the tariff price for all six tariff types (summer and winter peak, intermediate, and base prices) for each hour of the day. It is multiplied by the tau matrix. If, for some hour h, h is a peak hour in winter time, then the column corresponding to the winter peak tariff (in our case, the first column) will contain the number of days a year that this row will be under that particular tariff. The unit is days.
- $\tau \in R^6$ is the vector corresponding to the hourly tariff rates for electricity for winter peak, winter intermediate, winter base, summer peak, summer intermediate, and summer base respectively. The unit is dollars
- $\delta_{station} \in R^u$ is a vector that corresponds to the number of cars that come to a station in a week. The unit is number of cars
- r is a constant that corresponds to the average revenue per month per car. In this scenario, we assume monthly membership rates for fast charging, as is common in the United States. The unit is dollars.
- $\hat{W} \in R^{7*24}$ is a vector that has, for every day, the amount of energy produced by every single station in that hour (which, in turn, is the proportion of time the charger is being used multiplied by the maximum power that a charger can produce in an hour multiplied by the probability distribution of when drivers arrive at chargers to use them). This is replicated seven times to represent each day. The unit is kWh
- $\phi \in R^{7*24}$ is a vector of the maximum capacity that a substation can take in an hour (every item is the same in this vector). The unit is kWh
- $\upsilon \in R^{7*24}$ corresponds to the load profile of a municipality of every hour in an average week. The unit is kWh.
- η is a constant that scales up the load profile to represent a higher-than-average load profile. It is unitless.
- $\hat{S} \in R^{u\ x\ uv}$ is a modified matrix, where the original vector is the "ones" vector. Performing the multiplication $\hat{S}n$ gives the number of chargers for an individual station $i \in 1, .., u$. It is unitless.
- c_{max} is a constant that corresponds to the maximum number of chargers that can be built at an individual station.
- θ is a coefficient create a buffer, since δ_{max} is the hourly maximum for the average number of cars arriving at a station (but it is just that, an average, so we want a gap to make sure that we can handle more cars in the event of an especially busy day). A higher value indicates a higher willingness to let people wait, while a lower value indicates a lower willingness to let people wait. It is unitless.

- $\hat{M}$ This is a vector corresponding to the capacities per hour of each of the chargers at each station, turned into the matrix format discussed in the appendix. The unit is number of cars. *

- $\delta_{max} \in R^u$ is the value corresponding to the average number of cars in the busiest hour and day of a representative week for each station. The unit is number of cars.

* The structure of such matrices (denoted by $\hat{X}$) is described in the appendix in the "Determining Infrastructure to Meet Requirements" section
** The "n" array contains how many of each type of charger should be at which station

The steps below, as numbered, correspond to each line of the optimization problem shown at the beginning of the section. **(i)** In the objective function, we are minimizing $1^T(C_{sta} + C_{ener} - C_{rev})$, where we have the cost of building C_{sta} and maintaining the station added to the costs of energy C_{ener}. We subtract the revenue from this sum to reflect the fact that we will be getting some of this money back from our revenue C_{rev}. Lastly, we add an L2 Regularization term in order to weigh public discontent for having to wait for charging. Such discontent is weighed by parameter α.
(ii) This constraint basically defines the station cost as the cost of setting up the station (parking lots, land, electrical connections), cost of infrastructure (i.e. buying each charger and connecting it), and O & M cost of each charger
(iii) This constraint defines the energy cost at each station. This is done in two steps. The first part of this involves calculating the cost per kWh over the lifetime of the charger, which is done by taking the tariff cost, which is done by taking the tariff cost vector τ, multiplying that by Ψ, which gives the tariff cost of hour h over an entire year , assuming that the charger is always on. We sum up all of these hours to get the overall cost for a year, assuming we use a single kWh for every hour of the year. Multiplying this by γ, or the number of years, gives the overall cost for the entire phase assuming we use a single kWh for the entire year. The other part of this is $p_{sc}\hat{E}n$ gives the energy use by station per hour (assuming that it is always in use), multiplying that by the proportion of time the charger is in use.
(iv) We get the revenue for each station by looking at the hourly rate for charging and multiplying this by the total demand at each week at the station.
(v) This constraint tells us that the amount of energy produced in total at all of the stations at each hour in an average week must be less than the gap between the capacity of a substation and the demand load profile at this average hour.
(vi) This constraint states that we must have at least one charger per station.
(vii) This constraint states that each station can have at most c_{max} chargers.
(viii) This constraint states that each station must meet customer demand at all hours of the day.
(ix) This constraint states that we can never have a negative number of a particular charger at a station.

3.4 New Load Profile

In the long term, the load profiles of any studied city will change substantially due to the new loads from EV chargers at home (the primary charging source for most EVs, mostly used at night), at work, and in other public places (fast chargers fall under the latter category) [12]. Knowing the projected new load profile is important in knowing whether the current electrical infrastructure will be able to handle increased demand or whether new infrastructure must be built in order to increase capacity.

We start out by getting the load profile without the new EVs. Many municipal governments will have this information available. To get the information on the the home and work charger load profiles, it is necessary to first know the number of EVs and the average size of an EV in the area studied. It is also necessary to know the proportion of charges that are done at home, work, and at social charges. While data may not be necessary on the municipality in question, it is certainly possible to study the home, work, and social charging habits of individuals around the world and make generalizations. Some of the most useful insights came from charging habits in Melbourne [15] and in Massachusetts [19].

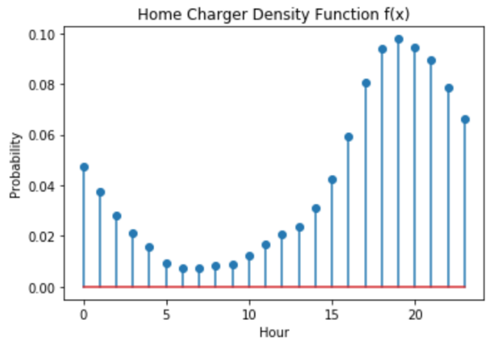
To get the EV Profile of a particular charger type, we run the following circular convolution:

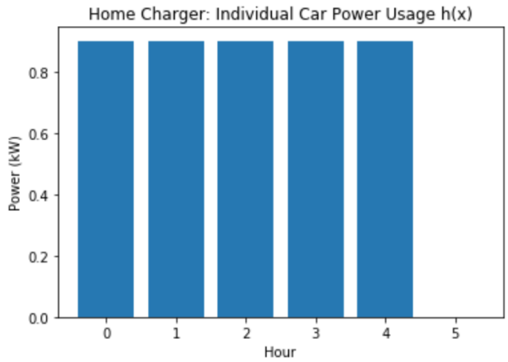
$g(x) = \sum_{s=0}^{23} f(s)h((x-s) \ mod \ 24)$

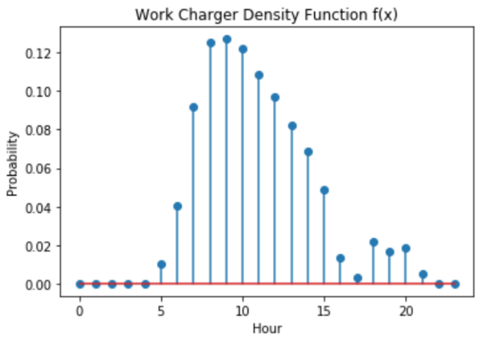
In the above equation, $f(x)$ is the probability density function that represents the probability people begin to charge their vehicle at hour x and $h(x)$ is the amount of power for every hour x after you begin charging, assuming you leave a single car charging. This is an impulse train that is of length *hours_to_charge* and height *energy_per_hour*, given below:

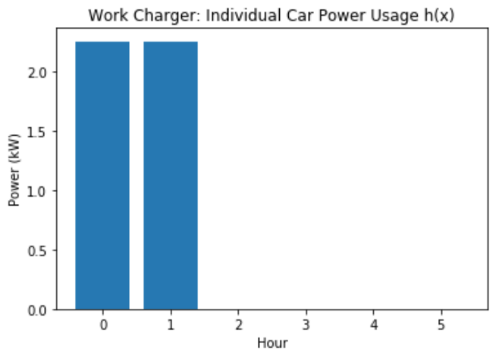
$$hours\_to\_charge = \left\lceil \frac{avg\_proportion\_commute\_drain * battery\_size\_kw}{charger\_capacity\_kw} \right\rceil$$
$$energy\_per\_hour = \frac{avg\_proportion\_commute\_drain * battery\_size\_kw}{hours\_to\_charge}$$

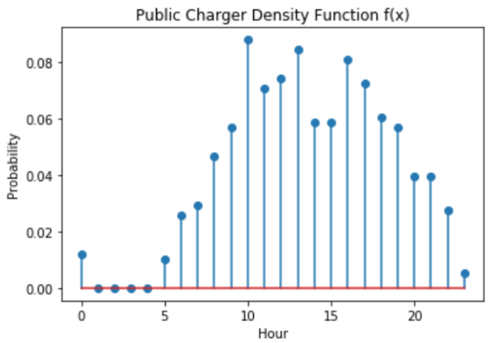
Assume a 30 kW battery, 15 percent battery drain (calculated from the assumed range of 200 miles, and an average commute of 30 miles) [16]. Assume values for home charger (Level I - 1 kW), work charger (Level II - 2.2 kW), and public charger (Level III - 10 kW) sizes for the final battery size values. We thus get impulse train lengths for Level I, II, and III chargers of 5, 2, and 1 hours respectively, with heights of 0.9 kW, 2.25 kW, and 10.0 kW respectively. The different graphs for f(x) and h(x) are given below.

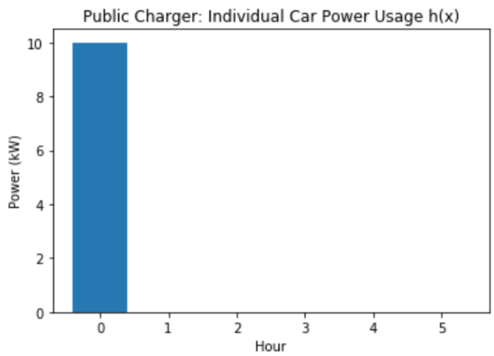






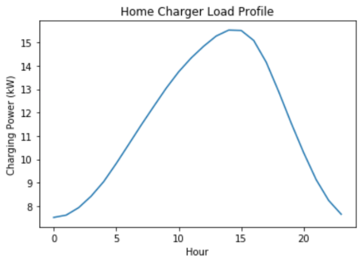


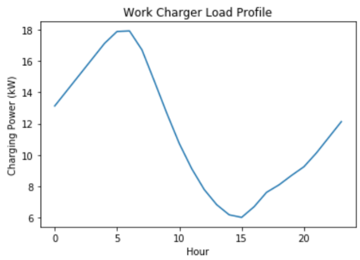


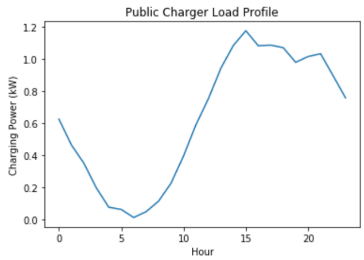


Once a representative day's worth of charging data is obtained, this series is replicated over the entirety of the time series of the original load profile (in other words, there is a repeated day for every single day in the time series). The overall new load profile is found by adding the different charger load profiles to the original baseline load profile without the EV data. This is done by considering the proportion done at home, work, and public places. Such data should also be scaled up to reflect population increases. In the end, for a particular year, the load curve can be

calculated with the following:
$overall\_profile = baseline\_profile + n\_evs(p_{social} * lp_{social} + p_{work} * lp_{work} + p_{home} * lp_{home})$. In each case, $baseline\_profile$ is the baseline representative load profile for a day. p_{home}, p_{work}, and p_{social} refers to the proportion of charges that are done at home, work, and publicly (for instance if 85% of charges are done at home chargers, then $p_{home} = 0.85$). Furthermore, lp_{home}, lp_{work}, and lp_{social} corresponds to the circular convolution described above for home, work, and social respectively (i.e. $lp_{home} = g_{home}(x) = \sum_{s=0}^{23} f_{home}(s)h_{home}((x-s) \; mod \; 24)$). The result of these convolutions are below:







3.5 Adapting to New Load Demand

The last step in this process is running the scenario in question on a specifically-designed module of for the SWITCH Power System planning tool, which was developed in RAEL to plan new generation and transmission assets as well as in end-use and demand-side management options (including electrified vehicles and storage) [23]. The parameters required to run SWITCH are described in the next section. Once the SWITCH module is run, output information includes the amount that is necessary to invest in transmission and distribution infrastructure, as well as operating and management costs for this infrastructure.

4 Running a Scenario

4.1 Overview

4.1.1 Getting inputs

The purpose of the infrastructure planning framework is for it to be as generalizable to different scenarios as possible. The program requires the following pieces of data provided in CSV format in order for it to function properly (see the "example" folder in "inputs" for specific details on what information is necessary):

(1) Charger types - We want to have our program select the optimal configuration of different brands of chargers that we may want to construct at our charger site.
(2) EV Profiles - Information relating to what the situation for EVs looks like for a given year (*i.e.* the number of EVs in the city in question, the proportion of people using social vs. home chargers, etc.)
(3) Load PDF - For home, work, and social chargers, we want to see a probability density function for what proportion of charges start at a certain hour.
(4) Load Profile - This will usually be obtained from the city government in question. It will be a time series, generally by hour, of what the load demand is for that particular time.
(5) Miscellaneous - Various pieces of information that doesn't really fall under any other category. This can include, say, things like charger lifetime, the amount of time a social charger is used by EV owners on average, etc.
(6) Municipality - City information (city name, population)
(7) Planning - Information about the different planning phases for the EV stations, including the year of the phase in question, and the number of stations that should exist in that phase.
(8) Samples - These are the representative samples that you obtain from your Monte Carlo Sampling of the representative Waze/PopularTimes points.
(9) Stations - Sometimes, there may be existing stations for a particular scenario and you may want to build new stations. This CSV will give you information about station names, locations, and charger configurations.

(10) Tariffs - For the area in question, give the average seasonal rates and the hours for medium vs. peak times.

4.1.2 Outputs

Sample outputs also have the following format, which can be found in the "example" subdirectory of the "outputs" folder. The results are by year and include:

(1) Costs - Considers Construction and O&M
(2) Load Profiles - Looks at Baseline, Home Charger, Work Charger, Public Charger, and Combined Loads.
(3) Stations - Looks at the new stations that will be built during the phase in question (includes location, charger configuration, etc.)

4.1.3 Running SWITCH

SWITCH Requires the following inputs in order to run:

(1) The load profile corresponding to each scenario (for example, different EV growth scenarios). If load profile information of all load zones is already being run by default, simply place the scenario you are interested in under the desired load zone.
(2) A list of loads zones for the municipality in question.
(3) A list of generation projects (i.e. power plants and other distribution assets) for the entire country in question
(4) Time Series and Time Points corresponding to the desired planning period (see example code for details).
(5) Municipality location (latitude, longitude)
(6) Cost of transmission and distribution in the area in question in dollar per megawatt year ($\frac{\$}{MW year}$).

4.2 Running the Guadalajara Scenario

4.2.1 Making our Scenario for Guadalajara

When going about seeing what EV Charging Station scenario was optimal for the situation of Guadalajara, it was first necessary to gather general data about Guadalajara and EV Chargers in general. This process is defined in the Appendix section entitled "Gathering common data for Guadalajara".

Since little data was available about charging habits in Guadalajara, charging habits were found for other parts of the world and then generalizing to Guadalajara. It was found that 85 percent of charges in the United States are done at home, while the remainder of charges are done outside of home [14]. From this information, around 7.5 percent of charges are done at a Level II charging location (usually a workplace) and the remainder is done at social chargers [14]. The average battery size is found by looking at the sizes of battery packs in EVs available on the market today; 30 kWh seemed to be an adequate battery size according to this metric [18]. It is also necessary to know when people charge. Probability distribution functions on where to charge were found using the studies in [19] and [15]. This procedure is not perfect, since work habits and automobile usage habits may vary quite widely between cultures, but since limited data is available on this topic, back-of-the-envelope calculations and data reuse are necessary in order to gain insights for this particular problem.

One thing that we found is that there could have been several growth trajectories that could have been possible, given that Guadalajara's growth was in no way guaranteed to follow a particular trajectory. Thus, scenarios were created to reflect low, medium, and high EV growth.

From INECC, we know that there were 7,155 electric vehicles sold in 2017. 42% of these were sold in Mexico City. Data related to electricity consumption was given in MWh. Population data for Guadalajara and Mexico City for 2020 and 2025 are available, so linear interpolation is used to find population in 2020-2025 and 2025-2030. Calculations to find Low, Medium, and High EV growth numbers are described.

Table 1: The population in Mexico City and Guadalajara and EV power consumption in Mexico City used to find number of EVs in Guadalajara in low, medium, and high growth scenarios using the aforementioned equation.

Year	CDMX Pop	GDH Pop	CDMX EV Consmp (MWh)	GDH Low Cars	GDH Med Cars	GDH High C
2018	21493000	5068000	1456.22	708	2834	11337
2019	21680500	5139000	5022.69	2456	9827	39309
2020	21868000	5210000	10522.12	5173	20693	82772
2021	22077600	5276800	18118.89	8936	35747	142988
2022	22287200	5343600	27987.15	13847	55389	221558
2023	22496800	5410400	40311.01	20006	80024	320098
2024	22706400	5477200	55285.54	27520	110081	440325
2025	22916000	5544000	73115.91	36502	146011	584047
2026	23105800	5602600	94020.44	47046	188184	752736
2027	23295600	5661200	118228.53	59291	237164	948656
2028	23485400	5719800	145985.41	73370	293483	1173935
2029	23675200	5778400	177544.95	89424	357696	1430784
2030	23865000	5837000	238258.15	120256	481025	1924101

To get the approximate number of cars that will be in Guadalajara in 2020 once EV growth proliferates, assume that the battery sizes and MWh usage per car does not change significantly in the next 10 years. In such a case, say that the number of cars will grow proportionally to the growth in EV electricity use. When calculating the Guadalajara numbers, the main idea is to scale up the Mexico City numbers to the projections for 2020 and 2025. Then we take the ratio of the Guadalajara Metro Area population to that of the CDMX (the Federal District that Mexico City is located in) for 2020 and 2025. An exponential growth model is assumed for the population and EV growth of all cities.

For general number of EVs in a particular year, we get the following calculations:

$$nevs_{yr} = 0.42 * \frac{pop_{guad}}{pop_{mxc}} * \frac{elec_{mxc}}{1{,}456.22} * 7,155$$

For 2020, this is:

$$nevs_{2020} = 0.42 * \frac{5{,}210{,}000}{21{,}868{,}000} * \frac{10{,}522.12}{1{,}456.22} * 7,155 = 5,173$$

More aggressive scenarios showcase what the algorithm outputs for different scenarios. The scenarios are summarized as follows:

Table 2: Number of cars, stations, and regularization coefficient for different Guadalajara EV Growth Scenarios

Scenario Name	Phase I Cars	Phase I Stations	Regularization Coefficient
One Phase, Light	5,173	15	200
One Phase, Moderate	10,346	20	300
One Phase, Aggressive	20,692	25	375

In all of the scenarios below, the maximum chargers per stations is set to an upper bound in order to indicate that a station can have limited spacial capacity for chargers. The value was set to six after internal discussion about reasonable upper bound values. All Level II Chargers have virtually the same capacity and little data was available for O&M costs. Optimization was done mainly for base costs and always picked the General Electric DuraStation charger, which costs a mere $400 while having the same capacity of cars per hour of 0.67. For Level III chargers, it is a similar scenario. The optimization algorithm always automatically picked the Delta EV DC Quick Charger. This charger had a cost of $30,000 (relatively low for a Level III charger) while having a capacity of 15 cars per hour.

For SWITCH, it was determined that the best way to actually run the scenarios was to get the SWITCH module for the entirety of Mexico and then swap the load profile for Guadalajara with the hypothetical load profiles from the EV growth. This meant that all of the other portions of Mexico stayed the same, while only Guadalajara changed. This is not the ideal setup, since overall, the EV growth in Guadalajara will account very small percentage growth for the entire average and peak loads for Mexico, so it is likely that no new infrastructure will be necessary. It is also likely that other load areas can easily redirect electricity to meet the increased demand from the Guadalajara load zones. Once new projections are made for more of Mexico, better predictions can be constructed to better reflect the growth in the entire country.

4.2.2 Light Scenario

Figure 2: EV Charging Station placement for low penetration scenario (darker squares correspond to higher traffic, while yellow dots correspond to representative cars from data processing)

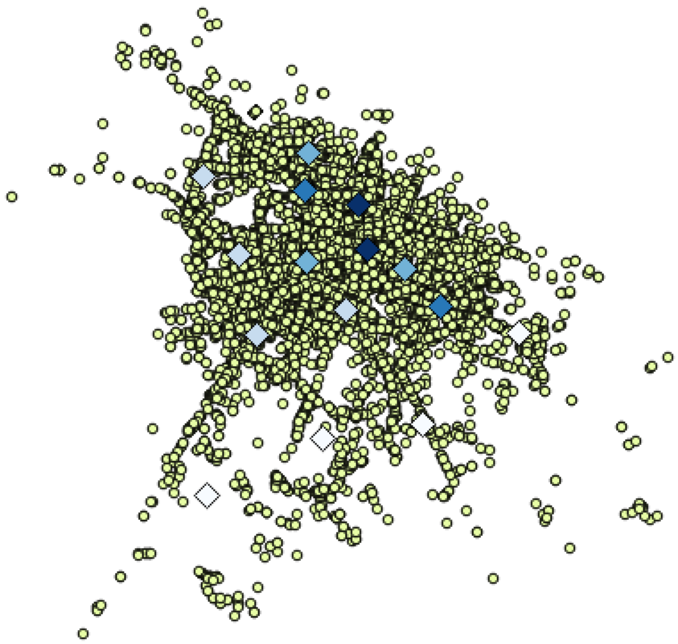


Table 3: EV Station Locations and Charger Configurations - Low Penetration Scenario

Number	Longitude	Latitude	GE Durastation Chgr (Lvl 2)	Delta DC Wallbox Chgr (Lvl 3)

0	-103.386282164	20.6716386092	5	0
1	-103.324990936	20.6666196406	5	0
2	-103.303125454	20.6432771379	5	0
3	-103.385239446	20.7396758971	5	0
4	-103.417336944	20.6259782562	4	0
5	-103.387258242	20.715746364	5	0
6	-103.313810851	20.5703138422	1	0
7	-103.253758809	20.6272018742	2	0
8	-103.450962481	20.7248086194	4	0
9	-103.448854086	20.5256974078	1	0
10	-103.429178162	20.6763656796	3	0
11	-103.354015753	20.7067087864	5	0
12	-103.348117524	20.6795045081	5	0
13	-103.375951178	20.5612240837	1	0
14	-103.361812579	20.6411060074	2	0

Table 4: EV Station Cost and Electrical Usage - Low Penetration Scenario

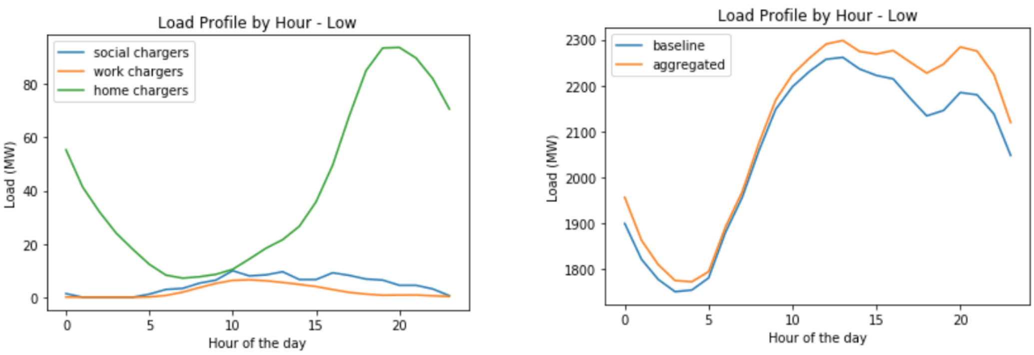
Number	Construction + O&M	Electricity
0	5583.98	2000877.66
1	10793.11	3489709.66
2	2419.82	620306.53
3	4074.02	1348629.74
4	6939.79	2388325.10
5	1902.76	395668.24
6	10473.32	3398273.04
7	6688.86	2316638.79
8	2859.12	813420.71
9	3309.29	1011411.48
10	1902.64	395668.03
11	3293.78	1004584.21
12	8669.47	2882570.51
13	4228.72	1416902.42
14	6060.75	2136935.35

Table 5: EV Load Profile by Type - Low Penetration Scenario

Hour	Baseline	Home EV	Work EV	Social EV	Overall
0	1900	55	0	1	1957
1	1822	41	0	0	1863
2	1778	32	0	0	1810
3	1751	24	0	0	1776
4	1755	18	0	0	1773
5	1781	12	0	1	1795
6	1880	8	0	3	1892
7	1956	7	2	3	1969
8	2058	8	4	5	2075
9	2148	9	5	6	2169
10	2197	10	6	10	2224

11	2230	14	7	8	2259
12	2257	18	6	8	2290
13	2261	22	6	10	2298
14	2235	27	5	7	2274
15	2222	36	4	7	2268
16	2214	50	3	9	2276
17	2173	68	2	8	2251
18	2134	85	1	7	2227
19	2146	94	1	6	2246
20	2185	94	1	4	2284
21	2180	90	1	4	2275
22	2138	82	1	3	2224
23	2048	71	0	1	2119

Figure 3: Load Profiles of miscellaneous load types (including EV Loads) - Low Penetration



4.2.3 Moderate Scenario

Figure 4: EV Charging Station placement for medium penetration scenario (darker squares correspond to higher traffic, while yellow dots correspond to representative cars from data processing)

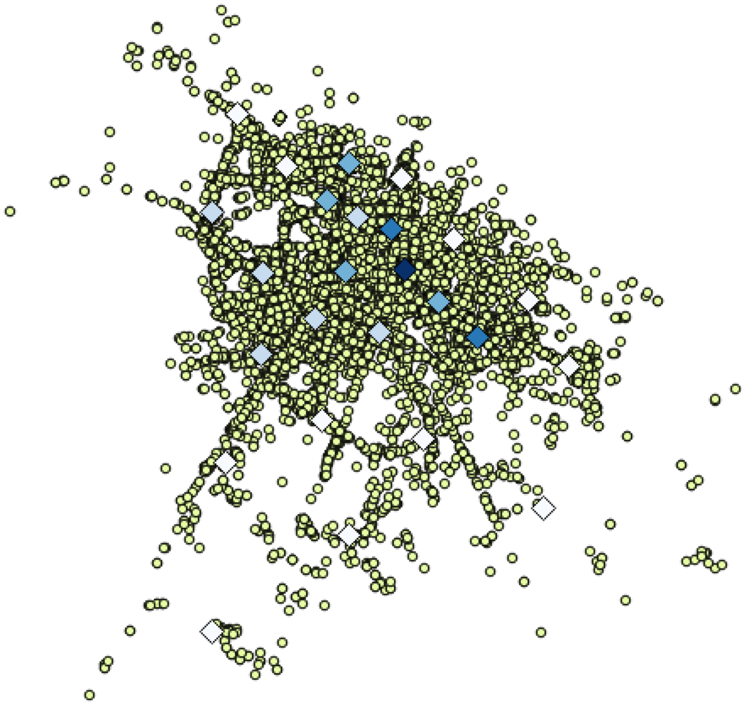


Table 6: EV Station Locations and Charger Configurations - Medium Penetration Scenario

Number	Longitude	Latitude	GE Durastation Chgr (Lvl 2)	Delta DC Wallbox Chgr (Lvl 3)
0	-103.348935331	20.7302617075	2	0
1	-103.32823251	20.6610162375	4	0
2	-103.428521145	20.6317337813	3	0
3	-103.390806642	20.7184038151	4	0
4	-103.306352561	20.6412645108	4	0
5	-103.380892962	20.6781569178	4	0
6	-103.414320663	20.7371329374	3	0
7	-103.378532617	20.5287577982	1	0
8	-103.254270121	20.624273904	3	0
9	-103.355029185	20.701978361	3	0
10	-103.441533159	20.7672524041	1	0
11	-103.427953369	20.6770871956	3	0
12	-103.347786709	20.6788576557	3	1
13	-103.397819062	20.6511755658	3	0
14	-103.39404054	20.5937505006	2	0
15	-103.337013146	20.5839799858	2	0
16	-103.361350317	20.6441062409	3	0
17	-103.379046258	20.7388583368	4	0
18	-103.448786174	20.5701103914	1	0
19	-103.456326526	20.7119522097	3	0
20	-103.456067393	20.4743112445	1	0
21	-103.277738804	20.6614387881	2	0

22	-103.374307733	20.7089674165	3	0
23	-103.269272057	20.5442199977	1	0
24	-103.319447422	20.6965468191	2	0

Table 7: EV Station Cost and Electrical Usage - Medium Penetration Scenario

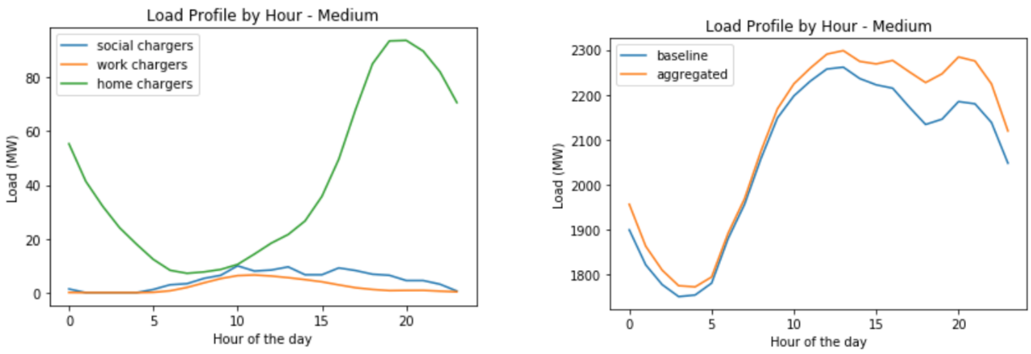
Number	Construction + O&M	Electricity
0	4003.53	1200626.25
1	21747.05	6550766.01
2	11403.67	3609676.55
3	35161.99	10386958.84
4	28324.76	8432165.86
5	4454.85	1377159.9
6	19013.47	5769043.89
7	7573.95	2477081.65
8	1914.29	395672.77
9	12667.22	3971521.77
10	8200.13	2663612.34
11	3186.87	885109.22
12	22250.69	6694870.12
13	13593.37	4232908.61
14	5862.54	1928218.07
15	7331.24	2404176.18
16	2810.11	748808.02
17	7840.18	2556570.54
18	22727.92	6831415.47
19	9008.43	2903542.01
20	8426.8	2730909.69
21	3005.92	817568.18
22	37868.09	11160634.54
23	5463.51	1776555.16
24	28596.8	8509947.94

Table 8: EV Load Profile by Type - Medium Penetration Scenario

Hour	Baseline	Home EV	Work EV	Social EV	Overall
0	1900	221	0	5	2127
1	1822	166	0	0	1987
2	1778	129	0	0	1907
3	1751	97	0	0	1848
4	1755	72	0	0	1827
5	1781	49	1	5	1836
6	1880	33	3	12	1928
7	1956	29	8	13	2006
8	2058	31	15	21	2125
9	2148	34	21	26	2230
10	2197	42	25	40	2305
11	2230	57	26	32	2346.01288642
12	2257	74	25	34	2389

13	2261	86	22	38	2408
14	2236	107	19	27	2388
15	2222	143	16	27	2408
16	2214	198	12	37	2461
17	2173	273	7	33	2486
18	2134	340	5	27	2506
19	2146	374	3	26	2549
20	2185	375	3	18	2581
21	2180	359	3	18	2560
22	2138	328	2	13	2481
23	2048	283	1	2	2334

Figure 5: Load Profiles of miscellaneous load types (including EV Loads) - Medium Penetration



4.2.4 Aggressive Scenario

Figure 6: EV Charging Station placement for high penetration scenario (darker squares correspond to higher traffic, while yellow dots correspond to representative cars from data processing)

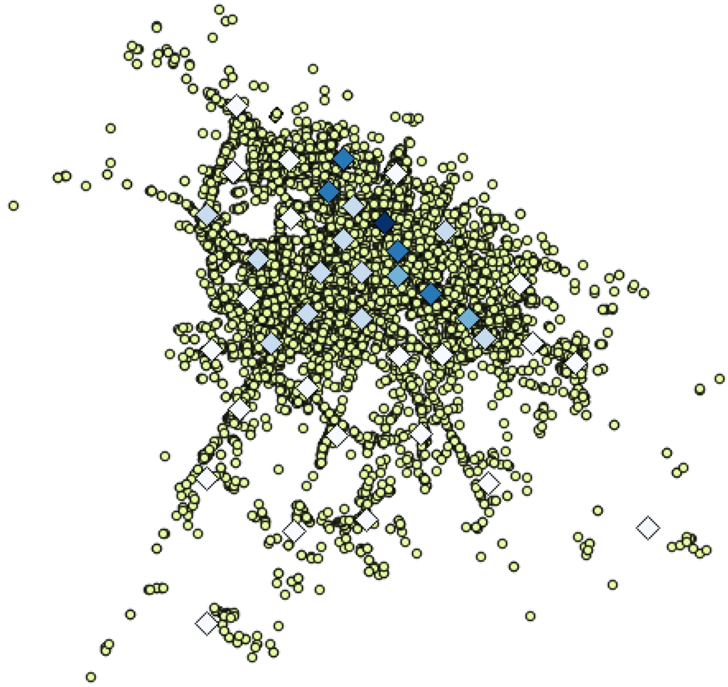


Table 9: EV Station Locations and Charger Configurations - High Penetration Scenario

Number	Longitude	Latitude	GE Durastation Chgr (Lvl 2)	Delta DC Wallbox Chgr (Lvl 3)
0	-103.410305829	20.7388171566	0	1
1	-103.328239503	20.6610734703	0	3
2	-103.382451709	20.5783864552	1	0
3	-103.347199431	20.6854189215	0	3
4	-103.400351927	20.6492076933	0	1
5	-103.296376123	20.6349483997	0	1
6	-103.42814094	20.6806202813	0	1
7	-103.387655646	20.7201298258	0	3
8	-103.407223257	20.5236901859	1	0
9	-103.244494984	20.6211124868	0	1
10	-103.455637489	20.6289271096	1	0
11	-103.368049782	20.6737822713	0	1
12	-103.44274652	20.731558642	0	1
13	-103.355319901	20.702346821	0	4
14	-103.379007452	20.7389096104	0	3
15	-103.346017644	20.6248209662	1	0
16	-103.458584177	20.7068256251	0	1
17	-103.439419875	20.5936671598	1	0
18	-103.348728121	20.730390327	0	1
19	-103.29427952	20.5510190288	1	0
20	-103.365361946	20.5304112402	1	0
21	-103.367973215	20.646844938	0	1

22	-103.420897163	20.6323106984	0	1
23	-103.319303641	20.6973060481	0	1
24	-103.277059313	20.6665286012	0	1
25	-103.391815329	20.6732787354	0	1
26	-103.441096336	20.769811641	1	0
27	-103.378644391	20.6922447286	0	1
28	-103.457910283	20.4694721789	1	0
29	-103.458645671	20.5538494662	1	0
30	-103.306335849	20.6470009238	0	3
31	-103.202380048	20.5256530758	1	0
32	-103.347162532	20.6715066532	0	3
33	-103.333765636	20.5797924415	1	0
34	-103.321852291	20.6259086229	0	1
35	-103.409221514	20.7053515808	0	1
36	-103.434373701	20.6584599084	0	1
37	-103.373266919	20.7117469693	0	2
38	-103.399963422	20.6063875934	0	1
39	-103.269318924	20.6321852968	0	1

Table 10: EV Station Cost and Electrical Usage - High Penetration Scenario

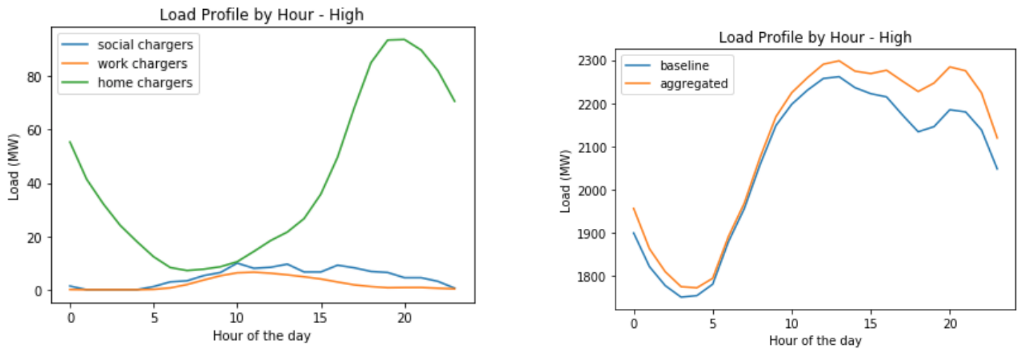
Number	Construction + O&M	Electricity
0	47410.8	13478977.79
1	103971.57	29906115.31
2	92341.66	26528568.46
3	23700.59	6628058.51
4	17267.68	4788597.53
5	138743.68	40005351.04
6	44684.75	12687258.57
7	21765.77	6074806.0
8	9511.44	2570954.68
9	28239.0	7924507.88
10	10877.52	2961571.93
11	13702.8	3769384.0
12	86824.83	24926355.03
13	18981.76	5278697.82
14	29531.16	8293911.83
15	91271.2	26217683.95
16	4250.08	1066517.44
17	6911.16	1827757.82
18	47341.12	13458739.82
19	100902.87	29014913.05
20	90481.16	25988238.99
21	21192.79	5910951.58
22	28456.67	7986684.78
23	8728.6	2347117.83
24	58347.0	16655364.07
25	10411.07	2828196.38
26	24006.77	6715593.84
27	7472.87	1988198.62
28	16570.07	4589143.78
29	44015.6	12492925.27

30	12055.16	3298302.52
31	14958.2	4128303.21
32	36787.77	10393540.46
33	2140.45	464498.81
34	22269.69	6218910.11
35	20626.62	5749047.8
36	24247.31	6784354.18
37	37310.5	10545447.17
38	3636.89	890959.13
39	1903.49	395669.1

Table 11: EV Load Profile by Type - High Penetration Scenario

Hour	Baseline	Home EV	Work EV	Social EV	Overall
0	1900	886	1	22	2809
1	1822	662	0	0.0	2484
2	1778	514	0	0	2292
3	1751	387	0	0	2138
4	1755	289	0	0	2044
5	1781	198	2	19	2000
6	1880	133	11	47	2071
7	1956	115	31	53	2155
8	2058	123	58	84	2324
9	2148	138	84	103	2473
10	2197	168	101	160	2626
11	2230	230	105	128	2693
12	2257	295	99	135	2785
13	2261	346	89	153	2849
14	2236	426	77	106	2846
15	2222	573	64	106	2965
16	2214	794	46	147	3202
17	2173	1091	29	131	3424
18	2134	1361	19	110	3624
19	2146	1497	12	103	3758
20	2185	1500	13	72	3770
21	2180	1437	13	72	3702
22	2138	1313	9	50	3511
23	2048	1130	5	9	3193

Figure 7: Load Profiles of miscellaneous load types (including EV Loads) - High Penetration



4.2.5 SWITCH Results

Table 12: Miscellaneous Grid Information for different EV Penetration Scenarios

	Default (No EV growth)	Low	Medium	High
Unserved Load - GDH (MW)	0	0	0	0
Incoming Dispatch - GDH (MW)	367763	367763	367763	367763
Outgoing Dispatch - GDH (MW)	343335	343335	343335	343335
New Generation Assets (GW)	211	211	211	211
Total Gen Fixed Costs (Pesos)	14995206641	14995206641	14995206641	14995206641
Variable O&M Costs (Pesos)	872977321	872977321	872977321	872977321
Under-served Penalty	539756425	539756425	539756425	539756425

In the table above, the "Unserved Load" refers to any load demand that cannot be met by the generation infrastructure available. The "Incoming Dispatch" refers to any incoming power coming from other load zones into Guadalajara. "Outgoing Dispatch" refers to any power that comes from Guadalajara and is transferred to other load zones. "New Generation Assets" refers to the size of new generation infrastructure that is built to address new demand. "Total Gen Fixed Costs" refers to the general cost to build new transmission and distribution assets. "Variable O&M Costs" are operation and maintenance costs. The "Under-served Penalty Cost" is the net cost for a System Operator to generate electricity that it is not paid for.

4.3 Scenario Analysis

This subsection begins with the discussion of charging station location placement. In the three above plots, darker blue stations indicates stations with a higher number of cars assigned to them, while lighter (whiter) stations indicate a lower number of cars assigned. The station placement algorithm spread the stations out to be placed evenly around the city; station sizes are determined such that stations closer to the urban center have larger capacities, while stations further away from the urban center have smaller capacities. As the number of stations is increased, the algorithm favors spreading smaller stations to less dense regions rather than building more stations towards the downtown region. This seems to be consistent with trends in many major cities, such as New York City, where gas stations are rare due to the high cost of building gas stations in areas of high urban density [17]. There is certainly a trade-off between (i) building more stations to meet demand in higher density areas through multiple stations versus (ii) building smaller stations in the outskirts of the city and simply increasing the size of stations in areas of higher population density. While this procedure favors the latter approach, in the future, tuning can be made to favor the first approach if it is desired.

It is also important to note the effect on charger costs on how the Linear Program selects charger configurations for stations. As can be observed above, for low and medium scenarios, Level II (i.e. smaller) chargers are heavily favored, and only in the aggressive EV growth scenario are Level III chargers ever favored. This is understandable given how the linear program works. If the L2 Regularization term is ignored completely, the main constraint that comes into play when setting the charger up is constraint (viii). If the only desire is to meet the demand for charging as cheaply as possible, the algorithm will favor placing more Level II chargers, since they are $\frac{2}{45}$ as efficient as Level III chargers and are $\frac{1}{60}$ as expensive. There are two factors that can be tuned by city planners to prevent this, which are shown by the aggressive scenario. The first is the maximum number of chargers. If the number of stations is bottlenecked and the number of chargers is bottlenecked, then the algorithm is forced to allocate Level III chargers, regardless of cost, since it is the only way to meet charger demand given the constraints. The second is the L2 Regularization coefficient, which corresponds to the amount of importance that EV owners place on not having to wait a long time for their vehicles to charge. Upon tuning the station parameter, below a certain number of stations, the linear program breaks because no charger configuration will allow for the stations to adequately meet demand. After a certain threshold is reached, the algorithm is forced to choose Level III chargers for the aggressive scenario, as described earlier. Furthermore, as described above, the L1 Coefficient also has a threshold of around 375 after which it heavily favors Level II chargers, so if city planners wish for a scenario where they want to force DC chargers, they can adjust this coefficient accordingly.

As shown in the graphs for all three scenarios, EVs have a fairly sizable effect on the grid. EV charging accounts for an average of a 2.3/9.1/36 percent load increase, with a maximum of a 4.7/18.8/75.1 percent load increase at 7 PM for the low, medium, and high EV growth scenarios, respectively.

The results of SWITCH showed that there is no change to the way the grid will operate given the new EVs in Guadalajara. There will be no issues with meeting electrical demand in the city (i.e. the unserved load is 0 for all scenarios), and the incoming and outgoing dispatch is the same, and the new generation assets that are being built in order to account for new demand in all three scenarios is the same. Fixed and variable costs are the same in all scenarios. The fact that all electrical demand will still be met regardless is not too surprising. While there is a high percentage growth in electrical demand from EVs in Guadalajara, wince SWITCH models Mexico as a whole, the new electrical demand can be met by generation assets elsewhere in Mexico. This also explains why the new generation assets that are built are the same in all scenarios. It was, however, unexpected that incoming transmission to Guadalajara stayed the same in all scenarios. It would be expected with the percentage increase in load at peak times that there would be an increase in incoming electrical transmission to the Guadalajara Load Zone. However, the Jalisco Load Zone is quite large, and includes both Guadalajara and various other cities, so this could be a reason why the incoming electrical transmission is the same in all scenarios. Another likely reason for the lack of difference between the three graphs is that the way the timepoints are sampled may have been done incorrectly. This would lead to all three scenarios having the same loads, which would then yield the same results.

5 Conclusion

This paper has presented a comprehensive approach for city planners and government officials to explore the process and effects of placing EV charging stations. The process starts with obtaining data related to heuristics about where EV drivers are at given points in time in order to predict where they might use public chargers. The next part of the process involves charger sizing and placement using said data. The last part of the process is constructing the load profiles for the scenarios with EVs. This gives a better idea of what investment and infrastructure must be added in order to meet new demand.

In the Guadalajara example, the results of this procedure for low, medium, and high EV growth were shown. The type of station placement and sizing that the procedure chose was discussed. The optimal selection of chargers for each stations was explored. Lastly, the effect of the increase in EV charging on the load was quantified for the city. Prior to the paper, we hypothesized that in the low-penetration EV scenario, most chargers would be Level II chargers and there would not be a drastic impact on the grid. This hypothesis turned out to be correct overall. For the medium-penetration scenario, it was hypothesized that there would be a mix of Level II and III chargers, and there would be some effect on the grid. This hypothesis turned out to be mostly incorrect, as most chargers were level II chargers, possibly due to improper tuning of hyperparameters (i.e. the coefficient in front of the L2 Norm); the lack of impact on the grid, particularly with regards to the inflow of electricity to Guadalajara, could be due to the fact that all electricity demand could already be met internally within Guadalajara's load zone. For the high-penetration scenario, it was hypothesized that most EV stations would be Level III stations and the grid would be drastically affected. Most station chargers were Level III chargers, and there was a large impact on the load; however, the actual grid was relatively unchanged, including the inflow of electricity due to Guadalajara, possibly for the reasons mentioned before. Overall, it would be interesting to re-run another impact study once scenarios are generated for multiple cities in Mexico.

In future work, key changes will be made to make this technology to be more accessible to city planners. First of all, a GUI or web application will be created so that the tools can be more easily utilized by individuals who wish to make explorations of these issues. Second of all, more comprehensive data collections will be performed for many of the parameters passed into this application. For instance, more research can be done into the actual sizes of the various charging stations in Guadalajara and any other cities for which projections are desired. For instance, information about Level III charger fixed and O&M costs were hard to come by online, so companies could be called to get quotes on such data. Third of all, several portions of the algorithm could be made to be substantially faster. Right now, the major bottlenecks to this process are in the Monte Carlo simulation portion of the process and the clustering process, especially for existing stations. The process can takes minutes for city planners with large amounts of data who wish to use this procedure in the form of a software application. This data process will likely be recreated using techniques involving State of Charge found via Kalman Filtering and Genetic Algorithms, as in [24]. This filtering also be available as a separate package for other researchers who wish to use it.

While many research papers have been written about the problem of placing and sizing EV charging stations, many focus on specific aspects of the EV charging station planning process - for instance, only the station placement process or an analysis of the load change. The procedure that is discussed in this document will empower policy makers who wish to look at what charging station configurations are both the most economically feasible and meet public demand the most effectively.

6 Appendix

6.1 Sampling - Waze Data

The first part of the sampling process for cities that do not have Imrix data is getting data relating to where traffic is at any given point in time. This data is provided in the form of an API that is provided privately. One particular endpoint of the API allows to get all traffic jams in a region at any given point in time.

To get all jams for some arbitrary period of time, simply keep all of the jams for the desired region in a NoSQL database as JSON blobs. From there, simply query the created database for desired data. In the example scenario for this project, there was too much data stored in the database, and thus timeouts were common unless subsections of data were queried. Thus, for the scenarios explored, only high-volume traffic jams (denoted Levels IV and V in the Waze API) were queried.

6.2 Sampling - Google Places

The second part of the process is obtaining Google Places data, which is meant to show, generally, where individuals park their cars before visiting commercial establishments. Specifically, this process involves obtaining data using a library the scrapes Google PopularTimes created by GitHub user m-wazr. PopularTimes data comes in the form of a JSON blob that, among other things, contains a histogram (normalized to height 100) of what the density of people for a representative day and hour of the week.

One thing to note is that for the PopularTimes package mentioned above, it is necessary to put in a latitude/longitude bounding box as an input. Putting in such a sampling box for the entirety of the city will result in timeout issues, so it is necessary to divide up your query into sections to avoid such a problem. For each of these queries, only sample one location type (i.e gas station, bank, park, etc.) at a time to avoid timeout.

To begin this process, start out by finding a GeoJSON file that corresponds to the municipality in questions. Note the minimum and maximum latitudes and minimum and maximum longitudes of this object. The corners of your bounding box are defined by:
$(lat_{min}, lon_{min}), (lat_{max}, lon_{min}), (lat_{min}, lon_{max}), (lat_{max}, lon_{max})$.
Using these corners, want to create smaller sampling boxes to prevent timeout. To do this, we define a grid of size (m, n) to sample with. We then have mn sampling boxes, where each box is defined by coordinate $i \in (0, n)$ and $j \in (0, m)$. If we define $\delta_h = \frac{lat_{max} - lat_{min}}{m}$ and $\delta_w = \frac{lon_{max} - lon_{min}}{n}$, we can say that our sample box (i, j) is defined by corners $(lat_{min} + i\delta_h, lon_{min} + j\delta_w), (lat_{min} + (i+1)\delta_h, lon_{min} + (j+1)\delta_w)$. We go through every $i \in (0, n)$, $j \in (0, m)$ to get the samples for the entire city, and run through one location type at a time.

6.3 Sampling - Combining the Data Sources

The Waze data, as presented in the API, is already presented in such a way to represent the general density of traffic in a particular location - in other words, it is already a line of time points. Thus, there is no need to modify it in any way. The Google Popular Times data, however, is normalized, so it is harder to get a valid population estimate for the number of people in a particular location at any point in time. Under the assumption that most charging stations near stores will be Level II chargers, and the information provided in previous sections that for all charges, we assume half will use work chargers and half will use social chargers, points are upsampled in such a way that the number of points from the PopularTimes data matches the number of points from traffic data. Such a sampling rate was found to be $num\_pt\_points = \lceil \frac{pt\_density}{10} \rceil$. Where num_pt_points is the number of representative points we will sample from Popular Times, and $pt\_density$ is the population heuristic for an individual day and hour as provided by Google Popular Times, normalized to 100.

6.4 Sampling - Monte Carlo Sampling

Before going about this sampling method, it is necessary to make sure that all of the required input data is available. The first piece of necessary information is a list of the processed sample points from the method described in the previous subsection. The second is a projection of the number of EVs for the years that planning is executed on (i.e. 2030, 2040, etc.). The last piece of information is the number of trials desired for the sampling. A good rule of thumb is to have one trial for each week for the "gap" between projections (i.e. for the aforementioned example, we have 10 year gaps, each of which will have 52 trials, for a total of 520 trials).

For each of these trials, we randomly choose n points, where n is the number of EVs for that given projection year. Repeat this process for every day and hour of a week. Thus, for each of these years, we have a new representative sample of where our EV owners will be for any given day and hour of the week.

6.5 Determining Infrastructure to Meet Requirements

For the linear program discussed in this section, let us first note that the vector $n \in R^{uv}$ where u is the number of stations and v is the number of charger types. The first v items are basically the number of each charger type allocated to station 1, the second v items are the number of each charger type allocated to station 2, etc. Scenarios arise involving matrix multiplication of some vector $\vec{x}$ with each of the number of chargers and other information for each station. For example, we may know the number of cars that can come to each charger type in an hour, and we may want to get the total car capacity for an hour of the entire station. Such a piece of information can be found using the following method:

$$\hat{X}n = \begin{bmatrix} \vec{x}^T & 0 & 0 & \dots & 0 \\ 0 & \vec{x}^T & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & \vec{x}^T \end{bmatrix} \begin{bmatrix} \vec{n_1} \\ \vec{n_2} \\ \vdots \\ \vec{n_u} \end{bmatrix}$$

Where $\vec{n_i} \in R^v$ is the vector of the number of each charger type corresponding to the i-th station, and $vecx \in R^v$ is, similarly, some vector where each entry corresponds to some piece of information for each entry. For example, the first entry of $\vec{x}$ may be the car capacity of the first charger type, the second entry the car capacity of the second charger type, etc.

6.6 Running a Scenario - Gathering common data for Guadalajara

In order to run the scenario for Guadalajara, it was necessary to obtain information about the Municipality, Planning, Chargers, Load PDFs, and Profiles, and Tariffs. The years for the different Guadalajara Scenarios were 2020 and 2025.

We begin with the information that we need about Guadalajara as a whole (i.e. Municipality and Population). The information for this CSV could be found using population growth projections for Guadalajara. We assume a growth rate of 1.53% from 2017 to 2025 [20]. Using these growth estimates, we obtain values of 5,210,000 in 2020 and 5,544,000 in 2025 [20]. Substation Capacity was not available, so such a capacity, for now, is estimated to be 20 percent greater than the maximum projected energy use for any hour between 2015 and 2020. This placeholder will be changed when more information is available.

For the chargers, we did research on the different Level II and III commercial chargers available on the market. We used figures from the internet. These chargers include Aerovironment DC Fast Charge Station, ChargePoint CT4000 Series, Delta EV DC Quick Charger, Efacec QC50, EVTEC PublicFastCharger, General Electric DuraStation, Leviton E40, LiquidSky Technologies Inc QuadZilla, and Shorepower ePump. Figures related to cost, capacity, average energy use, and car capacity were obtained for each charger. Average infrastructure connection costs were obtained through [22].

The EV Profile contains various information about EV user behavior in Guadalajara. Using internal projections from INECC, EV projection numbers were obtained for the city of Guadalajara. Calculations for the growth in EVs is shown in section 3.2 entitled "Running the Guadalajara Scenario". Numbers on the proportion of charges done at social vs. work vs. home chargers are found in [14]. Lastly, numbers on revenue from social vs. work chargers are found through using public charging cost models from the United States; many chargers use monthly subscription models [21]. We assumed that a user is charger $25 per month for an entire year, much like in the Chargepoint subscription model [21]. That being said, these values can easily be changed when more information is available. For instance, if the individual running the model wishes to use a subscription based model paired that also has minute-by-minute charging rates, simply use the following calculation: $monthly\_revenue = base\_monthly\_rate + avg\_charges\_per\_month * avg\_length\_charging\_minutes$.

Next, we obtain information on the Stations. Unfortunately, while some charging station locations are available for Guadalajara, There is not information available on the charger sizes and numbers for each station, so for now, we assume that in this scenarios, all chargers are being built from scratch.

The Load Profile for Guadalajara was obtained. The profile is a 15 year projection of demand. For the one-phase scenario, a five-year projection from 2020 to 2025 was selected, while for the two-phase scenario, a ten-year projection from 2020 to 2030 was selected.

The Load Probability Density Function for home, work, and social chargers was obtained by looking at [19]. The data comes from a simulation of the average EV load profile over each hour of the day, under the assumptions that all EVs are battery electric vehicles with range of 200 miles. The exact values are obtained by using WebPlotDigitizer on the plot of the simulated EV load of charging at home, at work and in public.

In Mexico, tariff rates are seasonal for summer and winter. Each rate has a base, intermediate, and peak rate. We found from the government website [cite here] that the rates for winter base, intermediate, and peak rates are 0.5472 pesos, 0.9120 pesos, and 1.0159 pesos respectively. Assuming an exchange rate of 18.53 pesos per dollar, these values are $0.03, $0.05, and $0.055 respectively in American dollars. For summer, the base, intermediate, and peak rates are 0.6406 pesos, 1.0976 pesos, and 1.2277 pesos respectively, which are equivalent to $0.035, $0.06, and $0.066 respectively in American dollars by the aforementioned exchange rate.

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