Contents

1 Introduction

1.1 Problem

In response to the ever-increasing integration of personal electronics such as mobile phones, laptops, and electric vehicles in people's daily lives, public places are expanding the availability of electrical outlets for their visitors. However, this expansion comes with a economic cost that must be accounted for. In addition, different public destinations have unique characteristics, such as hours of operation, distribution of visitors, and availability of outlets, which impact electricity consumption throughout a day. Given the potential effects of increasing public charging of personal devices, initiatives must be implemented to reduce the costs of such trends.

Simply put, our objective is to model the change in public electrical charging availability and develop a model for the economic cost of this increase over the next decade in the United States. We also aim to explore how this cost varies over different destinations and ways to reduce it.

1.2 Problem Analysis

With the rise of personal electronic devices and the corresponding need to charge them, users are utilizing public charging stations more and more. Consequently, public places are faced with the increasing demand and need to provide public charging stations for the public. However, the increased energy consumption has required public places to install more outlets and resulted in higher electricity bills. For instance, as part of the 907 million dollar expansion of Terminal 2 opened at San Diego International Airport, USB - enhanced power ports at every seat were added, leading to the addition of more than 1600 in total [1].

Businesses and governments, thereby tax payers, are often the ones faced with the installation fees for the charging stations and the higher electricity bill. The median cost of installing one electric outlet is 193 dollars with a range from 148 to 200 dollars [2]. Electric vehicle stations cost even more with Level 3 chargers costing around 100000 per station [3]. Fortunately, for some electric vehicle charging stations, the government has offered rebates and incentives. In addition to the ability to qualify for public level 2 rebate, states such as Alabama have given grants to create charging stations. Similarly, California provides loans for the purchase and installation of charging stations to customers [4].

Yet, despite the additional cost, the increasing number of electric charging stations have also been found to have positive effects with places having a increased guest retention rates. The average guest stayed 17% longer at conventions and 14% longer at trade shows while guest engagement rates increased by 12% at trade shows[5]. Theorizing that these results are applicable across the board at coffee shops or other stores, the increased guest stay will lead to more goods being bought and higher revenues for each destination. In addition, more charging stations help alleviate the long waits at airports or the railway station. It also helps reduce the work on technicians and custodians who have had to deal with moving chairs and unplugged machinery from people searching for electrical outlets [1].

Keeping these factors in mind, when initially developing our model, we listed out the aspects of the problem that we aim to address along with the sections in the paper where they are discussed:

- How has public outlet energy consumption changed, and how will it continue to change? (Methods in Section 2.5; Results in Section 3.1)

- What are the impacts on and requirements of public places with increased demands? (Section 1.2)
- What is the financial cost of increasing outlet availability? How is it paid? (Methods in Section 2.3; Results in Section 3.2; Section 1.2)
- How does the model change for different types of public places? (Methods in Section 2.5; Results in Section 3.1)
- What can be done to reduce the costs of public energy consumption? How do these changes influence the model? (Section 4)

The quantitative questions to be addressed require a mathematical model that can predict economic cost over a span of time, taking into account outlet availability as well as various factors that capture the other differences between different types of public places [and allow us to explore ways to reduce cost]. Thus, it is intuitive to create a model of cost where cost is a function of time and depends on some other factors that, too, are time-dependent.

It is simultaneously known that the processes governing outlet availability on a location-by-location basis form a complex system consisting of location specifics and the number, behavior, and interactions of individuals within the location. To simulate such a random system, we choose an agent-based model. Using both the cost function and the agent-based model, we aim to integrate large-scale changes in electricity parameters over time with small-scale human charging behaviors to create a robust and accurate model to predict the cost of charging personal devices in public places. Additionally, to model the workings and behaviors associated with electric vehicle charging, we created an analytical model to understand the changing cost of public electric vehicle charging based on parameters such as battery capacity and varying charger rates at different charger stations.

2 Methodology

As explained above, our objective is to create a model to estimate the cost associated with the use of public electric outlets for charging personal electronic devices over a ten year period specifically for the United States. Using this base model, we plan to vary various factors to explore the impacts of increases in public outlet availability in several common public destinations. Finally, by analyzing our model's results, we will propose initiatives and guidelines to reduce the detrimental costs associated with the growth in energy demand associated with charging personal electronic devices in public locations.

2.1 General Definitions

Public Spaces: Areas available to the general public that do not require specialized access. Examples include public squares, parks, beaches, libraries, coffee shops, airports, train stations, bus stations, malls, movie, and rest stops.

Personal Electronic Devices: Non-commercial devices which require periodic charging to function, including *laptops, mobile phones, tablets*, radios, cassette players, portable digital assistants, audio devices, watches with input capability, and reminder recorders.

Destinations: Destinations are the different types of public places where a **Visitor** may consume electrical power from an outlet. Our definition for each destination we evaluate is given below:

Airports: Public airports of any size (rather than private airports).

Coffee Shops: Sit-down coffee shops with seating (rather than drive-through or on-the-go coffee shops located in larger businesses or institutions).

Railway Terminals: Only Amtrak Stations, which are official United States government passenger railroad stations.

Libraries: Public libraries (rather than academic libraries, school libraries, special libraries, Armed Forces libraries, and government libraries, since their public availability and use is unclear).

Schools: Public secondary and post-secondary schools, as it is more likely that students at these schools have devices to charge.

Shopping Malls: All malls open to the public, from strip malls to shopping centers.

Offices: Company offices, which are not available to the public.

Visitors: The people who go to each destination. For instance, for airports the visitors would be the people boarding the airplanes.

Capacity: The total number of visitors a destination can hold at any given time.

Usage/Electrical Consumption: Amount of energy consumed by personal device charging, in units of kWh.

Flybys: Visitors to a certain destination who do not sit/stay at the location for prolonged periods of time. For example, at a coffee shop a flyby would visit, buy a coffee and leave, without charging their devices.

2.2 General Assumptions

Assumption: The growth of number of US locations for each destination type of interest over the next 10 years is negligible.

Justification: The % changes in number of US locations per year for Airports, Coffee Shops, Railway Stations, Libraries, and Schools were found to be -0.5% (Appendix B3)[6], 0.56% [7], 0.125% (Appendix B2)[8], 0.011% (Appendix B4)[9], and 0.0037% (Appendix B1)[10], respectively. All of these values are too small to be of significant impact in our model; therefore, growth in number of locations can be safely ignored.

Assumption: Population growth over the next 10 years is inconsequential.

Justification: US population growth has stagnated to 0.62% per year, equating to a 6% growth in 10 years [11]. While this percentage is not insignificant, a majority of the growth can be attributed children under the age of 10 who generally do not have personal devices and thus do not contribute to our model.

Assumption: The weekday operational hours are a reasonable estimate for the operational hours throughout the week.

Justification: While there may be different operational hours during the weekend compared to the weekday, there are more weekdays and it can act like a good approximate for the weekend operational hours. The difference is negligible in the long run.

Assumption: Percentage of the population with personal electronic devices (excluding electric vehicles) does not change over a ten year period.

Justification: As discovered by the Pew Research group, personal electronic devices, specifically phones, laptops and tablets have reached market saturation and as such there has been no growth in recent years [12].

Assumption: Electric efficiency will remain constant over the next 10 years.

Justification: Since we are only projecting and thereby concerned about the next ten years of electricity consumption and cost, we can reasonably assume that there will be no extreme innovations in electric efficiency to have a non-negligible effect on our model.

2.3 General Cost Model

To model the growing cost of public electricity consumption for personal devices (C (\$)) over time, we split C into two factors: commercial price of electricity per kilowatt hour (P (\$/kWh)) and total electricity consumption for personal devices in the public commercial sector (U, kWh). Thus, the equation governing our cost model is

$$C(t) = P(t) * U(t) \tag{1}$$

$P(t)$ is a relatively straightforward function of time that can be derived from data and is discussed in Section 2.4. On the other hand, total electricity consumption by *only* personal devices in public locations $U(t)$ is complex and depends on interactions between visitors and charging spots in a destination on a small scale. Thus, the agent-based model will be used in the calculation of U, which will be fed into Equation 1 to produce cost.

2.4 Commercial Electricity Price

To determine the change in commercial electricity price P over the years, we analyzed electricity prices from 2001 to 2018 in cents per kilowatt hour (¢/kWh) from the US Energy Information and Administration (See Appendix A1) [13]. From a general practical understanding of trends in electricity use, a logarithmic regression is the most fitting. Specifically, the price of electricity has increased due to the cost of implementing infrastructure to support increased electricity demands. Over the years, as the necessary infrastructure is constructed, the *change* in the price of electricity has decreased, and thus price increases at a slower and slower rate.

The trend of commercial electricity price fitted to a trendline of $Price = 359.06 * \ln year - 2721.2$. Using this projected trend, the future price of electricity was calculated (Table 1) By 2028, the commercial price of electricity is expected to reach 12.97 ¢/kWh.

Year	Commercial Price of Electricity (¢/kWh)	% Change in Price
2019	11.37500643	—
2020	11.55280292	1.563045164
2021	11.73051141	1.538228366
2022	11.90813199	1.514175948
2023	12.08566475	1.490853143
2024	12.26310978	1.468227261
2025	12.44046715	1.446267537
2026	12.61773697	1.424944991
2027	12.79491931	1.404232297
2028	12.97201425	1.384103673

Table 1: The forecasted commercial price of electricity from 2019 to 2028 with % change in price between years.

As seen from Table 1, the percent increase in commercial price of electricity year to year is around 1.45% in the next 10 years. While the residential price and commercial price of electricity are not directly proportional, the US Energy Information Administration projected the residential price of electricity to increase 0.8%-1% from 2019 to 2020[14], indicating that our estimation produces reasonable values.

2.5 Personal Device Agent-Based Usage Model

This model produces U, the total electricity consumption for personal devices in the public commercial sector. We quantify the amount of electrical consumption from public charging outlets for personal electronic devices at each destination and how the energy consumption changes over time.

Since outlet usage at a destination is inherently contained within a system of randomly interacting components, we develop a computational agent-based model using the NetLogo language to describe the relationships between visitors and the availability of outlets. Our model represents a single instance of any destination (e.g., a single coffee shop) by an arrangement of outlet and non-outlet seats (Figure 3). Throughout the course of a "day", a certain number of visitors "enter" the destination according to a visitor influx distribution. A visitor may own any subset of mobile phone, laptop, tablet (including the empty set) with devices probabilistically assigned according to their prevalence within the general population.

For each device, a random initial battery level is assigned based on the tendency that devices have less battery later in the day due to use. Each visitor with at least one device chooses an available seat (favoring outlet seats) and stays for a random duration while visitors with no devices represent flybys who do not go to a destination to use devices (e.g., people at a coffee shop who simply grab coffee and go). Each device type has a constant battery drainage and charge rate; at each "tick" of the model, every device drains, and the device with minimum battery for every visitor at an outlet seat is charged (unless all devices are at 100%). A visitor leaves their seat when either 1) their stay duration expires or 2) they run out of battery (0%) on any one of their devices. The seat numbers and outlet ratios, total visitors, visitor influx distribution, and visitor stay duration are all destination-dependent and calculated from available data and statistics, which are detailed in the sections following the assumptions.

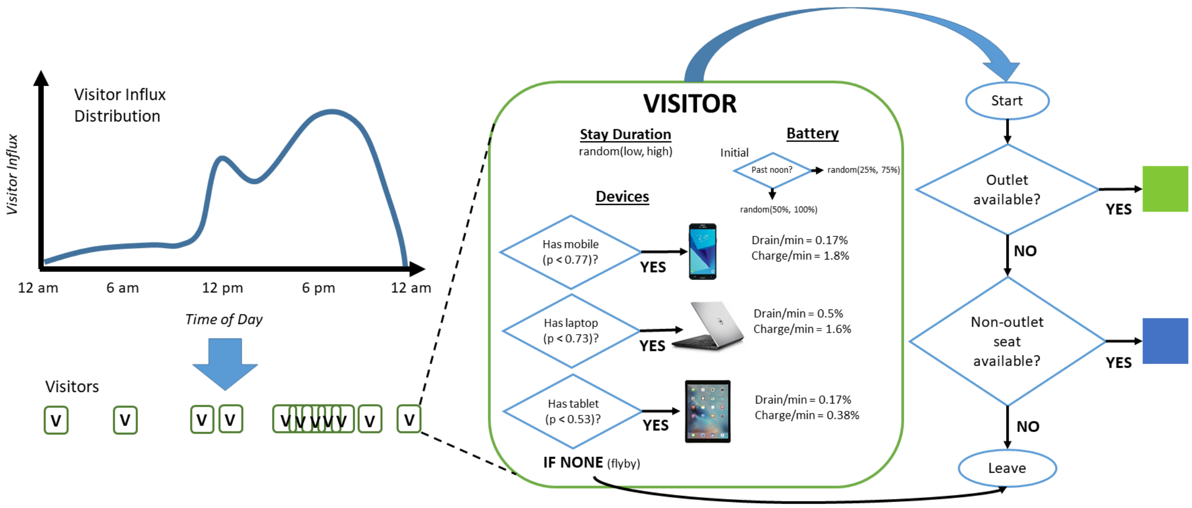
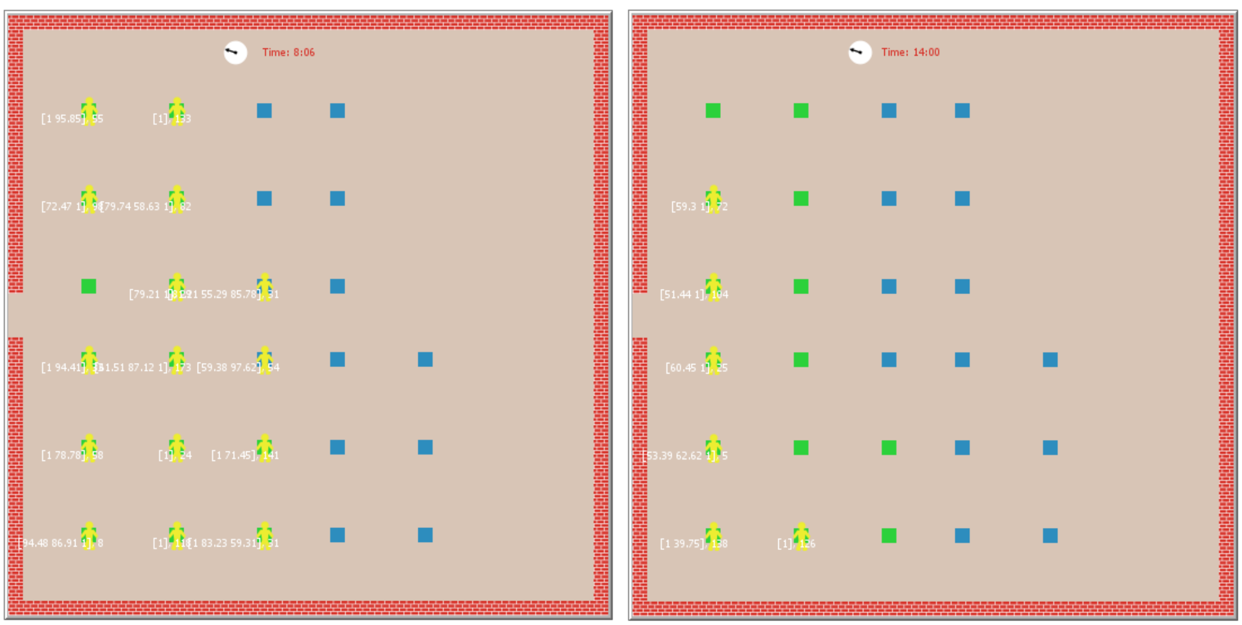


Figure 1: NetLogo Model Flowchart. Components are detailed in the following sections after assumptions



(a) During the morning rush hour (b) Later in the day

Figure 2: NetLogo model for Coffee Shop. Green seats have outlets, while blue ones do not. White text displays remaining battery levels and remaining duration in destination.

2.5.1 Agent-Based Model Assumptions

Assumption: Shopping malls, parks, beaches, movie theaters, rest stops and offices have a negligible amount of public charging, and consequently an insignificant cost.

Justification: People do not stop to charge their personal devices while they are shopping since they are constantly moving and there are not many outlets publicly available. Additionally, offices, as defined in General Definitions, are not available to the public, so there is no possibility of *public* charging. For parks and beaches, there are no available charging outlets. Finally, for movie theaters and rest stops, despite the presence of available charging outlets, the time spent charging is largely negligible because people have little time to do so.

Assumption: Charging in airports only occurs while passengers are waiting at boarding/departure gates. Similarly, charging in railway stations only occurs at platforms while passengers are waiting to board trains.

Justification: People are in transit at all other locations in an airport/railway station. Therefore, the only time travelers have to charge personal devices is when they are at gates or platforms.

Assumption: The number of Canadian Amtrak riders and stations are negligible.

Justification: Of the total 526 Amtrak stations in North America[8], only 9 stations are located in Canada [15]. This accounts for only 1.71% of total Amtrak service which is a negligible proportion for our calculations.

Assumption: At a school, students usually arrive between 7 and 7:30 am. There is a inconsequential amount that arrive/leave school throughout the middle of a school day for appointments or other obligations

Justification: Since the average U.S. public school day begins at 7:59 am, all students will arrive between 7:30 am and 8 am[16]. This assumption ignores tardy arrivals and slight variations in student attendance over the course of a day, which are both proportionally negligible.

Assumption: The population of teachers is negligible when compared against the student population in a school.

Justification: The average student to teacher ratio in the American Public School system is 16 students to 1 teacher[17]. Since teachers account for less than 6% of the total population in the school, it can be relatively safely assumed that students account for the vast majority of electricity usage for personal electronics in schools.

Assumption: The only devices that will be charged at a public place are a mobile device, laptop, or a tablet.

Justification: As concluded by the Pew Research Center in June 2019, nearly 77% of the American adult population have phones, 74% have laptops, and 53% have tablets. Other personal devices, including radios, CD, smartwatches, and E-readers are owned by less than 25% of the population and are not usually charged in public commercial destinations, making their impact on our model inconsequential[18].

Assumption: Before noon, the percent of battery someone initially walks into a destination is a random value between 50% - 100%. After noon, the percent of battery is a random value between 25% - 75%.

Justification: As the day progresses the battery of someone's devices decreases as they are being used more.

Assumption: The time it takes to charge the battery of a personal device is linear throughout the entire charging process, e.g. charging from 5% to 6% is the same amount of time from 90% to 91%.

Justification: According to Electropedia, the charging percentage vs voltage of a typical lithium ion battery (common phone battery) is relatively linear in all stages except for the very beginning and end stages of charging [19].

Assumption: A visitor will use all of their devices for the full duration at a destination.

Justification: This justification is used to simplify our model and is based on the fact that in an increasingly connected world, multiple devices are often used in conjunction for multi-tasking. Furthermore, devices consume power even when not being directly used.

Next, we describe the definitions and calculations of several important variables that change between destinations. The ways in which the various factors change here represent our answer to how the model changes for different destinations.

2.5.2 Capacity and Size of Destination

The average capacity determines the maximum amount of people at a given destination at the same time. As capacity is dependent on the layout of each individual destination, we estimated average capacity. When lacking sufficient data, we calculated capacity based on the approximation that there is 1 seat for every 36 ft^2 [20]. Please reference [WHICH APPENDIX] to view the derivations for each destination's average capacity number.

Destination	Average Capacity Number	Square Foot
Airports	visitors 2,709	97,541
Coffee Shops	50 - 70 guests on average	1000 - 1750
Railway Stations	70 Visitors	2534
Schools	— Students	173,727
Libraries	600 people	21,500

Table 2: The average capacity number and square foot for each destination

2.5.3 Public Outlet Density

To determine how cost changes in relation to an increase in the number of publicly available outlets, we created a measure called public outlet density (*POD*) that gives the number of square feet per 1 outlet available to the public.

Additionally, we wanted to find the ratio between the number of outlets that existed with a certain public destination and the number of seats that existed. This saturation of seats with outlets was thought to be a well-off metric of what a public destination might strive to increase and an easy-to-understand value. The number of seats that are in an establishment was determined to be its square footage divided by 36 sq. ft./person as this is the square feet for an occupant to fit comfortably in an establishment.

$$\frac{\frac{sq.\ footage}{pod}}{\frac{sq.\ footage}{36}} = \frac{outlet}{seat} ratio \tag{2}$$

In our agent-based model we varied the *POD* value as we believed that public destinations would strive to increase this value, thus making more outlets available to the public. To find bounds in which to vary *POD* we looked at the $\frac{outlet}{seat}$ ratio. A 1 to 1 ratio for number of outlets to seats would be optimal and thus we found the *POD* value that would produce this ratio, $\frac{1}{36}$, and set this to our upper bound. However, this upper bound was then decreased for Airports and Schools because it would be impossible (and undesirable in the latter case) to install so many outlets. On the other hand, a 0 to 1 ratio is least optimal. This gives a range of 0 to upper bound, between which 3 more evenly spaced *POD* values are evaluated; in order, the 5 levels for *POD* are named zero, low, low-mid, mid-high, and high. Note that low-mid is twice the density of low, and high twice the density of low-mid.

2.5.4 Destination Attendance over Time

Energy consumption of a particular destination was thought to be reliant on the number of that particular destination in the United States as well as the average number of people (v) that go to these destinations (d) per day. Because these two attributes are inherently correlated, we deemed it necessary to incorporate them into one variable describing the number of people per destination.

To understand how this value changes over time, we differentiated it producing the equation:

$$\frac{d}{dt}\left(\frac{v}{d}\right) = \frac{dv}{dt} * \frac{1}{destinations} - \frac{dd}{dt} * \frac{1}{destinations^2} * v \tag{3}$$

Looking at (site assumption) , we see that the change in the number of a particular destination is insignificant and thus can be reduced to 0. This makes our differential equation completely dependent on the first term as the second one reduces to 0.

$$\frac{dv}{dt} = \frac{\%\Delta * destination\,visitors}{year} * v$$

Integrating this gives us the equation below where *I* is our initial value of people per destination.

$$\frac{v}{d} = Ie^{\%\,change\,*\,t} \tag{4}$$

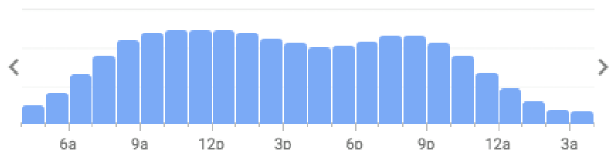
Through our research, we were able obtain *% change* values for the number of attendees of a particular destination. For secondary schools, the *% change* followed a piecewise function meaning the *% change* value projected to be constant from 2016 to 2023 and then change to another value that would stay constant from 2023 to 2028.

2.5.5 Visitor Influx Distribution

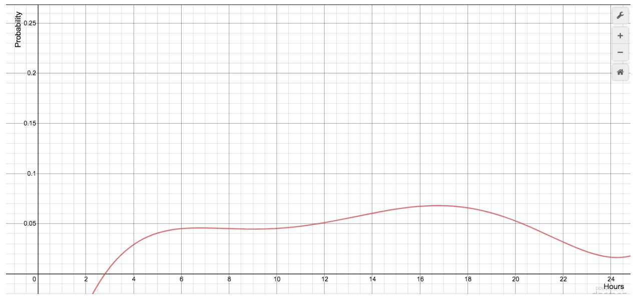
To develop a distribution function describing the density of people that come at a certain time at which a destination is operational, we researched the"peak" hours of every destination based on the Google Popular Times. In order to determine Google Popular Times, Google uses aggregated and anonymized data from users who have opted in to Google Location History and the popular times are based on the average popularity over the past several weeks[21]. Popular times correspond to the relative number of visitors who came to the destination which we can define as visitor influx.

We looked at multiple locations across the United States to ensure that the trends in popularity were not influenced by regional differences. Figure **??** describes one of such data points for the

Los Angeles International Airport. Looking at airports across the nation, we noticed that airports tend to follow a bimodal distribution with peaks around 11 am and 8 pm.



(a) L.A. International Airport Distribution



(b) Normalized Airport Distribution Function

Figure 3: The influx distribution and normalized airport distribution function of the L.A. International Airport.

Once we collected visitor distributions of each destination, we devised quintic and quartic fits to describe this distributions of people throughout the day by utilizing specific data values of time and number of people. We then normalized these distribution curves for any location of a specific destination by ensuring that the trapezoidal Riemann sum of the function was equal to 1. By doing so, we created a probability density function so that we could calculate the percentage of total visitors arriving in a given time period.

For example, in the Airport distribution of the L.A. Internal Airport shown above, the area under the curve between 3 and 4 am can be calculated to be 0.0188, so approximately 1.88% of the total visitors come in this time frame.

$$\sum_{n=1}^{\frac{t_2-t_1}{2}} \frac{f(x_i)+f(x_{i+1})}{2} * \frac{1}{2} = normalization\,factor \tag{5}$$

The process of normalization was undertaken by performing a trapezoidal Riemann sum for our quintic functions (for each destination) using the hours that a particular destination is operation as our bound and a 30 minute interval. The function was then divided by the value of the Riemann sum (normalization factor) as to make the new Riemann sum value 1 while maintaining the x-intercepts of the function.

For the equation above $t_2 - t_1$ is equal to the working hours of a destination divided by 2 for the number of 30 min interval that this time span contains. Note that all students at a school come in from 8:00 - 8:30 as noted in our assumptions.

Destination	Working Hours
Airport	24 Hours
Coffee Shops	04:00 - 16:00
Railway Stations	24 Hours
Schools	08:00 - 15:00
Libraries	09:00 - 18:00

Table 3: Working Hours of each destination.

This normalization is important as then at every 30 minute interval our model is able to retrieve a certain density from our normalized equation and then multiply this by the average number of visitors for a particular destination, thus giving us the number of people that would visit within the specified 30 minute interval. The calculated number of people that would visit within a specified 30 minute interval was rounded and then they were randomly distributed across the 30 minute interval.

Destination	Normalized Visitor Influx Distributions
Airport	$y = \frac{1}{36.648}(-6.991 + 4143x - 0.7746x^2 + 0.06206x^3 - 0.002372x^4 + 0.00003342x^5)$
Coffee Shop	$y = \frac{1}{28.395}(109.8 - 72.36x + 17.47x^2 - 1.932x^3 + 0.09991x^4 - 0.001963x^5)$
Railway Station	$y = \frac{1}{36.648}(-6.991 + 4143x - 0.7746x^2 + 0.06206x^3 - 0.002372x^4 + 0.00003342x^5)$
School	$y = 2$
Library	$y = \frac{1}{14.307}(-208.4 + 64.58x - 7.340x^2 + 0.3651x^3 - 0.006703x^4)$

Table 4: Normalized Visitor Influx Distributions for each destination.

2.5.6 Device Assignment

Based on research, we found the percentage of US adults that have a mobile phone, laptop, or tablet, as per our assumption regarding personal devices. These probabilities were implemented within our NetLogo model, as when a visitor enters the destination, they are either assigned a possibly empty subset of mobile phone, laptop, and tablet based on the probabilities. If a visitor is assigned no devices, they are considered a “flyby” meaning that they are at a particular destination for purely commercial reasons and will not be sitting down to charge their device. The probability that someone had a mobile device is 0.77, laptop is 0.73, and tablet is 0.53.

2.5.7 Battery Life

Additionally, every device type (mobile phone, laptop, and tablet) was assigned its own linear rate of battery drainage and charging (in % per min). Every minute in the simulation, every device of every visitor drains, and for the visitors at an outlet seat, their lowest-charged device is also charged (unless all devices are at 100% battery, in which case no charging and no electrical consumption occurs).

Drainage rate ($\frac{de}{dt}$) was derived from each device’s average battery life . Charging rate ($\frac{dc}{dt}$) was derived from the electrical capacity of each device’s battery as well as the electricity that each device’s charger can intake from an outlet per minute.

$$\frac{de}{dt} = \frac{100\%}{device\, avg.\, battery\, life\,(min)} \quad (6)$$

$$\frac{dc}{dt} = \frac{100\%}{\frac{device\, battery\, capacity\,(kWh)}{device\, charge\, rate(\frac{kWh}{min})}} \quad (7)$$

2.5.8 Duration of Stay

Table 5 displays the range of time that an average US visitor will spend at a destination; each visitor is assigned a random duration of stay within the range. These values influence the time spent charging personal devices.

Note that airport and railway station waiting time does not include time spent in the security line because of our assumption that nobody charges their phone while waiting in the security line.

Destination	Range of Stay Duration
Airports	1 hour - 3 hours
Coffee Shops	1.12 - 3.4 hours
Railway Stations	30 - 45 minutes
Schools	6.5 hours
Libraries	0.65 - 1.42 hours

Table 5: The range of time an average visitor spends at each destination

2.6 Electric Vehicles Energy Usage Model

With the rise of electric vehicles (EVs) over the past couple of decades, electric vehicles are a common occurrence used by people and considered a personal device. However, due to distinct differences between electric vehicles and other personal devices such as mobile phones or laptops, we considered their factors separately. A computational Python model was created in order to analytically calculate the EV electricity consumption and its dependence on time.

$$0.3 * battery\ capacity * outlets = daily\ EV\ \ electricity\ consumption \tag{8}$$

$0.3 * battery\ capacity$ represents the amount of energy it takes to charge an EV battery by 30% per one outlet. An average battery capacity of 58.8 kwh for electric vehicles was used in order to simplify our model. This resulting number is then multiplied by the number of available public outlets to find daily EV electricity consumption. This equation was restricted by the amount of charging that could occur in one day by summing up the time a charge would take.

$$0.3 * \frac{battery\ capacity}{charger\ wattage} = charging\ time \tag{9}$$

Once a 24 hour limit was reached, a day was ended, and a new day would start until a 365 day cycle was completed. This process was done for multiple years.

2.6.1 Electric Vehicles Based Assumption

Assumption: An owner of an electric vehicle charges their car once a day

Justification: Since electric vehicle charging is cheap and common, owners tend to charge their car once a day, similar to phones, to prepare for the next day.

Assumption: Charging stations are always being used.

Justification: Due to the high frequency of electric vehicles, low number of charging stations, and long time to charge, charging stations are always occupied.

Assumption: 20% of all charging for electric vehicles are done at a public charging station.
Justification: According to the Office of Energy Efficiency and Renewable Energy, "electric vehicle drivers do more than 80% of their charging at home" [22] due to the low, stable residential electricity rates.

Assumption: Location of types of electric vehicle charging stations are randomly distributed across the country.
Justification: In order to simplify our model, the concentration of electric vehicle charging stations in locations such as California was ignored [23].

Assumption: An electric vehicle charges 30% their battery when at a public charging station.
Justification: An average EV battery can handle 100 miles [24] and thus 30% of this allows a person to drive 30 miles. We deemed this a valid amount at a public station as an average person's work commute is 30 minutes[25] and 30% would be plenty to get home where they can charge their car.

2.6.2 Electric Vehicle Charger Types

There are three different type of electric vehicle charges: DC fast, Level 1, and Level 2. Each is able to charge at various voltages and currents, thus charging vehicles at different rates. Our chosen unit was kW as our metric for measuring EV battery capacity was kWh.

Charger Type	Volts	kW	Relative Amounts
Level 1	120	1.44	5.4%
Level 2	240	9.6	79.7%
DC Fast	480	45	14.9%

Table 6: Charging intensity of various EV charger types [26].[27].

2.6.3 Electric Vehicle Count

The electric vehicle industry is booming and thus the rate at which electric cars on the road within the United States is increasing rapidly. By running different kinds of regressions on the data found for the number of electric cars in the US over time, we were able to produce the quadratic equation $18,590t^2 - 418,483t + 2 * 10^6$ with a coefficient of determination of 0.9947 [28]. This equation is able to model the number of electric vehicles on the road in the US t years after 2000, as electric vehicles weren't substantive enough to contribute to electricity consumption pre-2000.

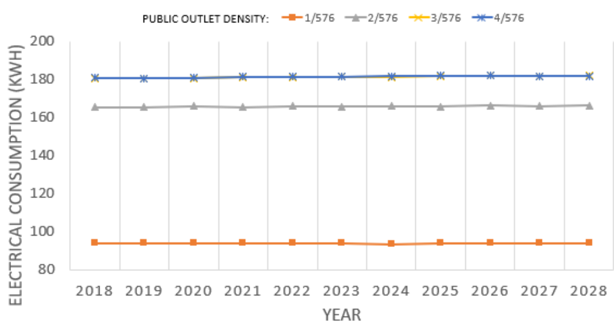
2.6.4 Electric Vehicle to Outlet Ratio

A meaningful metric to consider when looking at the demand for public energy consumption, is the electric vehicle to outlet ratio. Similar to the previous section, various types of regressions were run for data over time for this ratio [28] and produced the quadratic equation $0.1247t^2 + 0.6053t + 5.5952$ with a coefficient of determination of 0.9776.

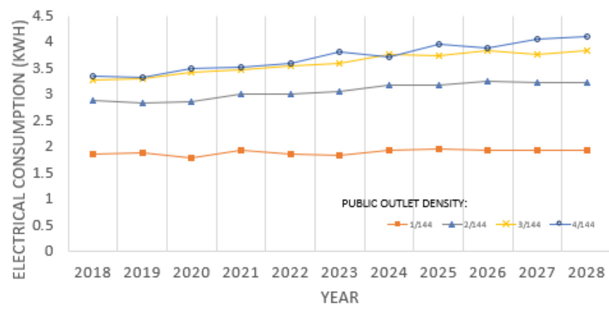
3 Results and Analysis

3.1 Electrical Consumption Results

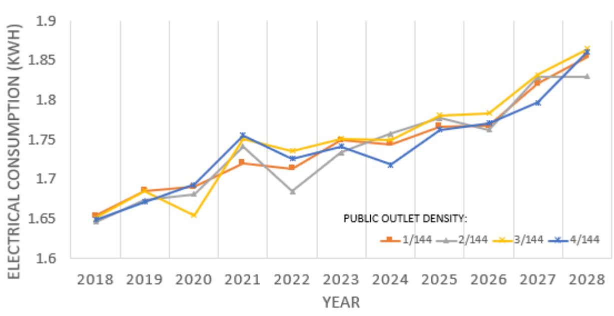
We run the NetLogo simulation 100 times for each combination of Year and Public Outlet Density and plot the mean daily electrical consumption (Figure 4). Note that outlet density of 0 is not plotted as 0 outlets necessarily results in an electrical consumption of 0.



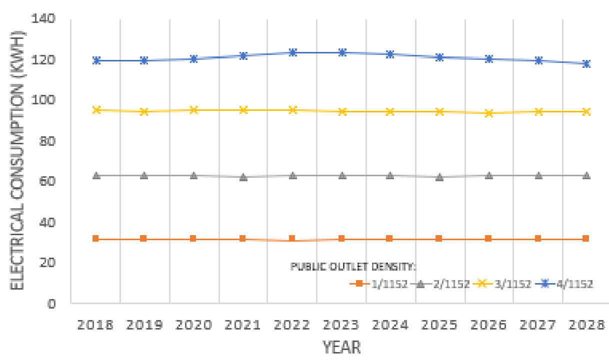
(a) Airports



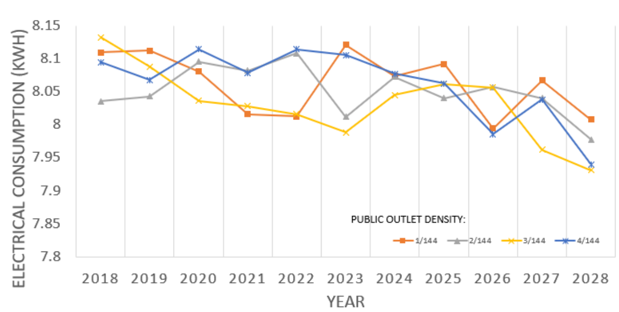
(b) Coffee Shops



(c) Railway Stations



(d) Schools



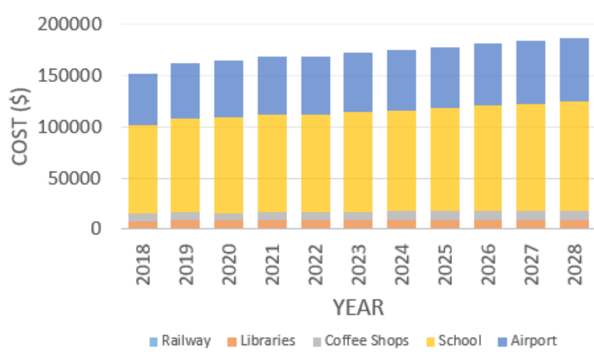
(e) Libraries

Figure 4: The forecasted daily electrical consumption (kWh) from 2018-2028 for different public outlet densities (colors) for each defined destination (a-e).

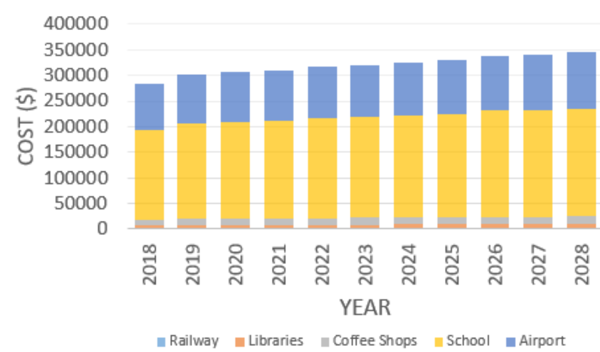
Several trends are revealed in these graphs. First, all trends generally follow trends in number of visitors over the years, which makes sense. Electrical consumption in Railway Stations and Coffee

Shops increases as more visitors come to these destinations. Libraries experience a decrease in electrical consumption, and Airports and Schools remain relatively constant, again reflecting the visitor data. Secondly, Railway Stations and Libraries do not depend greatly on the public outlet density. This is because even under the lowest density, all visitors to each of these destinations has outlet access. For railway stations this is due to the low daily visitors, and for libraries is due to the general high availability of outlets. A similar effect is observed with only the highest two densities in both Airports and Coffee Shops; this means that for airports, a public outlet density of 3 outlets every 576 ft^2 is the minimum threshold at which every visitor throughout the day is guaranteed outlet access, and for coffee shops the same occurs at 3 outlets every 144 ft^2. For libraries, it is interesting to observe the great variability in daily electrical consumption; this is attributable to the visitors being condensed in the short working hours, which the random agent-based model simulated well. Schools showed a clear separation between each public outlet density, showing that even at a relatively high outlet availability, the school cannot provide an outlet for every student, which makes practical sense.

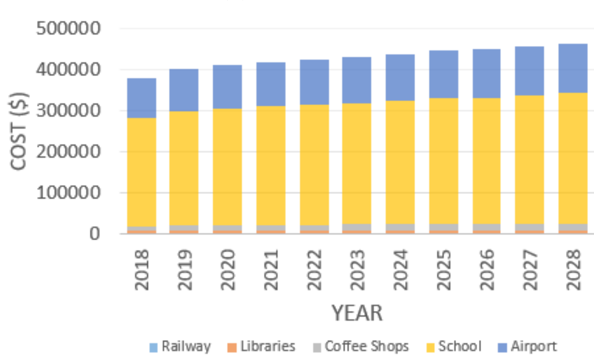
3.2 Cost Results



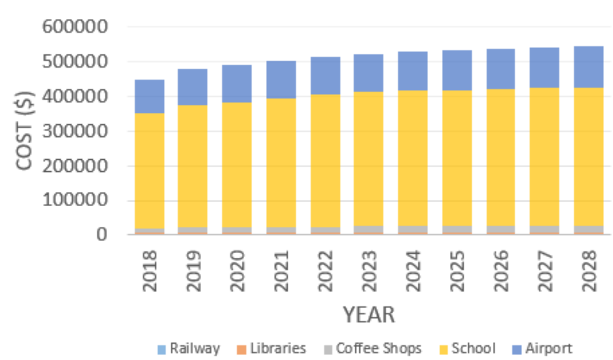
(a) Low POD



(b) Low - Mid POD



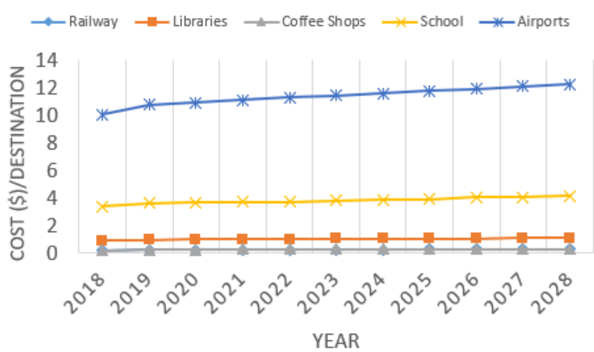
(c) Mid - High POD



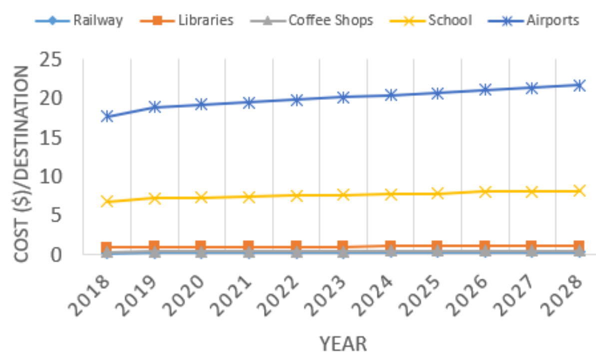
(d) High POD

Figure 5: The total projected electricity cost from public charging stations for the years 2018 - 2028, separated by the Public Outlet Density.

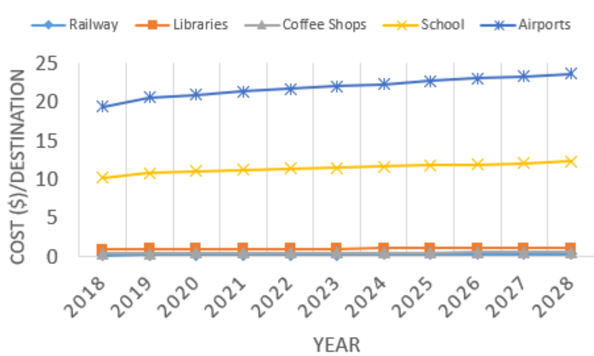
To go from per-day kWh for each destination to total annual costs, we multiplied by 365 days and used Equation 1 to generate Figure 7. As years go on, due to increasing numbers of visitors to each destination, cost also increases slowly. More drastic increases in cost, from $150,000 to $500,000, are observed as *POD* increases from the Low to High setting. Additionally, it is clear that in all cases, School and Airport are the two destinations with the highest total annual cost. This is attributable to the large number of Schools in the US and the high number of visitors to each airport. Coffee Shops, Libraries, and Railway Stations contribute much less to the overall electrical cost of personal device charging. In fact, as *POD* increases, large contributors to cost are made even larger contributors; under High *POD*, Schools contribute to about 80% of total annual cost.



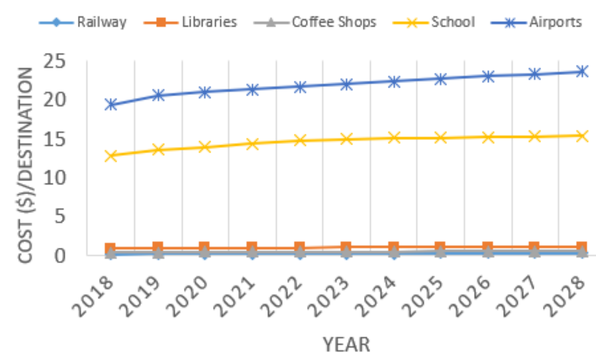
(a) Low POD



(b) Low - Mid POD



(c) Mid - High POD

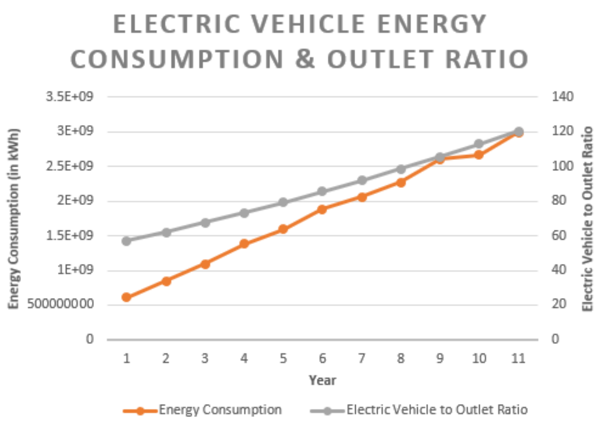


(d) High POD

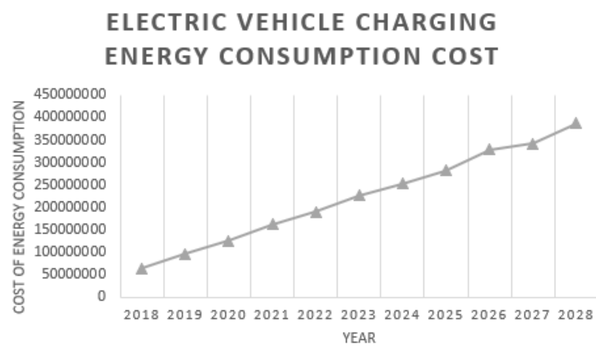
Figure 6: The projected electricity cost from public charging stations for the years 2018 - 2028 for each individual destination, separated by the Public Outlet Density.

In addition to analyzing total annual cost from all destinations, we also investigate annual cost per individual location of each destination, e.g. how much money a single coffee shop expends on providing personal device charging per year 6. Schools and Airports remain the highest-valued destinations, but Airport is now greater than School because each individual School does not expend as much as each individual Airport, which has many more people per day. Again, cost increases over time and increases with *POD* as well, except in the cases discussed in Section **??** where electrical consumption does not increase with *POD*. Overall, cost per destination increases by a factor of 2-3 from the low to high *POD* setting.

3.3 Electric Vehicle Cost Analysis



(a) Energy Consumption and EV to Outlet Ratio



(b) EV Energy Consumption Cost

Figure 7: The projected energy consumption, electric vehicle to outlet ratio, and cost for electric vehicles for the next 10 years.

As per seen through our graph, our computational model was able to predict the yearly consumption of electricity from public charging of electric vehicles. This data was seen to be quite accurate when compared to known data for yearly consumption of electricity for EV. For the year 2018 our model predicted a public electricity consumption of 0.618 TWh. 2.85 TWh of electricity were consumed in total for electricity cars, but it's important to note that only 20% of charging is actually done at public charging locations [22] which provides us with a value of 0.57 TWh of electricity consumed through public charging.

The graph above also shows a clear trend of the increasing cost in electricity consumption as time progresses which is most likely attributed to the rapidly increasing number of EVs and the demand for charging. Additionally, the electric vehicle to outlet ratio is also increasing over time but at a faster rate. Theoretically, if the vehicle to outlet ratio was able to decrease then the consumption of electricity by electric vehicles would be able to increase faster since the additional outlets could also become saturated.

3.4 Strengths

Our model is robust with nearly all inputs in the model and destinations statistically based on real-world data from trusted websites and governmental agencies such as the Department of Energy and U.S. Energy Information Administration. With the large data set of information we accumulated, our agent-based model accounts for a number of factors that determine electricity consumption, such as availability of outlets depending on the influx of visitors to a destination over time, to the change in the number of destinations in a category over a series of year.

Additionally, our agent-based model for usage allows accurate representation of the inherent random interactions present within any system. We can run a large sample size of 100 trials for every combination of outlet density and year, giving an accurate estimation of the expected cost of energy consumption.

Our time-based equation allows us to take into account how factors will change over time. For instance, the number of visitors that go to libraries will decrease in the future as people convert more to electronic reading devices.

Finally, one of the most unique aspects of our model is the ability to take account the varying characteristics of each destination and develop a model specifically for each destination and public outlet density. Rather than give a generalized cost due to public electric consumption over the years based on the average destination characteristics, we are able to specify the inputs. For example, the visitor influx distribution of a school is a constant with all visitors, otherwise known as students, coming at the beginning of the day and not leaving. On the other hand, in a coffee shop, visitors may come variably throughout the day with a peak during breakfast and lunch hours.

3.5 Weaknesses

Our model was designed using information from the US and is not easily applicable to other countries. For instance, since the US is one of the most developed countries in the world, it has a majority of the necessary infrastructure needed for the transmission of electricity. Consequently, we are able to model the commercial price of electricity change for the next 10 year as a logarithmic function. On the other hand, the commercial price of electricity may be significantly higher and increase faster for a developing country such as Albania.

Moreover, in our research to back our data, there was an inconsistency in sources for related pieces of information due to specificity of information needed for different inputs. However, they are still a good estimate.

Our model only considers certain public spaces as defined in *General Definitions*. While this assumption was based on sound justifications, the sum of negligible contributions towards the cost of charging personal devices in public could impact our model.

Our model likely overestimates electrical consumption because in reality, a large proportion of visitors to a coffee shop, for example, would be flybys who only intend to grab coffee.

Finally, the agent-based model does not take into account that most outlets in the US are paired, nor the possible impacts of tables with multiple seats or visitors arriving in groups. However, the model is still a good representation of the effects of limited and increasing outlets in a destination with non-uniformly arriving visitors.

4 Suggested Guidelines (Initiatives, Requirements)

As our model has shown, in the coming years, as public places continue to increase outlet availability and demand for electricity continues to grow, electricity consumption will only increase. To combat this increasing cost, several measures can be taken to improve device efficiency and reduce associated costs for public places.

Specifically, battery life can be greatly improved through research in more efficient batteries and improved battery usage through the further development of charge recovery and low battery algorithms. Researchers across the world are currently tackling this problem with advances in Sodium and Potassium based batteries [29], and nanolithia cathode batteries[30] creating new batteries with increased charging capacity and energy efficiency. Energy efficiency can also be improved through the improvement of individual components within each device will bring down the total energy consumption of the device. For example, the optimization of energy consumption for hardware such as monitors, CPU's and interfaces, will improve energy efficiency. Our model allows for these adjustments through the draining and charging rates of individual devices described in Section 2.5.7.

Additionally, individual destinations may implement restrictions on the availability of charging outlets to reduce the cost associated with charging personal devices. In doing so, our model predicts the cost of electricity to decrease as a result of fewer outlets for visitors to use. Our model allows for this adjustment with variation in the POD or public outlet density described in Section 2.5.3.

Furthermore, with the integration of electric vehicles into mainstream automobiles, it is essential to improve the car battery efficiency. One of such ways is the implementation of silicon based electrodes which have an increased capacity of almost 20 times the value for current lithium-ion based batteries. Implementations of these devices in the future will, reduce charging necessity and increase battery efficiency [31].

All of these future implementations will alter our model; however, given our robust model, only slight changes must be made to account for these changes in the coming years. For example, to account for increased battery efficiency, our model would change the rate of depletion of charge as it is being used, the rate of battery replenishment, and the ranges for initial battery charge. These variables would need to be altered because with higher efficiency batteries, less charge is lost in a given unit of time leading to lower rate of depletion, and a higher range of initial battery charge. By accounting for these adjustments, our model would predict would decrease in total cost associated with charging personal devices in public areas.

Finally, our model reveals an interesting pattern: decreasing public outlet availability is no use in reducing cost if a destination's visitor influx is so sparse that everyone will be able to use an outlet. In these cases, only other initiatives like increasing battery efficiency would effectively reduce costs.

5 Conclusion

As our world becomes more and more connected, personal electronic devices from phones and laptops to electric cars are becoming increasingly prevalent. A rise in electricity demand has accompanied the growth in personal electronic devices, creating a demand for charging stations and outlets. Public locations have recently began to satisfy the demands of public consumer needs by increasing the number of electrical outlets available to the public. In our model, we modeled growth by estimating the costs incurred by governmental and private business when fulfilling this demand by integrating an agent-based model and algebraic model. Since each location within the larger subset of public destinations is inherently different with regard to visitation hours, number of visitors, duration of stay, capacity to hold visitors, and number of destinations, we created a model to incorporate each of these factors.

By measuring the cost of electricity over a ten year period at various public locations, we were able to find that over time, the total cost of charging of personal electronic devices in public areas increased. We noticed that for airports and schools, there seemed to be insignificant growth in electrical consumption, and for railway stations and coffee shops we found that energy consumption increased; however, we also found that library consumption will decrease over time. These trends closely aligned with data we found regarding the change in visitors over time. To model increases in the number of public outlets available, we ran our model with varying public outlets densities and found that for railway stations and libraries, variation of public outlets showed very little impact since almost all visitors had access to outlets regardless of the density. At a low outlet density we found an electricity cost for personal devices to grow from \$150,000 to \$180,000 over a ten year period. On the other hand, for high outlet density, we determined a price change from \$450,000 to \$525,000 per year over the same period. However, for electric vehicles, we estimated a cost change from \$50,000,000 to \$400,000,000 per year between 2018 and 2028. For Airports and Coffee Shops, we deduced an ideal public outlet density of 3/ 576 ft^2 and 3/144ft^2 respectively to ensure each visitor had access to at least one outlet. When comparing total cost due to energy consumption of all public destinations defined in our model, we noticed that a majority of the contributions originated from Schools and Airports. This is likely due to the relatively vast number and visitor volume of schools and airports in comparison to other public areas. These destinations' contributions continued to increase as public outlet density increased, indicating that each of these destinations were more reliant on outlet density than the others. However, per-location, airports have the highest annual cost due to the large visitor volume.

Another increasingly prevalent electric cost associated with personal devices is the charging of electric vehicles. Our model for electricity consumption of elect vehicles was found to very closely resemble existing data as it was able to predict electricity consumption of publicly charged electric vehicles within 0.048 TWh. We also saw that electric vehicle energy consumption will continue to increase linearly as a function of time.

While these costs are expected to increase in the coming years, action can be taken to reduce the cost sustained from offering "free" charging services at public locations. One such way is the restriction of the availability of outlets to the public. As can be seen in Figure 7, as *POD* decreases, cost of electric charging drastically decreases with a difference of nearly around \$200,000 between our low and high POD metrics. Another possibility to reduce costs associated paying for electricity is the implementation of new technologies into the market. Specifically, new batteries such as sodium and potassium based batteries that have increased charge capacity, efficiency, and charging capabilities. While this may not occur in the ten year scope of our model, its impacts reducing the cost of electricity can easily be modelled through the implementation of an energy efficiency factor.

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Appendices

A Commercial Price of Electricity

Year	Price (¢/kWh)	% Change
2001	7.92	–
2002	7.89	-0.37878
2003	8.03	1.774397
2004	8.17	1.743462
2005	8.67	6.119954
2006	9.46	9.111880046
2007	9.65	2.00845666
2008	10.26	6.321243523
2009	10.16	-0.974658869
2010	10.19	0.295275591
2011	10.24	0.490677134
2012	10.09	-1.46484375
2013	10.26	1.684836472
2014	10.74	4.678362573
2015	10.64	-0.93109869
2016	10.43	-1.97368421
2017	10.66	2.205177373
2018	10.67	0.09380863

Table A1: Commercial price of electricity (¢/kWh) 2001-2018, with % change between years

B Number of Destinations over the year

B.1 Public Schools

Year	Number of Public Schools	Percent Change
2005	26,011	–
2006	25,929	-0.3152512399
2007	26,647	2.7691002353
2008	26,345	-1.1333358352
2009	26,640	1.1197570697
2010	26,559	-0.3040540541
2011	26,368	-0.7191535826
2012	26,275	-0.3527002427
2013	26,047	-0.8677450048
2014	26,145	0.3762429454
2015	26,005	-0.5354752343
	Average	0.0037385057

Table B1: Number of Public Schools and accompanying percent change over an eleven year period

B.2 Railway Stations

Year	Stations	% Change
2000	515	–
2001	512	-0.58252427
2002	515	0.5859375
2003	514	-0.19417476
2004	529	2.91828794
2005	531	0.37807183
2006	510	-3.95480226
2007	508	-0.39215686
2008	510	0.39370079
2009	511	0.19607843
2010	512	0.19569472
2011	511	-0.1953125
2012	512	0.19569472
2013	516	0.78125
2014	518	0.3875969
2015	521	0.57915058
2016	525	0.76775432
2017	527	0.38095238
2018	526	-0.18975332

Table B2: Number of Railways over an eighteen year period and accompanying percent changes

B.3 Public Airports

Year	Public Airports	% change
2000	5,317	–
2001	5,294	-0.43257476
2002	5,286	-0.151114469
2003	5,286	0
2004	5,288	0.037835793
2005	5,270	-0.340393343
2006	5,233	-0.702087287
2007	5,221	-0.229313969
2008	5,202	-0.363914959
2009	5,178	-0.461361015
2010	5,175	-0.057937428
2011	5,172	-0.057971014
2012	5,171	-0.01933488
2013	5,155	-0.309417908
2014	5,145	-0.193986421
2016	5,136	-0.174927114
2017	5,104	-0.62305296
2018	5,087	-0.3330721

Table B3: Number of Public Airports in the United States of America over an eighteen year period and accompanying percent changes

B.4 Public Libraries

Year	Number of Public Libraries	% Change
2000	9074	0.309529074
2001	9129	0.606127397
2002	9137	0.087632818
2003	9211	0.809893838
2004	9207	-0.043426338
2005	9198	-0.097751711
2006	9208	0.108719287
2007	9214	0.06516073
2008	9221	0.075971348
2009	9225	0.043379243
2010	8951	-2.970189702
2011	8956	0.05585968
2012	9082	1.406878071
2013	9070	0.099097115
2014	9070	-0.23099769
2015	9068	-0.022050717
2016	9057	-0.12130569

Table B4: Number of Libraries over a sixteen year period and accompanying percent changes

C Airport Terminal Data

Table C1: A listing of the medium sized airports in the United States and their number of terminals

Airport	**Terminal Number**
Atlanta	206
Chicago O'Hare	182
Dallas DFW	161
Detroit DTW	147
Denver	136
Washington Dulles	135
Houston Bush	130
New York Newark	129
Minneapolis	127
Philadelphia	126
New York JFK	125
Miami MIA	123
Toronto	122
Phoenix	116
Los Angeles LAX	112
San Francisco SFO	108
Las Vegas	103
Orlando Int'l	96
Charlotte	95
Baltimore-Washington	84
Vancouver	81
Salt Lake	79
New York La Guardia	72
Tampa	62
Portland	60
Kansas City	59
Saint Louis	59
Sydney	59
Miami Ft Laud.	57
Montreal	56
Milwaukee	48

Melbourne	47
Chicago - Midway	45
San Diego	45
Calgary	44
New Orleans	44
Washington National	44
Brisbane	34
Edmonton	32
Halifax	32
Sacramento	32
Oakland	30
Fort Myers	28
Miami Palm Beach	28
San Jose	28
Houston Hobby	26
Ottawa	26
Austin	25
San Antonio	24
Reno-Tahoe	23
Jacksonville	20
Dallas Love	19
Winnipeg	18
Boston Manchester	15
Des Moines	15
El Paso	15
Sarasota-Bradenton	14
St Pete-Clearwater	13
Orlando Sanford	12
Pensacola	12

D Amtrak Station Size and Capacity

Railway Stations	Platforms	Size	Capacity
Aberdeen, Maryland	2	3294	91.5
Albany, Oregon	1	1647	45.75
Albany-Rensselaer, NY	2	3294	91.5
Albion, MI	1	1647	45.75
Alpine,TX	1	1647	45.75
Alliance, OH	1	1647	45.75
Allensworth	1	1647	45.75
Alexandria, VA	2	3294	91.5
Alderson, WV	1	1647	45.75
Aldershot, Ontario	3	4941	137.25
Alvarado	4	6588	183
Alton, Illinois	1	1647	45.75
Altona, PA	1	1647	45.75
Amsterdam, NY	1	1647	45.75
Anaheium, Ca	2	3294	91.5
Ann Arobor, Mi	1	1647	45.75
Anniston, AL	1	1647	45.75
Antioch-Pittsburg	1	1647	45.75
Arcadia Valley, MO	1	1647	45.75
Ardmore, Ok	1	1647	45.75
Ardmore, Pa	2	3294	91.5
Arkadelphia	1	1647	45.75

Ashland, KY	1	1647	45.75
Ashland, VA	2	3294	91.5
Atlanta, Ga	2	3294	91.5
Auburn Ca	1	1647	45.75
Austin, TX	1	1647	45.75
Bakersfield, Ca	2	3294	91.5
Maryland, Baltimore	3	4941	137.25
Bangor, MI	1	1647	45.75
Barstow, California	1	1647	45.75
Battle Creek Mi	1	1647	45.75
Beaumont, TX	1	1647	45.75
Fairhaven Stations	1	1647	45.75
Bellow Falls, VT	1	1647	45.75
Benson AZ	0	0	0
Berkely CA	1	1647	45.75
Berlin Connecticut	2	3294	91.5
Bingnen-White	1	1647	45.75
Birmingham Station	2	3294	91.5
Uptown Station	2	3294	91.5
Back Bay	4	6588	183
North Station	9	14823	411.75
South Station	7	11529	320.25
Union Station	1	1647	45.75
Bridgeport Station	2	3294	91.5
Godbold	1	1647	45.75

Browning Station	1	1647	45.75
Brunswick Maine	1	1647	45.75
Buffalo-Depow	1	1647	45.75
Bufallo Exchange	1	1647	45.75
Burbank	2	3294	91.5
Burke Centre	1	1647	45.75
Burlington	2	3294	91.5
Burlington NC	1	1647	45.75
BWI Rail Station	2	3294	91.5
Camarillo	2	3294	91.5
Camden	1	1647	45.75
Carbondale	1	1647	45.75
Carlinville	2	3294	91.5
Carpinteria	1	1647	45.75
Cary	2	3294	91.5
Castleton, VT	1	1647	45.75
Centralia	1	1647	45.75
Centralia Union Depot	1	1647	45.75
Illinois	1	1647	45.75
North Charleston Station	1	1647	45.75
Charleston Station	1	1647	45.75
Charlotte Station	1	1647	45.75
Charlotteseville Union	2	3294	91.5
Chatsworth Station	3	4941	137.25
Chemult	1	1647	45.75
Chicago Union	30	49410	1372.5

Chico Station	1	1647	45.75
Cincinnati Union	1	1647	45.75
Claremont Station	1	1647	45.75
Cleburne	1	1647	45.75
Clemson	1	1647	45.75
Cleveland	1	1647	45.75
Clifton Forge	1	1647	45.75
Coatesville	2	3294	91.5
Colfax	1	1647	45.75
Columbia	1	1647	45.75
Columbus	1	1647	45.75
Connellsvile	1	1647	45.75
Connersvile IN	1	1647	45.75
Corcoran	1	1647	45.75
Cornwells	2	3294	91.5
Crawfordsville	1	1647	45.75
Creston	2	3294	91.5
Croton	3	4941	137.25
Culpeper	1	1647	45.75
Cumberland Station	1	1647	45.75
Cut Bank	1	1647	45.75
Dallas Unoin	3	4941	137.25
Danville	1	1647	45.75
David CA	2	3294	91.5
John D. Dingell	2	3294	91.5
Deerfield Beach	2	3294	91.5
Del Rio	1	1647	45.75
DeLand	1	1647	45.75
Delray	2	3294	91.5
Deming	0	0	0
Denmark	1	1647	45.75
Denver	7	11529	320.25
Detroit	1	1647	45.75

Detroit Lakes	1	1647	45.75
Devils Lake	1	1647	45.75
Dillon Station	1	1647	45.75
Dodge City	2	3294	91.5
Dover Transportation Center	1	1647	45.75
Dowagiac	1	1647	45.75
Downington	2	3294	91.5
Du Quoin	1	1647	45.75
Dunsmuir	1	1647	45.75
Durand	1	1647	45.75
Durham NH	1	1647	45.75
Durham NC	1	1647	45.75
Dwight Station	1	1647	45.75
Dyer Station	1	1647	45.75
East Glacier Park	1	1647	45.75
East Lansing	1	1647	45.75
Edmonds	1	1647	45.75
Effingham	1	1647	45.75
El Paso	1	1647	45.75
Elkhart	1	1647	45.75
Elizabethtown	2	3294	91.5
Elko	2	3294	91.5
Elyria	1	1647	45.75
Emeryville	2	3294	91.5
Ephrata	1	1647	45.75
Erie	2	3294	91.5
Essex	1	1647	45.75
Essex Junction	1	1647	45.75

Eugene Springfield	1	1647	45.75
Everett Station	2	3294	91.5
Exeter Station	1	1647	45.75
Exton Station	2	3294	91.5
Fairfiel-Vacaville	1	1647	45.75
Fargo Station	1	1647	45.75
Fayetteville	1	1647	45.75
Flagstaff	1	1647	45.75
Flint	1	1647	45.75
Florence	1	1647	45.75
Fort Edward	1	1647	45.75
Fort Lauderdale	2	3294	91.5
Fort Madison	2	3294	91.5
Fort Morgan	1	1647	45.75
Fort Worth	2	3294	91.5
Farmingham	2	3294	91.5
Fraser-WinterPark	1	1647	45.75
Fredericksburg	2	3294	91.5
Freeport	1	1647	45.75
Freemont	2	3294	91.5
Santa Fe	2	3294	91.5
Fullerton	3	4941	137.25
Fulton	1	1647	45.75
Gainesville	1	1647	45.75
Gainesville, TX	1	1647	45.75
Galesburg	2	3294	91.5
Gallup	1	1647	45.75
Garden City	1	1647	45.75
Gastonia	1	1647	45.75
Gilman	2	3294	91.5

Glasgow	1	1647	45.75
Glendale	2	3294	91.5
Glenview	2	3294	91.5
Glenwood	1	1647	45.75
Goleta	1	1647	45.75
Granby	1	1647	45.75
Grand Forks	2	3294	91.5
Grand Junction	2	3294	91.5
Vernon J Ehlers	1	1647	45.75
Green River Station	1	1647	45.75
John W. Olver transit Center	1	1647	45.75
Greensburg Statoin	2	3294	91.5
Greenvile SC	2	3294	91.5
Greenwood	1	1647	45.75
Grimsby	0	0	0
Grover Beach	1	1647	45.75
Guadalupe	1	1647	45.75
Hamlet	1	1647	45.75
Hammond Station	1	1647	45.75
Hammond-Whiting	1	1647	45.75
Hanford	2	3294	91.5
Harpers Ferry	2	3294	91.5
Harrisberg	4	6588	183
Hartford Union	1	1647	45.75
Hastings	1	1647	45.75
Hattiesburg	1	1647	45.75
Haverhill	2	3294	91.5
Havre	2	3294	91.5

Hayward Stiation	2	3294	91.5
Hazlehurst	1	1647	45.75
Helper Station	1	1647	45.75
Hermann Station	1	1647	45.75
High Point	1	1647	45.75
Hinton	1	1647	45.75
Holdrege	1	1647	45.75
Holland Station	1	1647	45.75
Hollywood Station	2	3294	91.5
Holyoke	1	1647	45.75
Homewood Station	2	3294	91.5
Hope Station	1	1647	45.75
Houston	2	3294	91.5
Hudson Station	2	3294	91.5
Huntingdon Station	1	1647	45.75
Hunting WV	1	1647	45.75
Hutchinson Station	1	1647	45.75
Independence Station	1	1647	45.75
Indianapolis Station	1	1647	45.75
Irvine	2	3294	91.5
Jackson	2	3294	91.5
Jacksonville	2	3294	91.5
Jesup	1	1647	45.75
Johnstown	1	1647	45.75
Joilet Il	2	3294	91.5
Kalamazoo	2	3294	91.5
Kankakee	1	1647	45.75
Kannapolis	1	1647	45.75
Kansas Station	1	1647	45.75

Kelso	1	1647	45.75
Kewanee	2	3294	91.5
Kingman	1	1647	45.75
Kingston	2	3294	91.5
Kingstree	1	1647	45.75
Kirkwood	2	3294	91.5
Kissimmee	2	3294	91.5
Klamath	2	3294	91.5
La Crosse	1	1647	45.75
La Grange	2	3294	91.5
Jefferson City MO	1	1647	45.75
La Junta	2	3294	91.5
La Plata	1	1647	45.75
Lafayette	1	1647	45.75
Lafayette LA	1	1647	45.75
Lake Charles	1	1647	45.75
Lakeland	1	1647	45.75
Lamar CO	1	1647	45.75
Lamy	2	3294	91.5
Lancaster Pa	2	3294	91.5
Lapeer	1	1647	45.75
Las Vegas	1	1647	45.75
Latrobe	2	3294	91.5
Laurel	1	1647	45.75
Lawrence Station	1	1647	45.75
Icicle	1	1647	45.75
Lee's Sum-mit	1	1647	45.75
Lewistown	1	1647	45.75
Lexington	1	1647	45.75
Libby Sta-tion	1	1647	45.75
Lincoln Station	1	1647	45.75
Lincold NE	1	1647	45.75
Little Rock	1	1647	45.75
Lodi	1	1647	45.75

Lompoc-Surf	1	1647	45.75
Longview	1	1647	45.75
Lordsburg	0	0	0
Lorton	1	1647	45.75
Union Station LA	6	9882	274.5
Lynchburg	1	1647	45.75
Macomd	1	1647	45.75
Madera	1	1647	45.75
Malta	1	1647	45.75
Malvern	1	1647	45.75
Manassas	2	3294	91.5
Maricopa	1	1647	45.75
Marks	1	1647	45.75
Marshall	1	1647	45.75

Table D1: Amtrak stations and corresponding platform numbers, estimated sizes and capacities

E Destination Public Outlet Density Cost Analysis

E.1 Library POD Cost Analysis

Year	P (Cents/kWH)	Low POD	C Low POD	Low-Mid POD	C Low-Mid POD	High-Mid POD	C High-Mid POD	High POD	C High POD
2018	10.670	8.109	7836.715	8.036	7765.370	8.133	7859.168	8.095	7822.457
2019	11.375	8.112	8357.313	8.043	8285.963	8.088	8332.743	8.068	8311.518
2020	11.553	8.081	8455.237	8.096	8470.630	8.036	8408.439	8.114	8490.366
2021	11.731	8.016	8516.117	8.082	8586.340	8.028	8529.388	8.078	8582.514
2022	11.908	8.013	8641.841	8.108	8744.607	8.016	8645.345	8.114	8750.959
2023	12.086	8.121	8889.142	8.012	8769.393	7.989	8744.227	8.106	8872.389
2024	12.263	8.074	8967.517	8.072	8965.815	8.044	8934.764	8.077	8970.817
2025	12.440	8.092	9117.783	8.040	9059.220	8.062	9083.600	8.063	9084.325
2026	12.618	7.994	9135.678	8.057	9207.706	8.057	9206.969	7.985	9125.397
2027	12.795	8.067	9348.002	8.040	9317.246	7.962	9226.741	8.038	9314.696
2028	12.972	8.008	9408.388	7.977	9372.334	7.931	9318.092	7.940	9328.226

Table E1: Cost of electricity at Libraries at varying POD

E.2 Railway POD Cost Analysis

Year	P (Cents/kWH)	Low POD	C Low POD	Low-Mid POD	C Low-Mid POD	High-Mid POD	C High-Mid POD	High POD	C High POD
2018	10.670	1.653	92.773	1.646	92.395	1.651	92.657	1.649	92.529
2019	11.375	1.685	100.818	1.674	100.130	1.685	100.830	1.672	100.010
2020	11.553	1.690	102.689	1.681	102.148	1.654	100.529	1.693	102.869
2021	11.731	1.720	106.158	1.741	107.415	1.751	108.042	1.755	108.303
2022	11.908	1.713	107.311	1.684	105.499	1.736	108.715	1.726	108.096
2023	12.086	1.748	111.156	1.733	110.198	1.751	111.331	1.741	110.675
2024	12.263	1.744	112.497	1.757	113.338	1.749	112.843	1.718	110.802
2025	12.440	1.766	115.566	1.777	116.278	1.780	116.484	1.762	115.303
2026	12.618	1.767	117.286	1.762	116.965	1.783	118.324	1.771	117.511
2027	12.795	1.820	122.489	1.828	123.046	1.832	123.267	1.796	120.900
2028	12.972	1.854	126.532	1.829	124.798	1.865	127.222	1.861	126.985

Table E2: Cost of Electricity at Railway Stations at varying POD

E.3 Airport POD Cost Analysis

Year	P (Cents/kWH)	Low POD	C Low POD	Low-Mid POD	C Low-Mid	High-Mid POD	C High-Mid POD	High POD	C High POD
2018	10.670	93.926	50981.490	165.303	89723.782	180.507	97976.238	180.851	98162.656
2019	11.375	94.027	54408.153	165.509	95771.247	180.439	104410.400	180.449	104415.955
2020	11.553	94.102	55303.178	165.878	97485.220	180.372	106002.810	180.706	106199.530
2021	11.731	94.021	56105.502	165.361	98675.759	181.045	108035.076	181.379	108234.681
2022	11.908	94.183	57053.086	165.990	100551.471	181.130	109722.255	181.233	109784.958
2023	12.086	94.167	57893.574	165.797	101931.494	181.357	111498.093	181.354	111495.854
2024	12.263	93.818	58526.073	165.834	103451.439	181.166	113015.695	181.636	113309.073
2025	12.440	94.134	59572.107	165.626	104815.880	181.668	114967.913	182.020	115190.475
2026	12.618	94.052	60368.735	166.193	106673.278	182.007	116824.013	181.916	116765.161
2027	12.795	94.085	61237.692	165.969	108025.274	181.538	118159.320	181.554	118169.541
2028	12.972	94.127	62113.006	166.340	109765.429	181.873	120015.607	181.668	119880.519

Table E3: Cost of Electricity at Airports at varying POD

E.4 Coffee Shop POD Cost Analysis

Year	P (Cents/kWH)	Low POD	C Low POD	Low-Mid POD	C Low-Mid POD	High-Mid POD	C High-Mid POD	High POD	C High POD
2018	10.670	1.861	7070.762	2.888	10975.989	3.279	12461.944	3.362	12777.717
2019	11.375	1.882	7623.673	2.838	11497.210	3.309	13404.933	3.322	13456.474
2020	11.553	1.791	7368.113	2.863	11778.458	3.415	14052.085	3.495	14381.698
2021	11.731	1.929	8061.136	3.004	12549.217	3.472	14507.556	3.525	14726.733
2022	11.908	1.868	7921.768	3.004	12739.349	3.542	15022.698	3.605	15287.842
2023	12.086	1.852	7970.895	3.069	13208.382	3.596	15476.600	3.815	16419.369
2024	12.263	1.930	8428.083	3.188	13923.673	3.769	16463.079	3.723	16259.018
2025	12.440	1.950	8641.926	3.194	14152.556	3.734	16543.222	3.964	17565.005
2026	12.618	1.936	8700.977	3.260	14648.761	3.830	17213.933	3.896	17506.398
2027	12.795	1.926	8778.122	3.237	14751.276	3.773	17194.668	4.054	18475.583
2028	12.972	1.949	9003.672	3.233	14936.382	3.846	17770.019	4.102	18950.906

Table E4: Cost of electricity at Coffee Shops at varying POD

E.5 School POD Cost Analysis

Year	**P(Cents/kWH)**	**Low POD**	**C Low POD**	**Low-Mid POD**	**C Low-Mid POD**	**High-Mid POD**	**C High-Mid POD**	**High POD**	**C High POD**
2018	10.670	31.189	86541.061	63.044	174929.515	94.587	262454.729	119.202	330752.837
2019	11.375	31.300	92587.186	62.762	185654.032	93.931	277853.896	119.036	352117.327
2020	11.553	31.230	93824.145	62.522	187833.755	94.636	284316.495	120.086	360775.643
2021	11.731	31.426	95866.410	62.304	190060.976	94.683	288832.873	121.501	370640.504
2022	11.908	30.957	95863.907	62.844	194609.176	94.619	293008.656	123.210	381546.973
2023	12.086	31.095	97727.882	62.362	195997.434	94.094	295725.196	123.060	386761.206
2024	12.263	31.030	98955.193	62.583	199579.968	94.522	301433.824	122.596	390962.793
2025	12.440	31.145	100757.086	62.137	201023.020	94.543	305860.914	120.761	390677.702
2026	12.618	31.561	103558.036	63.053	206891.972	93.600	307123.123	120.196	394391.359
2027	12.795	31.389	104441.328	62.580	208224.619	93.880	312368.994	119.260	396815.936
2028	12.972	31.420	105990.557	62.567	211060.962	94.313	318153.062	118.076	398314.597

Table E5: Cost of electricity at Schools at varying POD

F Capacity Derivations

For Airports, we found an average of 40.2 enplanements, the number of people boarding flights, per departure.

Since every departure is at a gate, the gate can hold at least 40.2 people. Using the 36 ft^2 per seat rule, each gate is approximately 1447.2 ft^2. Given that the average number of gates per airport was calculated as 67.4, an average airport is determined to be 97,541 ft^2.

For Coffee Shops, we found statistics detailing the average attendance of coffee shops to be 68 people per day (Insert Citation).

For Railway stations, we estimate the average visitors based on official statistics of Amtrak stations and platforms across the nation. Using 1647 m^2 per platform (CITATION), we found an average railway station size of 2534 m^2, which equates to approximately 70 seats. (Citation)

For Schools, we defined capacity to be equivalent to the number of visitors, since public schools have variable capacity and will accommodate all students necessary to guarantee a right to a free public education.

For Libraries, we found an average size of 21,500 ft^2 for a community library. Using the 1 seat per 36 ft^2 rule, 21,500 ft^2 can comfortably host 600 people (CITATION).

G Agent-based Model NetLogo Code

```
globals [
  visitors
  capacity
  square-footage
  outlets
  nseat-coords
  noccupied
  oseat-coords
  ooccupied
  enter-ticks
  device-list
  device-ps
  device-drains
  device-charges
  device-wattages

  not-charging
  no-capacity
  no-charge
  time-done
  total-laptop-charge-time
  total-mobile-charge-time
  total-tablet-charge-time
  energy-consumption

  run-results
  average
]

turtles-own [
  devices
  init-batts
  per-minute-drains
  per-minute-charges
  curr-charging
  batts
  stay
  charge-times
  remaining-time
  at-outlet
]
```

```
to-report visitor-years [yr]
  report round(68 * ((1 + 0.017) ^ yr))
end

to-report coffee-shop-density [x]
  report ((109.8 - 72.36 * x + 17.47 * x * x - 1.932 * x * x * x + 0.09991 *
end

to initialize-variables
  set visitors visitor-years year
  set square-footage 1000
  set capacity round(square-footage / 36)
  set outlets outlet-density * square-footage
  set device-list ["laptop" "mobile" "tablet"]
  set device-ps [0.73 0.77 0.53]
  set device-drains [0.00476 0.0016666666666666667 0.0016666666666666667]
  set device-charges [0.01641 0.01835 0.0038]
  set device-wattages [65 6 15]
  set total-laptop-charge-time 0
  set total-mobile-charge-time 0
  set total-tablet-charge-time 0
  set not-charging 0
  set no-capacity 0
  set no-charge 0
  set time-done 0
  set energy-consumption 0
end

to setup-world
  resize-world 0 40 0 40
  ask patches [set pcolor 38]
  let xy 0
  repeat max-pxcor + 1 [
    crt 1 [setxy xy max-pycor set shape "tile brick" set color red]
    crt 1 [setxy xy 0 set shape "tile brick" set color red]
    crt 1 [setxy max-pxcor xy set shape "tile brick" set color red]
    crt 1 [setxy 0 xy set shape "tile brick" set color red]
    set xy xy + 1
  ]
  ask turtles with [xcor = 0 and (ycor = max-pycor / 2 or ycor = max-pycor
  crt 1 [setxy (max-pxcor / 2 - 5) (max-pycor - 2) set shape "clock" set co
  set nseat-coords []
  set noccupied []
  set oseat-coords []
```

```
  set ooccupied []
  let seats-placed 0
  let seat-x max-pxcor / ((ceiling sqrt capacity) + 1)
  let x-change seat-x
  let seat-y max-pycor / ((ceiling sqrt capacity) + 1)
  let y-change seat-y
  repeat (ceiling sqrt capacity) [
    set seat-y max-pycor / ((ceiling sqrt capacity) + 1)
    repeat (ceiling sqrt capacity) [
      if seats-placed < outlets [
        ask patch int(seat-x) int(seat-y) [set pcolor 65]
        set oseat-coords insert-item (length oseat-coords) (oseat-coords) (
        set ooccupied insert-item (length ooccupied) (ooccupied) (False)
      ]
      if seats-placed >= outlets [
        ask patch int(seat-x) int(seat-y) [set pcolor 95]
        set nseat-coords insert-item (length nseat-coords) (nseat-coords) (
        set noccupied insert-item (length noccupied) (noccupied) (False)
      ]
      set seats-placed seats-placed + 1
      if seats-placed = capacity [stop]
      set seat-y seat-y + y-change
    ]
    set seat-x seat-x + x-change
  ]
end

to setup-turtle
  set size 2
  setxy 0 max-pycor / 2 - 0.5 + random-float 1
  set color 45
  set shape "person"
  let i 0
  set devices []
  set init-batts []
  set per-minute-drains []
  set per-minute-charges []
  set charge-times []
  repeat length device-ps [
     if random-float 1 < item i device-ps [
       set devices insert-item (length devices) (devices) (item i device-li
       set init-batts insert-item (length init-batts) (init-batts) (precisio
       set per-minute-drains insert-item (length per-minute-drains) (per-mi
       set per-minute-charges insert-item (length per-minute-charges) (per-
       set charge-times insert-item (length charge-times) (charge-times) (0
```

```
    ]
    set i i + 1
  ]
  set batts init-batts
  set stay random 67 + random 141
  if not empty? devices [set curr-charging item (position min init-batts in
  set label-color white
  set label (word batts ", " remaining-time)
end

to setup
  clear-all
  initialize-variables
  setup-world
  let people-per-30 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
  let i 0
  repeat 48 [
    if i >= 11 and i <= 32 [set people-per-30 (replace-item (i) (people-per-
    set i i + 1
  ]
  set enter-ticks []
  set i 0
  repeat length people-per-30 [
    repeat item i people-per-30 [
      set enter-ticks lput ((i * 30) + random 29) enter-ticks
    ]
    set i i + 1
  ]
  reset-ticks
  ask patch (max-pxcor / 2) (max-pycor - 2) [set plabel-color red set plabe
end

to find-seat
  if member? False ooccupied [
    move-to patch (item 0 item (position False ooccupied) oseat-coords) (ite
    set ooccupied (replace-item (position False ooccupied) ooccupied True)
    set at-outlet True
    set remaining-time stay
    stop
  ]
  if member? False noccupied [
    move-to patch (item 0 item (position False noccupied) nseat-coords) (ite
    set noccupied (replace-item (position False noccupied) noccupied True)
    set at-outlet False
    set remaining-time stay
```

```
    stop
  ]
  set no-capacity no-capacity + 1
  die
end

to go
  let ppl-enter length filter [i -> i = ticks] enter-ticks
  crt ppl-enter [setup-turtle]
  ask turtles with [shape = "person" and length devices = 0] [set not-charg
  ask turtles with [shape = "person" and xcor = 0] [find-seat]
  ask turtles with [shape = "person"] [set batts (map [ [batt pmd] -> max (
  ask turtles with [shape = "person" and (at-outlet = True and not empty? f
  ask turtles with [shape = "person" and at-outlet = True] [set batts (repla
  ask turtles with [shape = "person"] [set label (word (map [batt -> precisi
  ask turtles with [shape = "person"] [set remaining-time remaining-time -
  ask turtles with [shape = "person" and (remaining-time <= 0 or member? 0
    if member? 0 batts [
      set no-charge no-charge + 1
    ]
    if remaining-time <= 0 [
      set time-done time-done + 1
    ]
    show charge-times
    if member? "laptop" devices [
       set total-laptop-charge-time total-laptop-charge-time + first charge-
    ]
    if member? "mobile" devices and member? "laptop" devices [
       set total-mobile-charge-time total-mobile-charge-time + item 1 charge
    ]
    if member? "mobile" devices and not member? "laptop" devices [
       set total-mobile-charge-time total-mobile-charge-time + first charge-
    ]
    if member? "tablet" devices [
       set total-tablet-charge-time total-tablet-charge-time + last charge-
    ]
    if at-outlet = True [
      show (position (list [pxcor] of patch-here [pycor] of patch-here) ose
      set ooccupied (replace-item (position (list [pxcor] of patch-here [py
    ]
    if at-outlet = False [
       set noccupied (replace-item (position (list [pxcor] of patch-here [p
    ]
    die
  ]
```

```
  set energy-consumption total-laptop-charge-time * 60 * first device-wattag
  tick
  ask patch (max-pxcor / 2) (max-pycor - 2) [set plabel (word "Time: " int(
end

to run-one-day
  repeat 1440 [go]
end

to-report run-one-day-report
  repeat 1440 [go]
  report energy-consumption
end

to run-one-day-x-times
  set run-results []
  repeat x-times [
    initialize-variables
    setup-world
    let people-per-30 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
    let i 0
    repeat 48 [
      if i >= 11 and i <= 32 [set people-per-30 (replace-item (i) (people-pe
      set i i + 1
    ]
    set enter-ticks []
    set i 0
    repeat length people-per-30 [
      repeat item i people-per-30 [
        set enter-ticks lput ((i * 30) + random 29) enter-ticks
      ]
      set i i + 1\usepackage{listings}
    ]
    reset-ticks
    ask patch (max-pxcor / 2) (max-pycor - 2) [set plabel-color red set plal
    set run-results lput run-one-day-report run-results
  ]
  set average (sum run-results) / x-times
end
```

H Electric Vehicles Python Simulation Code

```
import numpy as np
import pandas as pd
import random

battery_capacity = 58.8
p = 0.2

def vor(year):
  x = year - 2000
  return 0.1247 *x* x + 0.6053 * x + 5.5952

def num_cars(year):
  x = year - 2000
  return 18590 * x * x - 418483 * x + 2e6

yenergies = []
for yr in range(2018, 2029):
  denergies = []
  for day in range(365):
    cenergies = []
    time = 0
    for i in range(int(num_cars(yr))):
      wattage = np.random.choice([45, 1.44, 9.6], p=[0.149, 0.054, 0.797])
      time += 0.3*battery_capacity/wattage
      if time >= 24:
        break
      cenergies.append(0.3 * battery_capacity * (num_cars(yr)) / (1 * vor(y
    denergies.append(sum(cenergies))
    print(cenergies)
  yenergies.append(sum(denergies))
```