Electric Vehicle Charging Stations Demand and Placement in New York City

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Abstract

Battery-electric vehicles offer a great opportunity to reduce carbon emissions from the transportation sector, but necessitate the installation of additional charging stations to satisfy their need. The number and location of these charging stations must be designed optimally in order to maintain high utilization rates and satisfy the needs of the customers, while accounting for the impact imposed on the local electrical distribution network. Furthermore, different standards for charging stations have been implemented all around the world which calls for a unified standard that account for charging speeds and the convenience of the user, while minimizing costs in grid upgrades and addition infrastructures. In this project, we predicted the future power demand and energy depleted of electric vehicles system under consideration using the Average, AutoRegressive with eXogenous inputs (ARX) and Neural Network models. And computed their accuracy and reliability for future use. We analyzed the effect of the charging time and frequency of the electric vehicles on the power demand and battery capacity requirement. The placement of electric vehicle charging stations to maximize utilization rate while keeping in mind the costs incurred by the electric vehicle owners and the city administration in charge of constructing the stations. We use the same model-based approach to identify a standard charging times best suited to meeting driver needs while avoiding grid overload. Our results provide insight on determining parking facilities suitable for implementing charging infrastructure as well as insight on charging demand induced from a hypothetical fleet of shared, autonomous, electric vehicles (SAEVs) in New York City. Our findings show a direct tradeoff between charger infrastructure costs and vehicle battery costs, as well as more complex interactions between the frequency of vehicle charging and the burden on the electrical grid.

Introduction

Motivation and Background

Electric vehicles (EVs) are one of the major technologies that dominated the modernization of the transportation sector. The increasing popularity of battery-electric vehicles offers an opportunity to reduce emissions produced by the transportation sector. It also ensures higher energy efficiency and reduced user cost, making it the focus of many researchers. One of the key issues in the utilization of electric vehicles is the availability and accessibility of charging stations. Thus, the optimization of electric vehicle charging stations is a very attractive subject. In addition to the importance of the problem, this topic serves as an intersection between infrastructure-scale energy systems and personal transportation. Thus, this topic allows each group member to practice what has been taught in class while making use of skills cultivated in other classes and projects.

Charging is a much slower process than gas filling. Furthermore, the size of batteries in EVs have been reduced to avoid excessive weight and cost, limiting battery capacity. This can cause charging delay and discomfort for EV drivers. As a result, much work is needed in the design and implementation of charging stations.

The placement of these stations is critical to electric vehicles gaining wider acceptance among drivers. Despite the increasing range of newer battery-electric vehicles (BEVs), "range anxiety" is still a concern for potential buyers. Furthermore, large numbers of charging electric vehicles could risk overloading the local electrical grid. While this risk can be mitigated through assigning dedicated distribution lines or by upgrading local infrastructure, both of these solutions add to the cost of the charging station. Proper placement of electric vehicle chargers must account for both of these issues, while accommodating local and commuting users. Finally, competing standards for fast-chargers also create obstacles for would-be drivers. Faster chargers allow drivers to charge faster but impose a greater load on the electrical grid.

To be considered satisfactory, the design and installation of these charging stations must answer the following questions:

1. What is the number and location of charging stations needed to address the demand? This must also consider differences in battery capacity between EV models.
2. What are the effects of the charging stop times on the power demand and battery capacity of electric vehicles? Which limiting factors that will govern the system? A few models will be used to predict the power demand are and energy depleted so the investigation of the analysis of which model is the best one for a given purpose is also a very important aspect of this project.

This report provides a solution for the above questions and also gives an insight for the effects of vehicle battery capacity and rated power of chargers on the placement of the charging stations.

Literature Review

The topic of understanding EV charging demand and planning infrastructure has been actively researched over the past decade. Public fleets such as buses and taxis are likely to adopt vehicle electrification early.[1] For example, the city of Shenzhen completely electrified its public buses before the end of 2017 and 99 percent of taxis in the city are powered by batteries as of early 2019.[2] Several works model fleets of Shared Autonomous Electric Vehicles (SAEVs)[3,4], while others model traditional taxi fleets with either Battery-Electric Vehicles (BEVs)[5] or Plug-in Hybrid Electric Vehicles (PHEVs)[6]. Our study assumes an SAEV fleet for modeling charging demand.

Two main approaches are typically used in modeling charging demand: computational geometry-based approach[5,6,7] and origin-destination flow-based approach[8,9]. With the computational geometry-based approach, charging demand can be estimated using real vehicle trajectory, simulated vehicle trajectory, or statistics from population density data and travel surveys. Origin-destination flow-based approaches consider EVs' driving range constraints in transportation networks.

Integration of public charging infrastructure typically has two forms: gas-station-based[6] and parking-facility-based[4]. Arguments can be made that gas-station-based infrastructure has benefits in that it is a familiar concept, may help reduce "range anxiety", and as EV integration increases, the decrease in Internal Combustion Engine vehicles (ICEV) at gas-stations can be offset by EV charging, thus keeping utilization rates of these public infrastructure resources at a reasonable level.[6] The downside to gas-station-based charging infrastructure is that charging may take up to hours and customers can't be expected to wait this long at a non-ideal location. Parking-facility-based public charging infrastructure has the benefit that charging can be done while a car is parked somewhere it may have been regardless, though parking fees may cost more than that of electricity used for charging.[6]

Focus of the study

In this project, we will use several models to determine the time and location of the charging demand. Using this output, we will optimize the placement of electric vehicle charging stations to increase their use, while maintaining realistic constraints. Finally, we will predict the impact of this network of charging station on the local electrical distribution grid and vehicle battery sizes.

Data Processing

In order to train and test our models we used an open source dataset on the famous yellow taxis of NYC, aggregating more than 15 million trips by 13,500 vehicles over a month. We were able to individually identify the behavior of each car by grouping the dataset by car .

The issue we ran into is that unlike our autonomous electric vehicle fleet, a traditional taxi does not work 24/7 and has to go home once in a while. Luckily, the dataset only compiles the trips where a fee was paid. Therefore, the trip to head home is not present to bias the data and we just see that the car stopped serving customers for 8 to 10 hours, sometimes more. The trips present in the dataset are therefore still representative of the behavior of taxi customers in NYC (places and times of departure and arrival). The problem is that we are looking at stop times and these halts in activity might disrupt our models.

In order to reconcile this we made an assumption moving forward that can only be applied to cities like NYC: a developed nightlife and the fact that a taxi driver can be found day and night shows two things. First, although drivers have to sleep, the taxi service overall is always delivered 24/7. Secondly, the taxi market knows its customers well and a decrease in service indicates a corresponding decrease in demand. Otherwise, an unmet demand would be supplied by enterprising taxi drivers. Thus, that these stops of 8 to 10 hours or more are justified by a fall in demand and if aggregated the number of taxis in service at any given time would correspond to the demand for the service.

After cleaning up the dataset of quirks and GPS errors we built 4 datasets based on this one depending on the duration of a vehicle stop. In order to study the impact on the electrical grid we need to know how often cars charge and that depends a lot on the cars used. We modelled with the following assumption: cars return to an optimal charging station (close to local demand) after dropping off each passenger. If the car reaches the station it would start charging immediately while waiting for an order. If it gets an order before that it would check if it had enough battery to make the trip, accept the offer and change course without charging. Cars with smaller batteries would be cheaper for the operator to buy but expensive for the city; more charging stations would need to be built because the cars would have to charge more often.

Therefore, we decided to simulate different battery capacity by modelling the fleet behavior if it had to charge every stop longer than 10 minutes, 30 minutes, 1 hour and 3 hours. For all the stops that go beyond the threshold we would aggregate the total distance traveled before that to estimate how much charge a EV with a similar behavior would have lost and therefore needed to charge. Using the stop times and the aggregated distances we were able to move forward with our models. Figure 1 shows a heat map of a sample of taxi stops greater than 10 minutes.

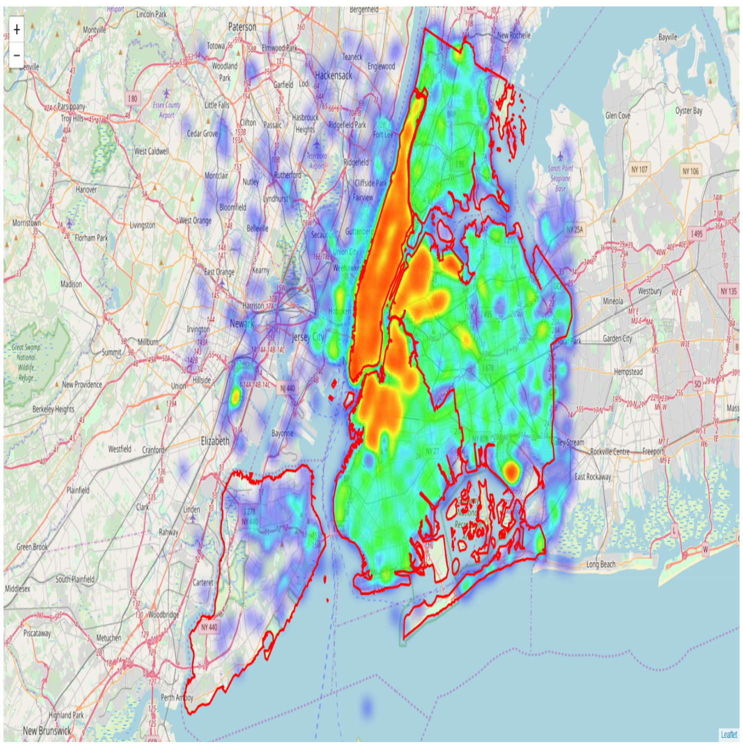

Figure 1. Sample data representing the location the cars stopped more than 10 minutes.

Data on parking facilities in NYC was obtained from NYC Open Data. Included in this dataset are all 1,912 registered parking facilities, their addresses, facility type, and number of spaces. Geocoding was used to find geographic coordinates of each facility and cleaning misidentified facilities from the set resulted in a total of 1,846 parking facilities throughout NYC.

Models

The Average Model

The average model was trained on the first three weeks of data, and tested on the fourth week. For each weekday and hour of day, the values for each week are averaged to produce the average model.

Mathematically, this can be accomplished through the following matrices:

$$\hat{P}_{avg} = \sum_{wd=1}^{7} \sum_{h=1}^{24} \bar{P}_{wd,h} U_{wd,h}(k)$$

Matrix P_bar shows the average values corresponding to each combination of weekday and hour of day, and matrix U is a matrix of ones and zeros where ones correspond to the weekday and hour-of-day indices of interest.

In code, this was instead implemented by iterating through each weekday and hour index with nested for-loops. This produced an average model for each weekday.

The ARX Model

Similar to the other models, for this model we took the first three weeks as training data and the fourth week is used as the sample data for comparison purposes. First, the data is converted into a matrix which is easy to use.

Table 1. Data before converted in to matrix form.

car_ID	stop_lon	stop_lat	start_stop_d	start_stop_tod	end_stop_d	end_stop_tod	prev_trip_dist	prev_trip_t	stop_t	accumulated_dist	energy_depleted	power_demand	weeks	day_of_week	hour_of_day
1	-73.925	40.744	1	9342	1	10248	3.2	707	906.0	14.9	0.864	3.452200	1	1	3
1	-73.919	40.747	1	10755	1	11392	2.9	506	637.0	14.6	0.783	4.460100	1	1	3
1	-73.913	40.748	1	13159	1	14183	5.1	883	1024.0	19.0	1.377	4.864800	1	1	4
1	-73.738	40.731	1	17372	1	42791	16.5	1684	25419.0	37.5	4.455	0.631070	1	1	5
1	-73.862	40.768	1	43806	1	47408	9.6	1015	3602.0	30.6	2.592	2.594200	1	1	13
1	-73.962	40.720	1	62602	1	63304	37.0	1082	702.0	100.8	9.990	51.598000	1	1	18
1	-73.872	40.774	1	64265	1	66519	7.7	960	2254.0	71.5	2.079	3.327900	1	1	18
1	-73.972	40.677	1	67780	1	69900	10.8	1260	2120.0	74.6	2.916	4.963400	1	1	19

The matrix constructed for each week. For example the sum of energy depleted matrix produced can be seen in Table 2.

Table 2. Summed values of the Energy depleted data for every hour of the week days.

	HOD	1	2	3	4	5	6	7
0	1	3157.2261	6753.5449	7669.3144	9488.5398	11006.3637	8732.5128	7836.9741
1	2	5830.8116	3904.0677	5542.6815	6674.1489	10989.6314	10441.5129	6249.2367
2	3	7477.7336	2704.9221	3531.5406	4370.6817	9725.2542	11253.4543	4682.7720
3	4	9902.2284	1786.8897	2281.2273	3201.0444	8561.1330	10914.7230	3693.2706
4	5	10370.9045	2880.5085	2808.2673	3265.4043	7173.9671	9406.3056	3907.7267
5	6	8171.2125	4046.5332	3592.5930	3558.0894	4463.8695	5188.4929	3715.0407
6	7	6939.7830	5578.6158	5125.6233	4987.6291	4552.0947	4404.0109	4950.6957
7	8	6624.6714	7108.9218	6956.7174	6617.0304	4763.8341	4390.6752	6131.0358
8	9	5886.1944	7636.4532	7793.9285	6606.4221	5814.4014	4782.9717	6672.9096
9	10	6010.6807	9622.1470	8633.4147	7972.1523	6206.4306	5379.7932	7110.7794
10	11	6093.2922	9552.6948	8527.5477	8024.5051	6865.8219	6152.0364	7220.4969
11	12	6623.5455	8900.4471	8036.1965	7397.1414	7343.1494	6737.9822	7398.8586
12	13	6662.2365	8603.0559	8050.2017	6828.5160	7254.8865	6868.1250	7019.0901
13	14	7185.5801	8752.2499	8093.1636	6925.4001	7527.4461	7441.7913	7778.2572
14	15	8419.6236	9684.4896	9087.4035	7865.1351	8405.8099	7783.8084	8233.6851
15	16	8597.5911	10095.1863	9141.8736	8746.8259	7944.5421	8616.9123	8839.0224
16	17	7691.8061	8698.5721	7851.6702	7616.4758	6405.6633	8040.1792	8558.3848
17	18	6350.8133	6777.0113	5917.0743	5854.2778	5655.2445	7115.8851	8137.1737
18	19	7188.2424	8543.3913	7264.9737	7221.1530	7380.9248	6915.7285	8558.8677
19	20	8221.6863	10544.2634	8921.4696	7602.6870	7197.1902	8290.2366	9514.3869
20	21	8265.6667	10101.9582	10392.4080	9767.3090	8814.3579	8002.7025	9632.2230
21	22	7650.9630	10556.6058	10797.6024	10161.5366	8118.8109	6704.3322	10147.7153
22	23	8193.7656	11084.1402	11282.5058	9461.9367	7902.2358	7875.9810	10118.8010
23	24	7412.3053	9510.6312	10421.3166	10240.7220	8256.8025	8277.1122	9800.4165

These values in the matrix, for the first two weeks, are used as "Phi" values to train the model. The ARX model is applied after sorting dates in to a proper 'Phi' matrix. This means our 'phi' matrix contains two columns of data which represents data from week one and data from week two of the same day, respectively.

$$Y = \begin{bmatrix} y(1) \\ y(2) \\ \vdots \\ y(k+1) \\ \vdots \\ y(K) \end{bmatrix} \qquad \Phi^T = \begin{bmatrix} --\phi^T(0)-- \\ --\phi^T(1)-- \\ \vdots \\ --\phi^T(k)-- \\ \vdots \\ --\phi^T(K-1)-- \end{bmatrix}$$

In this case, the Y Matrix is the data obtained from the third week of the same day.

We know that:

$Y=\Phi*\theta$

The **Theta** values are calculated using the formula:

After solving for **Theta** and using it to produce graph of the model, and further comparing it to the data from the fourth week we get the following graph.

This model produced an output which is very close the test data with small Mean absolute error which is going to be discussed in the following sections.

Neural Network Model

The simplified neural network model consisted of a single neuron, which uses a weighted function of the previous three hourly values to predict the value for the upcoming hour. The model is described through the following equations:

$$y = f\left(\Sigma_i w_i x_i\right) = f(w^T x)$$

$$\frac{\partial J}{\partial \delta} = \delta, \qquad \frac{\partial \delta}{\partial f} = -1, \qquad \frac{\partial f}{\partial z} = f'(z) = 1 - \tanh^2(z), \qquad \frac{\partial z}{\partial w} = x \in \mathbb{R}^3$$

$$w^{k+1} = w^k - \gamma \sum_{i=1}^{m} \delta^{(i)} \cdot (-1) \cdot f'(z^{(i)}) \cdot x^{(i)}$$

The model is then trained on three weeks of training data, where for each hour, the model uses gradient descent to find the optimal values of w. To improve applicability, the model is designed to be weekday-agnostic; the same values of w are used for each day of the week.
For the sum of energy depleted at 10-minute minimum stop time, these weights were as follows: w1 = 2.2359, w2 = -0.8024, w3 = -0.0930.

Locating Charging Infrastructure

For developing a method on locating charging infrastructure, the taxi dataset was filtered to include only idling instances between 1 and 3 hours. The day with the highest number of these instances was considered for analysis. An algorithm was developed to loop through each idling instance and determine the nearest parking facility. The logic behind this is that a ranking of parking facilities can be determined which may indicate facilities that are the best candidates for implementing charging infrastructure. Table 3 shows a sample of facilities and the number of parking instances nearest a given parking facility. A total of 22,520 idling instances between 1 and 3 hours occured on the day analyzed.

Table 3. Sample of parking facilities in order of most nearby idling instances between 1-3 hours

	Lat	Long	Spaces	Instances	Type	Location
257	40.6413	-73.7781	225	1694.0	Garage - Parking Lot Combo	PARKING COMPANY OF AMERICA AIRPORTS, LLC 130 S...
88	40.7671	-73.8671	259	387.0	Garage - Parking Lot Combo	FIELD LAGUARDIA ASSOCIATES INC DITMARS BOULEVA...
1164	40.7708	-73.8705	139	350.0	Parking Lot	AIR PARK LGA INC DITMARS BOULEVARD 11369
1438	40.7769	-73.874	323	269.0	Parking Lot	PARKING COMPANY OF AMERICA AIRPORTS, LLC GRAND...
242	40.7689	-73.8676	410	190.0	Parking Garage	LAGUARDIA MARRIOTT HOTEL CORP DITMARS BOULEVAR...
828	40.7574	-73.9754	116	180.0	Parking Garage	SWEETS PARKING I, INC. MADISON AVENUE 10022
1477	40.7369	-74.1694	200	176.0	Parking Lot	WELCOME PARKING LIMITED LIABILITY COMPANY 45 A...
812	40.7736	-73.9134	40	137.0	Parking Garage	SYLVAN ELM GARAGE, LLC 59 AVENUE 11373
1359	40.7221	-73.9871	182	111.0	Parking Lot	EDISON NY PARKING LLC LUDLOW STREET 10002
888	40.7133	-73.9584	6	111.0	Parking Lot	INGENITO, FRANK ROEBLING STREET 11211
1716	40.7536	-73.9781	145	105.0	Parking Garage	CENTRAL PARKING SYSTEM OF NEW YORK, INC MADISO...
35	40.7487	-73.9917	210	102.0	Parking Garage	CENTRAL PARKING SYSTEM OF NEW YORK INC 7 AVENU...
1789	40.7518	-73.9755	11	95.0	Parking Lot	MARAND REALTY COMPANY LLC EAST BURNSIDE AVENUE...
1107	40.7613	-73.9255	175	92.0	Parking Lot	T R PARKING STATION INC 31 STREET 11106
640	40.7281	-73.9805	90	92.0	Parking Garage	CITY PARKING LLC EAST 11 STREET 10009
1299	40.7591	-73.9123	50	91.0	Parking Lot	FIORE, GEORGE M 31 AVENUE 11103
643	40.7604	-73.9767	90	91.0	Parking Garage	MODERN PARKING LLC 5 AVENUE 10019
423	40.7853	-73.9531	74	91.0	Parking Garage	MAJESTIC CAR PARK, LLC PARK AVENUE 10128
162	40.7771	-73.9769	176	91.0	Parking Garage	15 WEST 72ND ST CORP WEST 72 STREET 10023
682	40.7571	-73.9718	200	85.0	Parking Garage	METROPOLITAN 51 PARKING, LLC LEXINGTON AVENUE ...

Discussion

Comparison of Models

All three models were trained and tested on the same data: energy depleted before each stop, for the case where vehicles begin charging at every stop 10 minutes or longer. The energy for each vehicle that stopped in the same hour was aggregated, producing hourly data for the total amount of energy that needed to be recharged during stops that hour. The mean absolute error (MAE) for each day of week is show in Table 4, along with plots from Sunday in Figure 2.

Table 4. MAE for each day of the week

Weekday	**Sun**	**Mon**	**Tues**	**Wed**	**Thurs**	**Fri**	**Sat**	**Week MAE**
Average Model	0.0303	0.0513	0.0635	0.0614	0.0809	0.0475	0.0710	0.0512
ARX Model	0.0421	0.0517	0.0315	0.0401	0.0804	0.0540	0.0811	0.0544
Neural Network	0.0612	0.0638	0.0776	0.0774	0.0734	0.0648	0.0739	0.0703

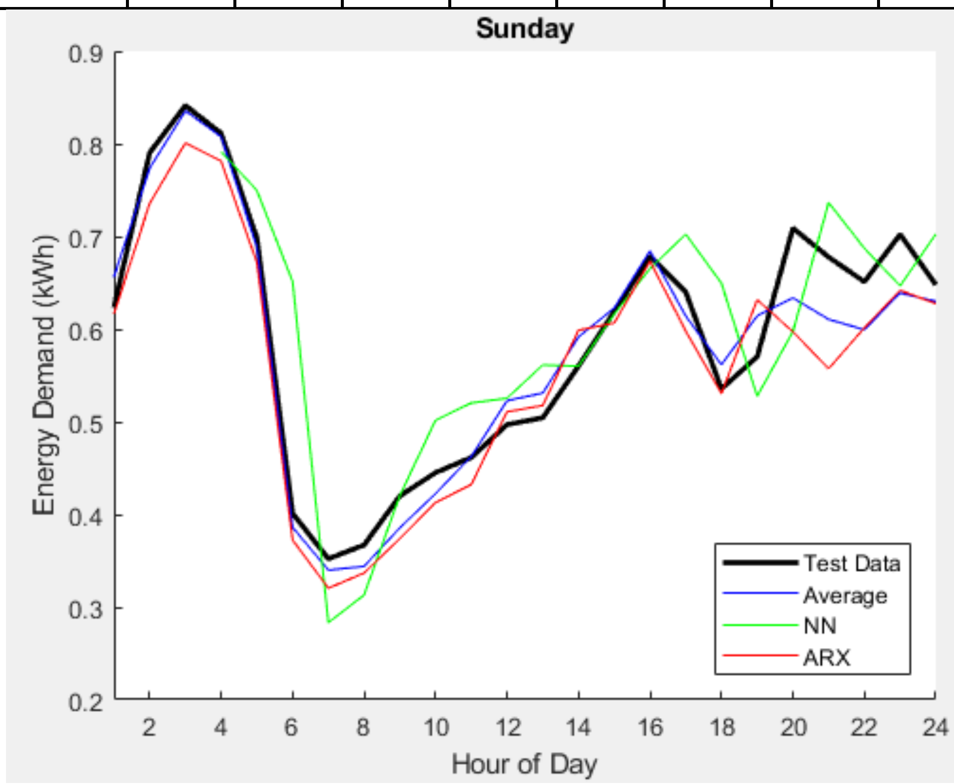

Figure 2. Plot of all model MAE for Sunday

Overall, the average model performed best by MAE, followed by the ARX model. The plot for Sunday serves as a good explanation for this phenomenon: the average and ARX models tend to follow the test data fairly closely, but the neural network tends to lag behind changes in the test data.

Given these trends, the average model is best suited for making long-term projections, such as the total energy demand for a day. It requires less training data, and the relative regularity and “cleanness” of the data itself helps to increase its accuracy. The ARX model was generally better at following the contours of the model, making it more suited for situations where the magnitude of individual peaks may matter more. For example, the ARX model could be employed for next-day forecasts of maximum charging energy demand. Both the ARX and neural network model could benefit significantly from access to additional training data; this is a good opportunity for future exploration.

Implications for fleet and grid

The length of charging stops has a significant impact on the vehicle composition of the taxi fleet. Vehicles are able to find more frequent opportunities to stop for 10 minutes or longer; by charging more often, they can complete their short trips between charges with smaller battery capacity. Conversely, stops of longer duration occur less frequently; vehicles which can only charge during longer stops require larger batteries to complete the longer stretches between charging stops.

By sorting the energy consumed between individual charging stops for each dataset and plotting, the relationship between energy consumed and number of trips becomes visible; most trips consume less than a set amount of energy, with a few outliers requiring large amounts of energy to complete the trip. These results are plotted in Figure 3, with dashed lines showing battery capacities which would allow for the completion of the vast majority of individual trips in that dataset. These dashed lines were visually placed to capture the vast majority of trips without wasting battery capacity trying to capture all of the outliers. Almost all trips which occur between 10-minute charging stops can completed with a 10 kWh battery capacity, trips between 30-minute charging stops can be completed with a 15 kWh battery capacity, trips between 1-hour charging stops can be completed with a 25 kWh battery pack, and trips between 3-hour charging stops can be completed with a 40 kWh battery pack. Increasing battery capacity beyond these values will help capture additional outliers, but will grant vastly diminishing returns; outlier trip lengths may be best captured by a few internal combustion engine vehicles.

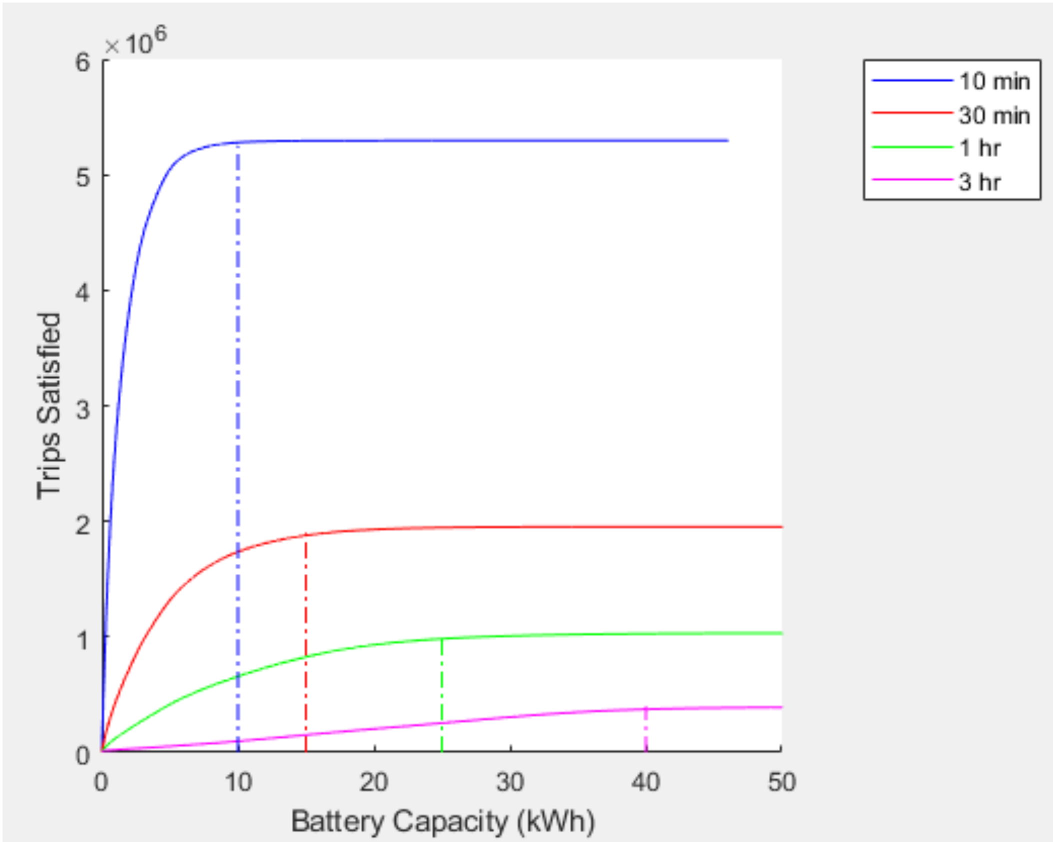

Figure 3. Battery capacity requirements

This also presents requirements for the chargers installed. Our problem setup assumed that the charging stops would be sufficient to keep battery SOC at near-unity. Given the 5-minute non-charging delay built into every charging stop and the amount of energy that must be rechargeable during the stop to allow for continuous driving until the next stop, we can calculate the maximum charger power needed to satisfy these conditions from dividing maximum energy demand by minimum charging time. This is summarized in Table 5.

Table 5. Charger power needed to satisfy assumptions

Minimum Stopping Time	**10 minutes**	**30 minutes**	**1 hour**	**3 hours**
Maximum Energy Demand	10 kWh	15 kWh	25 kWh	40 kWh
Minimum Charging Time	5 minutes	25 minutes	55 minutes	175 minutes
Maximum Charger Power	120 kW	36 kW	27.3 kW	13.7 kW

Furthermore, the total energy demands on the city's power grid can be visualized by aggregating the energy demanded for every stop in that hour. This results in a matrix of total energy consumption per hour, for each hour of day, weekday, and week. Tuesday of Week 4 has been plotted in Figure 4 as a demonstration.

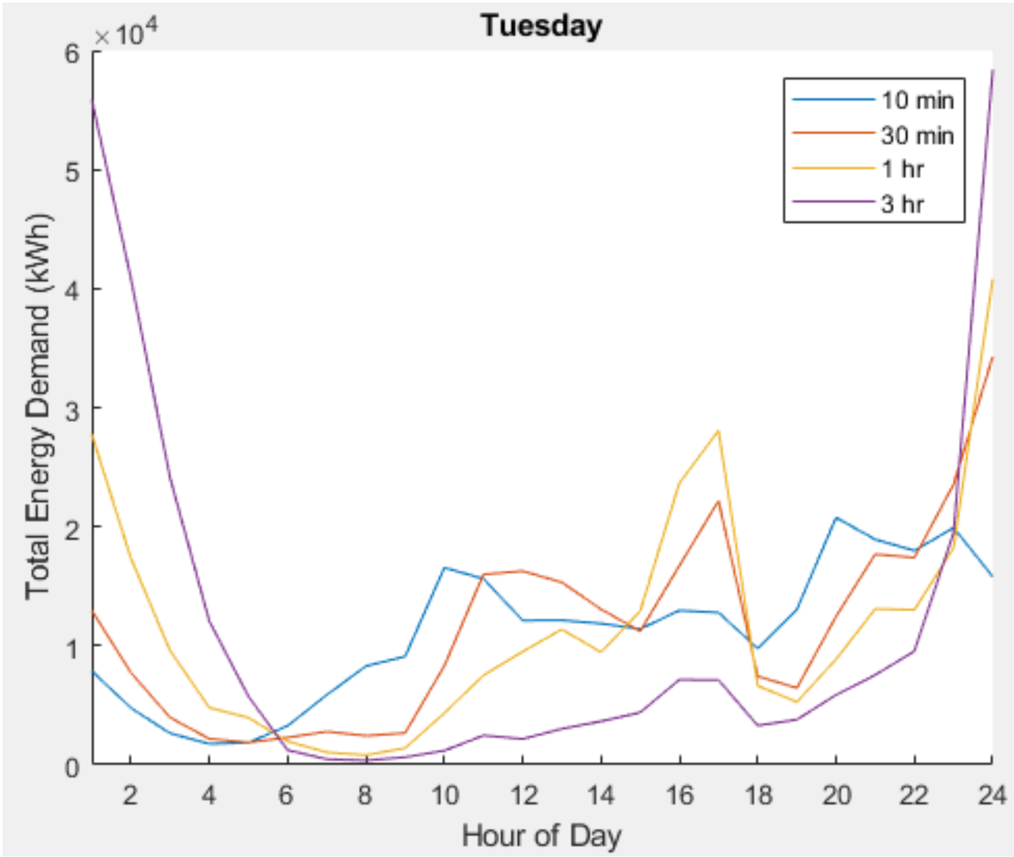

Figure 4.

The total energy demanded over the course of the day is consistent between each of the 4 datasets, because the total distance driven between stops is the same. There is a 5% max difference between the integrals of total energy demand over the whole day, likely due to small errors in aggregation. However, the energy demand shapes are different for each length of charging stop, and are dictated by the natural stopping times of taxis. Taxis naturally perform more 10-minute (or longer) stops during the day and early evening, thus they will demand more energy during those times by charging during their short stops. Conversely, taxis rarely stop for 3 hours (or longer) except overnight; this is illustrated by their energy demand, which would peak overnight if taxis were only permitted to charge while stopped for 3 hours or longer.

Finally, the total number of charging stops in each hour can be aggregated and plotted in Figure 5 to visualize the number of chargers that must be installed to meet demand.

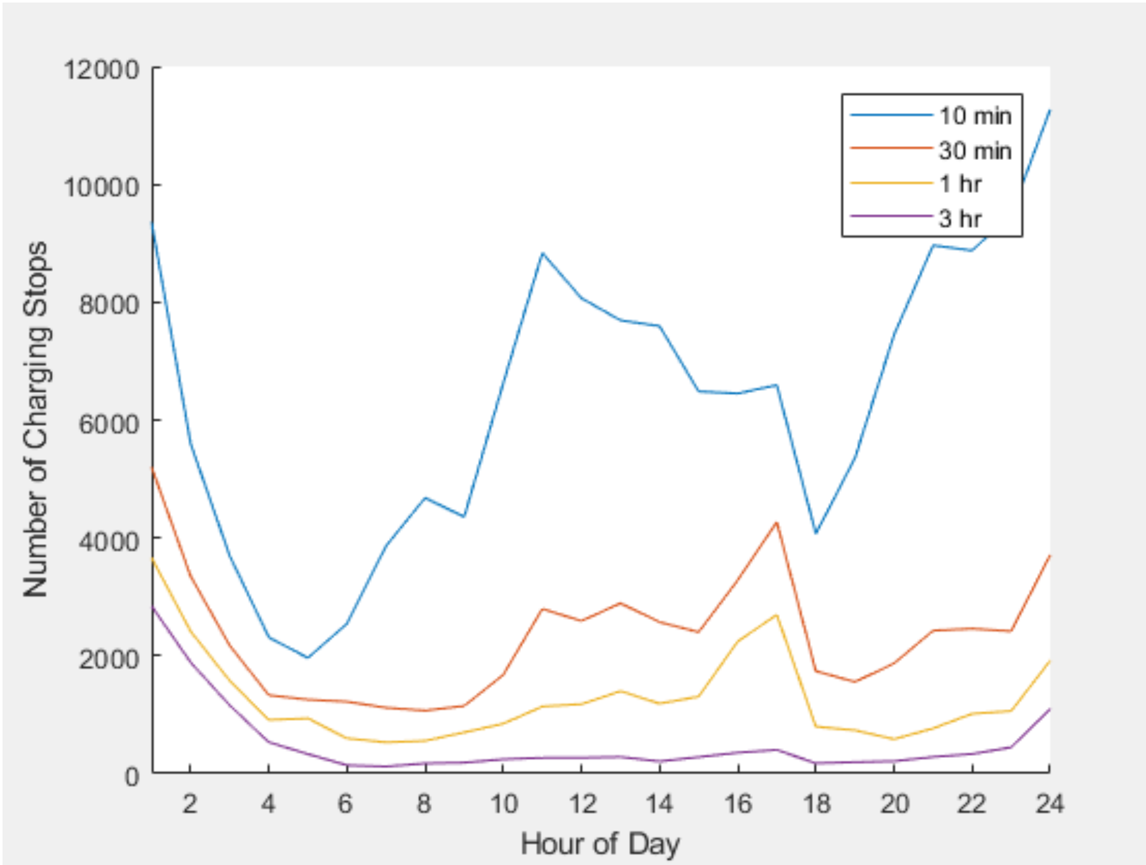

Figure 5.

The information in Figures 3, 4, and 5, and Table 5 allow us to generalize four options for the city's management of fleet charging, with trade-offs for each option. The first option is to install sufficient chargers to allow taxis to recharge every time they stop for 10 minutes or longer. Figure 5 and Table 5 show that this requires the city to install the highest quantity and fastest type of chargers to satisfy demand, which increases infrastructure costs for the city. However, this reduces the size of battery required for the fleet vehicles to complete their relatively short drives in between charging stops, which reduces costs for the fleet operator. Finally, Figure 4 shows that the energy demand shape caused by charging vehicles will be relatively flat, which may reduce line loads and ramping costs for the utility grid.

On the opposite end of the spectrum, the city can install a fewer number of slow chargers, such that fleet vehicles can only realistically charge when stopped for a period of 3 hours or longer. This combination of smaller quantity and lower charger power demand means that the city can spend the least on chargers. However, the more infrequent charging stops requires the fleet to invest in vehicles with larger batteries to endure the longer trips between charging stops, increasing vehicle costs for the fleet operator. Stops of 3 hours or longer primarily occur overnight; charging only during these stops would create the most extreme peak seen in Figure 4. However, the overnight timing of this peak may be advantageous for grid ramping costs if it does not coincide with daytime peaks caused by other users of electricity. The other options (enough chargers to charge when stopped for 30 minutes or 1 hour) result in costs between these extremes.

With these options, the city has enough information to perform cost-benefit analyses between charger infrastructure costs, electrical grid ramping costs, and burden on the vehicle operator. Ultimately, this will allow the city to make a more informed decision in charger installation and therefore facilitate the use of battery-powered vehicle fleets in reducing greenhouse gas emissions.

Locating Charging Infrastructure

There are several issues with the methods used in ranking parking facilities for their potential to implement charging facilities and with the idea of parking-facility-based charging infrastructure in general. The issue of costliness of parking in facilities is not considered - NYC has the highest parking costs in the US, without considering the added cost of charging[10]. Ideally, a future fleet of EV taxis may have priority to park in facilities at low or no parking cost, but rather the main cost incurred would come from charging fees. Another issue with parking-facility-based charging is that the availability of spaces will be difficult to guarantee in private parking facilities. For this analysis, the issue of who is using these facilities and when is not considered.

As for issues in the facility ranking model, by only considering one day of data, a bias may occur if this day had any special event which placed parking instances in a certain area. This bias can be avoided by expanding the analysis over many more days. Another issue that may result from the methods used is that parking facilities that have many nearby taxi idling instances may be favored by the algorithm, and other facilities just slightly further away may be disregarded even though they can be just as suitable. To address this problem, the algorithm for ranking facilities must be improved, perhaps to increase the rank of all facilities within a specified distance of an idling instance.

The reason 1 to 3 hours of idling instances are considered is that this is assumed to be a typical amount of time that EV taxis may spend charging. This is only an assumption and the model may improve if other lengths of stops are considered. The algorithm developed for parking facility ranking is just a framework for developing methods for siting charging infrastructure. The idea is that parking facilities nearby popular idling locations may be suitable candidates for integrating charging infrastructure, and the goal is to gain insight on where infrastructure may best be located in facilities that are already built and designed for storing vehicles.

Future Work

Our analysis does not look into the environmental impacts of implementing charging infrastructure, nor do we quantify the costs associated. Further work on these issues will greatly benefit this analysis. Secondly, the charging infrastructure location modeling was not directly influenced by our charging demand modeling. Future works can be improved by integrating charging demand found in our models with a spatial aspect and parking facility capacities.

Furthermore, the accuracy of our ARX and neural network models was limited by the small amount of available training data. Processing more weeks of data would take an excessive amount of computing time; future works could instead process a representative or random sample of the cars to include more weeks of data without lengthening the processing time.

Finally, future projects could model the number of simultaneous stops to calculate peak power demand.

Summary

The results of our project suggest that the increase in frequency and length of the charging stops greatly affects the power demand and battery capacity requirement of our vehicles. When the frequency of charging is increased the vehicles consume a lot less power leading to smaller battery sizes and when we have lesser frequency of charging the vehicles demand a lot higher power to compete a trip of approximately equal length. Thus, they require larger battery capacity and longer charging times. The trends captured while processing the data also suggest that the outlier areas are best captured by Vehicles using higher battery capacity or using internal combustion engine. This also alternatively can be solved by constructing more charging stations in those areas.

Furthermore, more frequent charging creates flatter energy demand curves, though their daytime placement may coincide with demand peaks caused by non-EV users. Very infrequent charging results in an extremely high overnight peak, which could be beneficial if offset from daytime peaks caused by non-EV users. As a result, the net cost or benefit for the electrical grid requires further analysis of electricity demand by non-EV users, or time-of-use electricity rates for NYC.

The inverse relationship between charger availability and required vehicle battery capacity represents a direct tradeoff in costs between city charger infrastructure and fleet vehicle ownership. Combined with the unclear net impact on the grid of flatter daytime energy demand vs. extreme overnight peak demand, the results of this report allow a city to begin considering trade-offs while suggesting avenues for further exploration. Ultimately, this will help cities like New York City optimize the use of electric vehicles in reducing emissions.

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