

# A Study on the Battery Size and Optimal Charging Schedule of Electric Taxicabs in New York City

## CE295 Final Project Report

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### I. ABSTRACT

The project uses data on the daily trip distribution of New York City taxicabs to study how the taxicab operator would be affected if the current diesel powered yellow cabs (GV) were substituted by electric vehicles (EV). Initially, it carries out a preliminary statistical analysis to identify trends in the operating patterns of NYC taxicabs for specific days. It then identifies an optimal battery size for a hypothetical NYC electric taxi. Finally, a charging schedule optimization problem is solved in order to understand how much operation time a NYC taxicab operator would lose as a result of a transition to an all-electric fleet.

### II. INTRODUCTION

#### A. Motivation and Background

This study is motivated by the increased awareness that both policy-makers and industry leaders are showing with regard to electrified transportation. Policy makers have a strong incentive to further the creation of clean and safe urban environments, and electrified transportation is a very important milestone towards achieving that ideal due to the potential it has to improve quality of life in cities. [cleanairworld.org](http://cleanairworld.org) estimates that between 50 and 90 percent of air pollutants in urban areas are directly attributable to combustion engines in vehicles (the exact amount depends on the pollutant in question). Gasoline powered surface vehicles are also responsible for 85 percent of environmental noise [1], and contribute noticeably to loss of urban visibility in many climates. The importance of stimulating electric vehicle adoption is therefore clear. However, it is only with the recently improved understanding of the effects of policy on EV development that the technology has grown enough to make its large scale implementation a reality. The first successful pro-EV policy, as far as the US is concerned, was the 1990 California Zero-Emission Vehicle Program, mandated by CARB [2]. It was a unique piece of legislation because it targeted the introduction of electric vehicles through the coupling of a zero emissions standard with a sales mandate to automakers. It set the trend

for future policy work, and caught the notice of automakers that were seeking to enter what was essentially a new market. Interest is now growing in areas that span beyond personal-use vehicles, particularly in transportation for hire such as taxicabs, where there is a compelling possibility to employ EV's. Exactly this "possibility" is what motivates this research project. The question of whether an individual driver should purchase an EV is a highly subjective one down to his own set of preferences and lifestyle choices. However, when the perspective of a transport-for-hire system is sought, a broader societal question is raised as to whether the public needs these systems to actively benefit it from a pollution mitigation point of view. The answer to this question is partly to do with whether or not EVs make financial and logistical sense in those systems when compared to the conventional alternative. This paper seeks to determine whether the technology has progressed to the point that there can be some financial and not solely idealistic incentive for the switch to electric in the world of taxicabs and vehicles-for-hire. The basis of this analysis will be the available NYC taxicab data and the taxicab fact book issued by NYC government.

#### B. Relevant Literature

To perform a statistical analysis on the NYC taxicab data, we need general background information on the current state of NYC taxicab industry, such as the type of vehicles used for taxicabs, taxicab fares, and daily trip distributions [3] to identify patterns. To create an electric vehicle operating model, we need to investigate battery properties such as battery size, charging time [4], and corresponding vehicle ranges [5]. To compare the passenger carrying time and number of trip completion upon switching to electric taxicabs from combustion engine powered taxicabs, studies on optimal design and cost implications of electric vehicle taxicab systems [6], and information on sustainable mobility of electric taxicab fleets in metropolitan area [7] are required.

For potential further study on advanced EV operation time modeling, we need average daily or hourly representative traffic data in NYC from the New York State Department of

Transportation to carry out the dynamic analysis. For optimizing charging station locations to facilitate electric taxicab charging, information on how to make site selections for charging stations, such as location optimization based on Game Theory [8], identification of electric taxicab radii [9], and charging station site selection based on big-data travel patterns [10] provides insight. This work does not incorporate an analysis of electricity prices in the context of taxicab-charging optimization, but a reference is provided nonetheless as there is scope for future work. Below is the complete list of reference categories:

- Background on current NYC taxicab industry [3]
- EV battery behavior [4][5]
- Monetary/op-time changes when taxicabs switches from gasoline to electric [6] [7] [11]
- Site selection for charging stations [8] [9] [10]
- Electric vehicle range loss in traffic [12][13]
- Electric vehicle ranges, prices and other specifications [14][15]
- NYC electricity price data [16]
- NYC traffic data [17]

### C. Focus of the Study

We have identified that there exists a drive to replace traditional gasoline-fueled taxicabs (GV) with EVs in order to reduce criteria air pollutant emissions in urban areas. This study makes use of a thorough data set made available by the New York City Taxi & Limousine Commission that contains never before seen trip details which make a switch to EV evaluation possible. The focus of this study is to optimize the charging cycle of New York City taxicabs with a goal of minimizing downtime and to compare the EV scenario to the current petrol vehicle scenario. This will enable potential policymakers and taxicab operators to gauge the feasibility of implementing EV taxicabs, assuming the existence of a reasonably developed charging infrastructure. The technical description deals with three main analysis: 1) a broad statistical analysis of NYC taxicab patterns; 2) the investigation of trip completion percentage as a function of battery size; 3) the optimization of charging schedules.

## III. TECHNICAL DESCRIPTION

### A. Data Processing

The data set used for this project was obtained through a Freedom of Information Law (FOIL) request sent to the New York City Taxi & Limousine Commission (NYCT&L). This data set contains two categories of data file: trip data and fare data. The trip data files contain information on the origin, destination and duration of taxicab trips, while the fare data files illustrate the fares associated with each trip. There are 10 data files for each category, spanning a period of four years between 2010-2013 and organized by both year and month. In this project we have focused on the trip data. A representative spread of data throughout the entire year would be desirable to analyse, given that it would account for changing mobility

patterns due to seasonal and weather effects. However, due to the project deadline constraint and with each data file being numerous gigabytes in size, we have elected to focus only on one trip data file and its corresponding fare data file to minimize the computational effort.

Within the selected data file, which pertains to trips that occurred almost exclusively in January 2013, three dates have been chosen for investigation: the 2nd of January, the 7th of January and the 15th of January. We are spreading out the risk of selecting a day in which mobility is severely affected by events like sporting events or public holidays. The data processing started with manually breaking up the raw file into 15 sub-files, each less than 100 MB in size, with a custom built parsing code. Then, we developed a code that parses out all of the trip and fare data for the days of interest.

Bearing in mind the goals of this project, the most important attributes of the data are:

- Medallion: a random identifier assigned to a specific vehicle
- Hack license: a taxicab driver identifier
- Pickup and drop-off spatial coordinates for each trip
- Pickup and drop-off time for each trip

### B. Statistical Analysis

Due to our interest in unlocking insights from the wealth of NYC taxicab information that we have at hand, we performed some statistical analysis on data from the three specified dates. We looked at the geographical distribution of pickups and deliveries on the 2nd of January, and investigated the daily distribution of operation time, downtime, and downtime-to-operation-time ratio across a range of 60 taxicabs active within the three examined days (20 from each day).

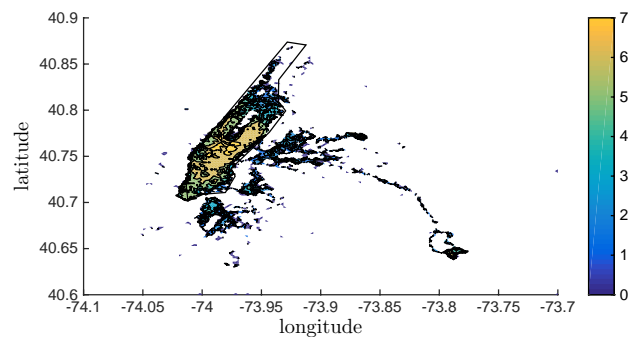


Fig. 1. Heat-map of daily pickup

- Heat-map of daily pickup

Figure 1 is a heat-map illustrating where the most pickups occurred within NYC on the 2nd of January 2013. The colour-bar indicates the logarithm of the number of pickups in a determinate square on the geographical grid. We can treat it as a relative index of pickup intensity. NYC is divided into a 200x200 square grid for the analysis. Each grid square is approximately 200m long.

Figure 2 illustrates a close-up of lower Manhattan with actual pickup locations. The NYC blocks as well as park spaces are visible. It can be appreciated that the most prominent pickup locations are Lower Manhattan and the JFK International Airport corridor.

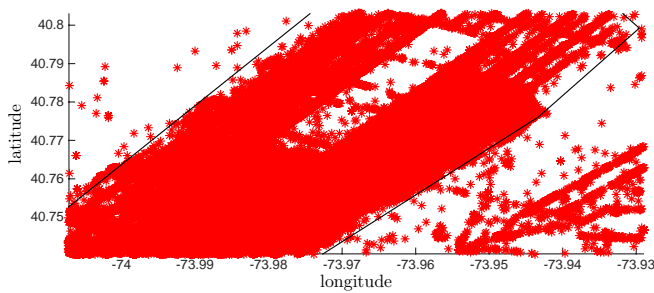


Fig. 2. Close-up of Pickup Locations

- Heat-map of daily drop-off

The drop-off heat-map as shown in Figure 3 and the drop-off distribution shown in Figure 4 shed light on the fact that drop-offs are much more geographically spread-out than pickups with a significant distribution witnessed in the Queens and Brooklyn areas - in particular Brooklyn.

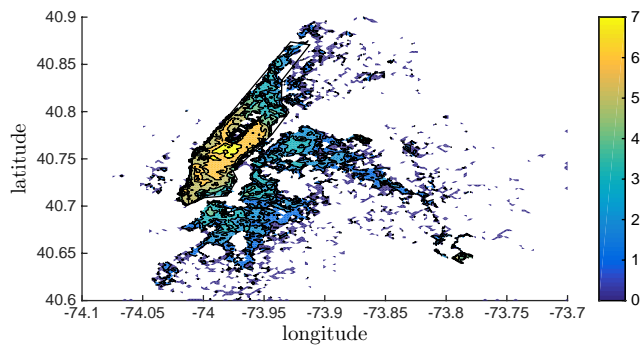


Fig. 3. Heat-map of daily drop-off

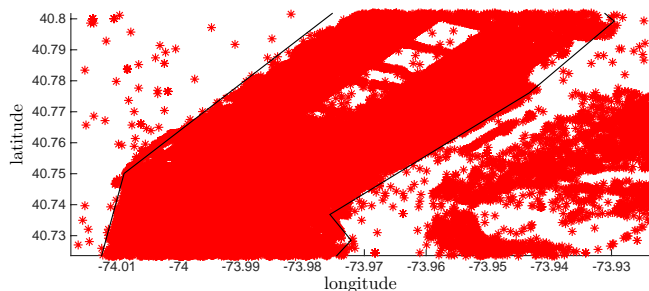


Fig. 4. Close-up of Drop-off Locations

- Distribution of daily operation time across a selection of examined taxicabs

Figure 5 is a histogram that shows the distribution of operation time. The average daily operation time across all 60 examined taxicabs is 7.4 hours with a standard deviation of 1.67 hours.

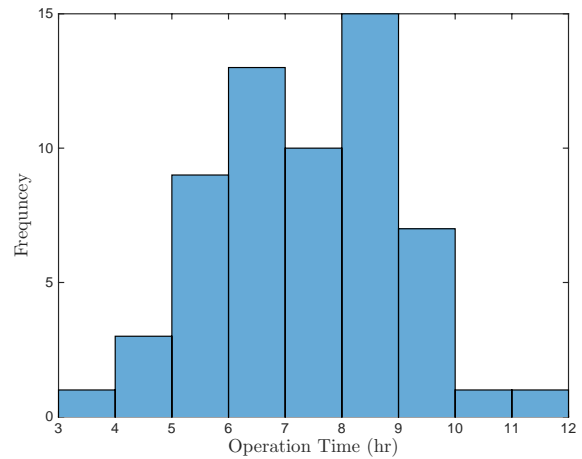


Fig. 5. Distribution of daily operation time across all examined taxicabs

- Distribution of daily downtime across all examined taxicabs:

Figure 6 is a histogram that shows the distribution of downtime. The average daily downtime across all 60 examined taxicabs is 16.6 hours with a standard deviation of 1.67 hours.

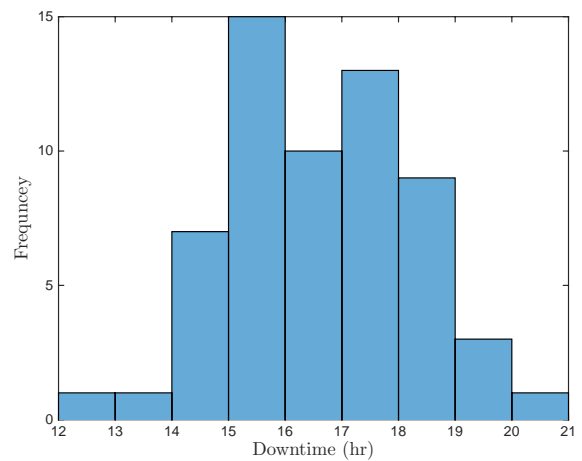


Fig. 6. Distribution of daily downtime across examined taxicabs

- Distribution of the daily ratio of downtime to operation time:

Figure 7 is a histogram that shows the distribution of downtime-to-operation-time ratio. The average daily ratio across all 60 examined taxicabs is 0.46 with a standard deviation of 0.15.

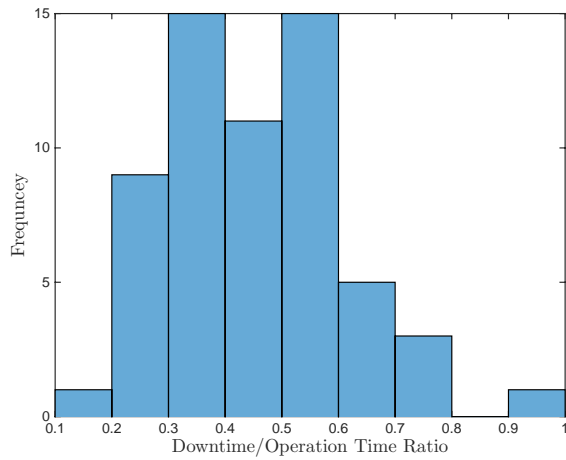


Fig. 7. Distribution of the daily ratio of downtime to operation time

C. Trip Distance Approximation

The distances between the trips carried out by individual taxicabs need to be determined in order to calculate velocity profiles of those taxicabs. They are approximated as straight line distances obtained by projecting the start and finish coordinates of trips on a geodesic surface. A correction factor is needed to magnify each calculated distance because the vehicles travel through NYC streets and not "as the bird flies". We carried out some distance trials on Google Maps to determine how straight line distances compare to effective urban distances to tune the factor appropriately. The correction factor we used is 1.3.

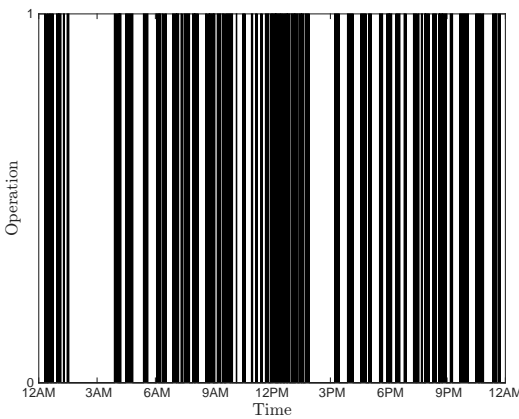


Fig. 8. Sample Operational Profile of a Taxi

D. Daily Operational Profile of Individual Taxicabs

The daily operational profile of a taxicab indicates the times at which the taxicab is carrying a passenger during the day. A sample profile corresponding to medallion B352A440CEAC5B82C18D6ECF37AC6D17 is shown in Figure 8. Zeros indicates "downtime", and ones indicates "passenger carrying time" or "operation time". It can be appreciated that the taxicab is working on a nearly 24 hr cycle since there are multiple drivers (multiple hack licenses) using it.

The following is some daily operation data for medallion B352A440CEAC5B82C18D6ECF37AC6D17 pertaining to 2nd of January:

- Number of Trips: 72
- Total Distance Covered: 398 km
- Longest Trip: 27 km

E. Vehicle Velocity Profile

A taxicab velocity profile illustrates the velocity of the taxicab throughout the course of the day. By using information on trip duration and approximated trip distance, the velocity profile can be calculated between each pickup and drop-off location.

Under the assumption that velocity remains constant within each trip, the velocity profile of a vehicle can be calculated by dividing the approximated trip distance by the trip duration. It must be noted that, although constant within each trip, the overall velocity profile is not constant because different trips naturally involve different velocities. In this sense, velocity is modelled in a manner that is entirely consistent with the data. Figure 9 is an example of a velocity profile that illustrate velocity exclusively during operating time for medallion B352A440CEAC5B82C18D6ECF37AC6D17 on the 2nd of January.

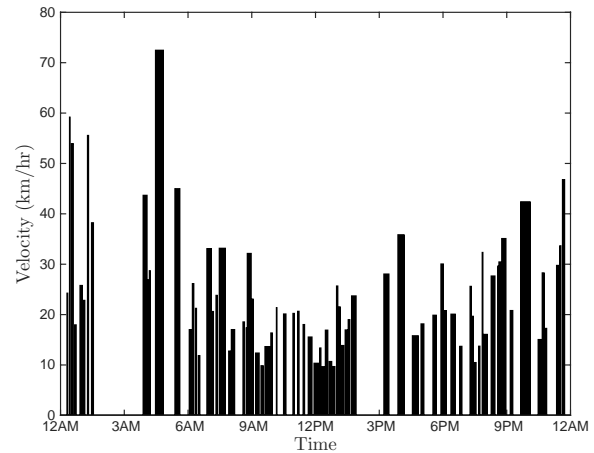


Fig. 9. Sample Velocity Profile of a Taxicab Exclusively during Operating Time

Although relatively slowly, the taxicab moves between a drop-off and a subsequent pickup, and therefore has a velocity. The velocity profile illustrated in Figure 9 is therefore strictly speaking incorrect, because the velocity is zero between drop-offs and subsequent pickups, when in fact the vehicle moves between those two points, and an equivalent EV would therefore lose charge. In light of this, we sought to create more complete velocity profiles that truly capture the way each vehicle behaves throughout the day. The complete velocity profile for medallion B352A440CEAC5B82C18D6ECF37AC6D17 is shown in Figure 10. The velocity profile is discrete because of the constant velocities assumed between coordinates. A



polynomial velocity profile is more realistic and the possibility of using it could be the focus of future work.

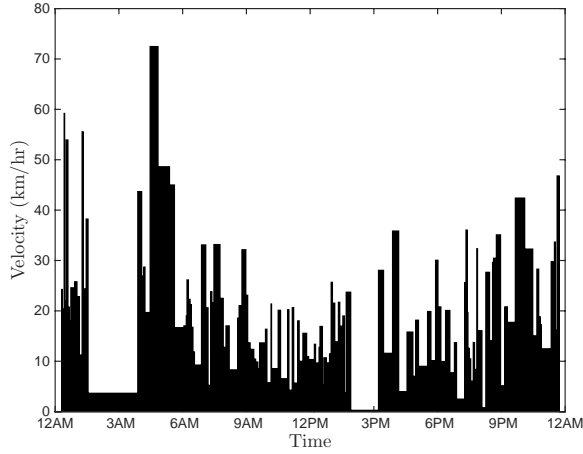


Fig. 10. Sample Velocity Profile of a Taxi

#### F. Vehicle Charging/Discharging Model

A vehicle charging and discharging model is needed to evaluate how an EV might operate in NYC. The model we are using consists of three equations:

Vehicle Discharge:

$$z(k+1) = z(k) - \frac{\Delta t}{E_{max}} P_d(k\Delta t) \quad (1)$$

Vehicle Charge:

$$z(k+1) = z(k) + \frac{\Delta t}{E_{max}} P_c(k\Delta t) \quad (2)$$

Power Demand Evolution [18]:

$$P_d(t) = m \frac{dv}{dt} v + \frac{1}{2} \rho A C_d v^3 + \mu m g v + \frac{b_w v^2}{r_{tire}} \quad (3)$$

where Table I summarizes the vehicle model symbols, definitions, units and representative values.

Symbol	Definition	Units	Value
$z(k)$	State of Charge at Time Step k	n/a	n/a
$\Delta t$	Time Step	s	1
$E_{max}$	Batter Size	kWh	10 - 200
$P_d(t)$	Power Demand	kW	Eqn 3
$P_c(t)$	Power Supply	kW	120
$m$	Vehicle Mass	kg	1300
$v$	Vehicle Velocity	m/s	n/a
$\rho$	Air Density	kg/m <sup>3</sup>	1.225
$A$	Effective Frontal Area	m <sup>2</sup>	1.2
$C_d$	Drag Coefficient	n/a	0.32
$\mu$	Rolling Resistance Coefficient	n/a	0.01
$g$	Gravitational Acceleration	m/s <sup>2</sup>	9.81
$b_w$	Bearing Damping Coefficient	Ns/m	500
$r_{tire}$	Tire Radius	m	0.46

TABLE I  
VEHICLE MODEL PARAMETERS

Notice the bearing damping coefficient  $b_w$  is set to be 500 Ns/m to correct the error due to the assumption of zero

acceleration and constant velocity. We were unable to model the acceleration of taxicabs but the acceleration should have a great contribution to the power demand as shown in Equation 3. Thus, we tuned  $b_w$  in order to result in a reasonable power demand.

#### G. Evaluation of EV Operational Profile and State of Charge

We used the operational profile (Figure 8) and velocity profile (Figure 10) of the medallion B352A440CEAC5B82C18D6ECF37AC6D17 on the 2nd of January as a sample baseline to evaluate the percentage of trips an EV is able to complete. As an example, we used a 50 kWh battery size for the vehicle model and the values used for other parameters are listed in Table I.

The EV is assumed to start the day with state of charge (SOC) of 1 (full charge). The SOC of the EV decreases as long as the EV is moving. In other words, its SOC decreases during operating time and also downtime since the EV moves from its last drop-off location to its new pickup location. The EV continues to follow the operational profile (Figure 8) until its SOC becomes zero. When the EV is out of battery, a charging station is assumed to be available instantly and the EV charges until it is fully charged (SOC = 1) again. During charging, its operational profile no longer follows the baseline operational profile. Zeros replace ones as an indication that operating times are sacrificed during charging. Once the EV is fully charged, it resumes to follow the baseline operational profile. This scheme repeats itself until the end of the day.

The SOC evolution of an EV using Figure 8 as the baseline is shown in Figure 11. A comparison between the operations completed by an EV and the baseline operation is shown in Figure 12. The trip completion percentage is approximately 75.06%. The ultimate purpose of this analysis is to optimize the battery size considering the trip completion percentage as the performance indicator.

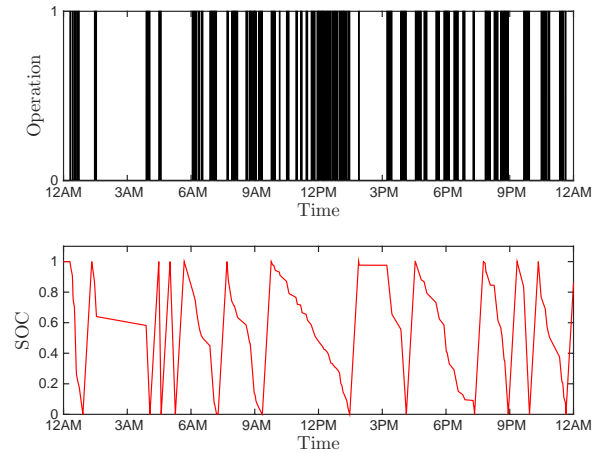


Fig. 11. EV Operational Profile and SOC

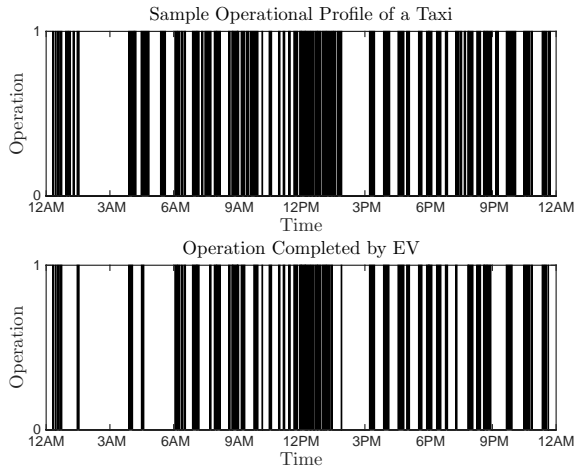


Fig. 12. Comparison of Operational Profiles

### H. Optimal Battery Size

To determine the optimal battery size, we evaluated the trip completion ratio for a range of battery sizes from 10 to 200 kWh with an increment of 10 kWh. We first obtained the operational and velocity profile of 20 random taxicabs for each date. We then applied the charging and discharging model to each EV to determine the trip completion ratios. This gave us 60 trip completion ratio data points for each battery size, which is a total of 1200 data points. A scatter plot is plotted as shown in Figure 13. The data points are wide spread and ranges from 0.6089 to 0.9981 with many outliers for each battery size. One possible reason for this phenomenon is due to the assumption that we made for the charging and discharging model. Since we are forcing the battery to discharge completely before it can be fully charged, the charging time does not always correspond to downtime, which means unnecessary sacrifices in operation time can happen.

A curve is fitted to the scatter plot using least squares. We formulated the equation for a 2nd order polynomial fit as:

$$y = Xa \quad (4)$$

where

$$X = \begin{bmatrix} 1 & x_1 & x_1^2 \\ 1 & x_2 & x_2^2 \\ \vdots & \vdots & \vdots \\ 1 & x_{1200} & x_{1200}^2 \end{bmatrix} \text{ is the battery size variables:}$$

$$x_1 = x_2 = \dots = x_{60} = 10$$

$$x_{61} = x_{62} = \dots = x_{120} = 20$$

$$x_{121} = x_{122} = \dots = x_{180} = 30$$

$$\vdots$$

$$x_{1141} = x_{1142} = \dots = x_{1200} = 200$$

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{1200} \end{bmatrix} \text{ is the trip completion data,}$$

$$a = \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix} \text{ is the polynomial coefficients to identify.}$$

We can solve Equation 4 by

$$a = (X^T X)^{-1} X^T y \quad (5)$$

The fitted 2nd order polynomial is

$$y = 0.7525 + 0.0009x - 2.7285 \times 10^{-6}x^2 \quad (6)$$

and it is plotted in Figure 13 in green. It can be seen that there is a maximum point on the curve, which is calculated to occur at 165 kWh. Therefore, based on our problem formulation and assumptions, we can conclude the optimal battery size to run in New York City is 165 kWh.

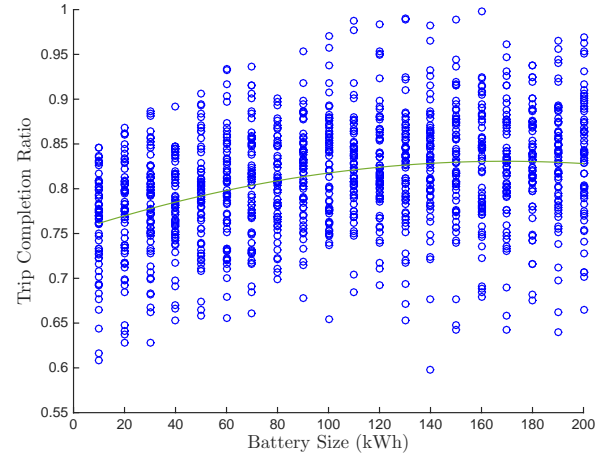


Fig. 13. Trip Completion Ratio of Battery Sizes from 10 to 200 kWh

### I. Optimal Charging Schedule

The final phase of this project involves the optimization of the charging schedules of select EV taxicabs. Our work thus far has calculated trip completion ratio by assuming that taxicabs only charge when they run out of battery. This impacts trip completion ratio significantly because it could be that vehicles run out of battery during peak transit hour, and therefore miss out on a substantial passenger flow. A more sophisticated approach to the problem would be to enable taxicabs to charge during hours of likely downtime. An elementary optimization framework is proposed in the following section that will enable the taxicab operator to achieve this goal.

There are some important limitations to this framework that need to be highlighted a priori. The time step used thus far has been 1 second - with a time horizon of 86400 seconds, which is a day. However, since the decision variables are tracked at

every single time step, the total number of variables is simply too large to be handled by mixed integer programming solvers like intlinprog in MATLAB. Consequentially, the time step is increased to 7.2 minutes, which results in a total of 200 time steps. For this optimization problem, an artificial constant discharge rate are created to solve a scaled down version of the problem. In practice, the discharge rate varies with each trip due to acceleration and velocity. The velocity of a taxicab is further assumed to be zero during downtime, whereas the taxicab should be moving in reality to new pickup locations.

To start forming the optimization problem, the definition of the notations we used is shown in Table II.

Symbol	Definition
$i$	Time Step
$T_{g_i} \in \{0, 1\}$	Gasoline Vehicle Operational Profile
$T_{e_i} \in \{0, 1\}$	Electric Vehicle Operational Profile
$x_{c_i} \in \{0, 1\}$	EV Charging Profile
$SOC_i \in [0, 1]$	State of Charge
$D$	EV Discharge Rate
$P$	EV Charging Rate

TABLE II  
OPTIMIZATION PROGRAM NOTATION

To understand what a GV operational profile means,  $T_{g_i} = 1$  indicates that the GV is carrying a passenger at time step  $i$ . It is similar for an EV operational profile. To understand what an EV charging profile means,  $x_{c_i} = 1$  indicates that the EV is charging at time step  $i$ .

The goal of the optimization problem is to maximize the trip completion ratio of an EV by comparing its operational profile to the given corresponding GV operational profile. In other words, we want the EV operational profile to be as similar as possible to the given GV operational profile. The optimization problem is expressed as a mixed integer linear program as follows:

$$\max \sum_i T_{e_i} \quad (1)$$

$$SOC_{i+1} = SOC_i - DT_{e_i} + Px_{c_i} \quad \forall i \quad (2)$$

$$T_{e_i} + x_{c_i} \leq 1 \quad \forall i \quad (3)$$

$$0 \leq T_{e_i} \leq T_{g_i} \quad \forall i \quad (4)$$

$$0 \leq SOC_i \leq 1 \quad \forall i \quad (5)$$

$$SOC_0 = 1 \quad (6)$$

$$T_{e_i} \in \mathbb{Z} \quad \forall i \quad (7)$$

$$x_{c_i} \in \mathbb{Z} \quad \forall i \quad (8)$$

There are three decision variables to this problem:  $T_e$ ,  $x_c$ , and  $SOC$ . The objective function (1) is the sum of the EV operational profile components. Constraint (2) represents the dynamics of the state of charge. At each time step, SOC is a function of the SOC at the previous time step as well as the charge and operation at the previous time step. Constraint (3) is particularly important because it hones in on the or in charge

or operation. In a single time step, charging and operating are mutually exclusive for the EV, and this constraint highlights that. Constraint (4) specifies that the EV operational profile in a given time step must be less than or equal to the given GV operational profile. This is constraint is formulated because EV cannot operate when the GV does not operate as the GV operational profile specifies passenger availability. Constraint (5) gives the state of charge limits, and constraint (6) provides the initial value for the SOC, which we assumed to be 1. Finally, constraints (7-8) ensure that the EV operational and charging profiles can only contain 0 or 1.

To approach this optimization problem, a GV operational profile is randomly generated as shown in Figure 14. Once again, it should be noted the time step is now 7.2 minutes. Also, a discharge rate  $D$  of 0.08 and a charging rate  $P$  of 0.04 are assumed. With this discharge rate, 12.5 units in time are required for a vehicle to discharge, which equals to around 1.5 hours of operation if translated to a 24 hr scenario. This shows that this artificial time-scale is consistent with a realistic discharge scenario.

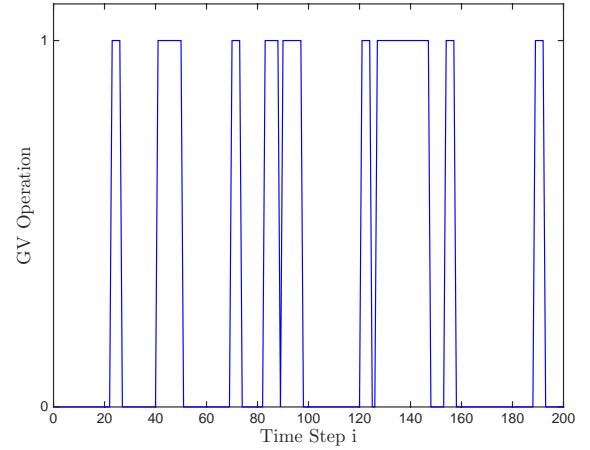


Fig. 14. GV Operational Profile

Finally, the optimization is carried out using intlinprog in MATLAB. This software requires the constraints to be expressed in matrix vector form as follows.

$$\begin{aligned} \min \quad & c^T x \\ \text{s.t.} \quad & Ax \leq b \\ & A_{eq}x \leq b_{eq} \end{aligned}$$

The results of the optimization are presented below. Figure 15 shows the original GV operational profile, the optimized EV operational profile and the EV charging profile. It can be appreciated that charging happens during downtime in the original GV operational profile in such a way that as much as possible of the GV operational profile is covered by the EV operational profile to maximize trip completion. One phenomenon that occurred due to the problem formulation is

that some of the longer trips are visibly interrupted due to the requirement to charge. Figure 16 shows the SOC evolution of the EV, which varies based on the charge/discharge alternation.

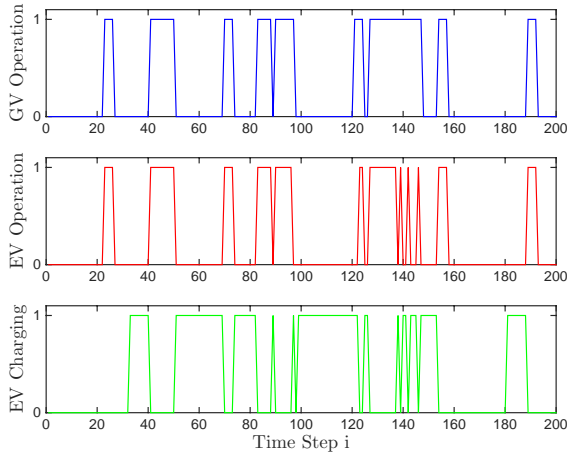


Fig. 15. Operational Profiles and Optimal Charging Schedule

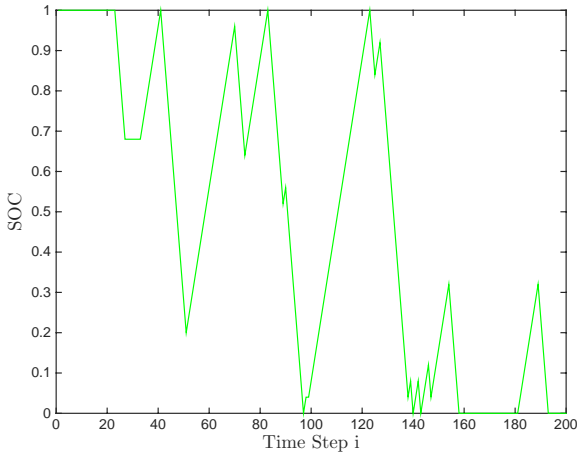


Fig. 16. EV SOC Evolution

IV. DISCUSSION

The operational profiles that we have generated are reasonably consistent with what one might expect in an urban taxicab system. The most prolific taxicabs take around 70 trips per day, while at the other end of the spectrum, there are some taxicabs that execute only 1 trip.

The sample velocity profile we have developed for taxi medallion B352A440CEAC5B82C18D6ECF37AC6D17 (Figure 10) also looks reasonable for the most part. The mean velocity for the investigated medallion is around 28 km/hr during passenger carrying time, and less than half that during downtime, measuring around 11 km/hr. Intuitively this makes sense because a taxicab travels more slowly (on average) when it searches for passengers or when the driver takes breaks. The maximum velocity peaked at around 70 km/hr, which may be large for an average velocity. However, it may well have been that the vehicle took an untraveled section of freeway

or highway, which seems to be supported by the significant trip length that suggests dual carriageway road transit. It also must be acknowledged that prior users of the data set have identified some inconsistencies in it. These errors may lead to outliers in the velocity profiles of certain vehicles, which we have to the best of our ability isolated throughout the analysis.

Regarding the vehicle charging and discharging model, it needs to be acknowledged that we have approached it from a relatively simplistic point of view. We did not model acceleration, which is an important consideration to dwell upon, as acceleration is the main driver of power demand. We could have assumed a constant acceleration, but this would have been highly unrealistic both from a real world perspective and given the fact that trip velocities are assumed constant (hence acceleration should be nought). We addressed the issue by using an artificially high bearing damping coefficient to obtain a reasonable discharge rate, which depletes a fully charged battery in approximately an hour and a half. An improvement to the results would be obtained if the velocities were not assumed constant and equal to the average velocities, but rather if a varying velocity profile with a consistent average velocity were created for each trip which modelled vehicle behaviour. The power demand in such a scenario would be more accurate. This does not mean, however, that our results are invalid because in any case the power demand would not differ significantly from that which we have calculated given that it yields discharge rates that are in line with current EV's (total discharge times are in the range of an hour and a half to two hours of operation for 50 kWh batteries).

Using the modified vehicle discharge model, the trip completion ratios that we generated hover around the 70-80% mark, which is realistic and what we were expecting at the project outset. The curve which fits trip completion ratio versus battery size as shown in Figure 13 plateaus around 100 kWh, which is consistent with the notion of there being a threshold battery size at which the EV's do not have to continuously charge and recharge and can therefore complete more trips. The slope of the curve is mild. From this analysis, it can be seen that larger batteries are not necessarily at an advantage, as it takes longer for them to be replenished, which can cause EV's to miss out on passenger carrying opportunities. Indeed, at very large sizes close to the 200 kWh mark, the curve begins to dip noticeably. The best possible battery is therefore an intermediate value around the 150 kWh range, where the peak of the curve is at 165kWh. Some scatter points show significantly high trip completion ratios even at low battery capacities, which may appear mystifying. The explanation for this has to do with the fact that the battery is made to charge to completion once it has been depleted.

Our assumption that the batteries are charged up fully upon discharge naturally leads an observer to question the validity of the results. However, such a scenario is not entirely unrealistic as many operators of electric vehicle fleets currently do exactly that: once vehicles run short of charge they charge them up to near-completion. An example is San Francisco based car-sharing provider Drive Now, which operates around 30 EV's.

At its recharge points, it does not effectuate partial charging even though that may mean keeping vehicles inactive during peak transit hours.

A more beneficial approach to EV fleet management would therefore be to incorporate partial charging. An additional motivation for this is the fact that battery charging rates are not actually constant, which is something we overlooked this analysis. Rather, they tend to decrease as SOC increases. If it were true that vehicles had to fully recharge before being dispatched, this would put all battery sizes at a disadvantage given that the final phases of charging are always the slowest ones. Partial charging would favour larger batteries as they would be able to on-load larger energy capacities in shorter time frames. A future consideration for this work would involve the incorporation of an SOC dependent charging rate.

It can be appreciated that the project draws from both mathematical modeling and optimization skills. Mathematical modelling has been applied in developing the vehicle discharge and charging models, while optimization skills have been applied in developing the optimization program for the optimal charging schedule. The limitations of the optimization framework were listed in the Technical section. It is important to acknowledge that taxicabs do not know their daily operational profiles beforehand, therefore the target profiles are not strictly speaking "real" profiles. It would be more correct to define them as "likely" profiles that highlight likely periods of inactivity. The EV profiles then attempt to match with these "likely" profiles. This is how the usefulness of the optimization framework needs to be interpreted in terms of real world applicability.

One important point could be raised in reference to the optimization framework, namely: why not simply charge during all periods of inactivity? The reason for this has to do with the speed of the charging. If a supercharger is used with a significantly high charging rate, then this could easily be accomplished. However, using conventional chargers, charging times are simply not rapid enough to allow all trips to be completed even if all of the inactive spaces are utilized. As a result, some operation time needs to be sacrificed. The optimization framework that we have developed tracks SOC and illustrates where the operation time would be lost. Moreover, it creates a partial charging schedule that enables a vehicle to get to the end of the day with just enough charge - hence without wasting time charging. The trips that are "incomplete" require some careful interpretation, because clearly it is not possible for a taxicab to execute incomplete trips and leave a passenger stranded. The results need to be viewed in terms of trip completion percentage - i.e. the taxicabs would need to substitute the incomplete trips with shorter ones, or forgo them altogether, making calculated trip completion actually an upper bound for real life trip completion.

Our analysis has adopted an artificial time-scale and charging/recharging rates to perform the optimization. A future update of this work could use more sophisticated optimization tools to scale it up to the real life scenario with several hundred thousand decision variables. This would enable representative

discharging and charging rates to be used. In particular, it would allow for the discharging rates to be suited to those of individual trips, which have varying velocities. In such a scenario, the results of the optimization could be compared to the "charge when you run out of battery" case to quantify the improvement in trip completion ratio post optimization.

## V. SUMMARY

This project has sought to identify the prospects that exist for switching the NYC taxicab fleet from GV's to EV's. First of all, we performed a high level statistical analysis of the NYC taxicab data-set. It has identified what the distribution of operation time is amongst a selection of taxicabs and therefore the distribution of downtime as well. Furthermore, we looked at the geographical distribution of pickups and drop-offs on the 2nd of January 2013 by creating a heat-map, which would be a great starting point for an analysis of where to best allocate charging stations.

Besides performing some preliminary statistical analysis on the data set, this project has developed two main deliverables. On the one hand, it determined an optimal battery size for a potential electric NYC taxicab. This was done by calculating trip completion ratios for different taxicabs across multiple battery sizes. Trip completion ratio has been expressed with respect to equivalent GV operational profiles. The results show that the battery needs to be not too small and not too large, given that at low sizes it is difficult to complete larger trips and at large sizes too much time is lost charging up. A battery size of 165kWh is appropriate, although it is worth noting that such a battery is not commercially available at the moment as the largest ones for use in privately owned vehicles are around 90kWh.

The other main deliverable is the optimization framework for the development of a partial charging schedule. This framework takes in a GV operational profile, a charging rate and a discharging rate and outputs an EV operational profile and an EV charging profile. The objective of this optimization problem is to optimize the EV operational profile so that it is as close as possible, if not identical, to the GV operational profile. The SOC evolution for the optimal charging schedule is also tracked.

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