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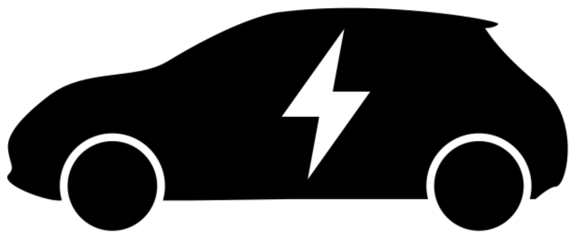

# EV FLEET CHARGING OPTIMIZATION

CE 295 FINAL REPORT

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Great work team! Your group was the only one to successfully execute dynamic programming in your project. This is VERY impressive. Also, your visualizations are excellent, and the results demonstrate significant impact. Very good work!

**ABSTRACT**

The focus of this project is to optimize the charging of a plug-in electric taxi fleet in San Francisco, CA, such that the cost of charging is minimized. Using San Francisco taxi data, a model of a hypothetical fleet of electric vehicles (EVs) was developed. Realistic assumptions based upon the charging characteristics of the electric car fleet, assumed to be 100 Tesla Model S 60D vehicles, were established in order to develop this model. Additionally, a Time-Of-Use (TOU) electricity pricing schedule was considered since such demand response programs are increasingly-prevalent and are anticipated to have an impact on the operating costs of the fleet in the near future. The optimization was done using dynamic programming and subsequently compared to a benchmark model based on a simple baseline policy to quantify cost reductions for the entire fleet.

## INTRODUCTION

### Motivation & Background

Today, the world is faced with an increasingly daunting climate crisis. Although some action has been taken, the future trajectory of the United States is not promising. According to the U.S. Environmental Protection Agency (EPA), the second largest contributor to greenhouse gas emissions, behind the electricity industry, is the transportation industry, accounting for just over 25% of domestic greenhouse gas emissions [7]. In an attempt to combat the large environmental footprint, there has been a push to transition towards more environmentally-friendly transportation options. Private cars dominate the transportation infrastructure of the United States, but communities have recently begun promoting the adoption of other modes of transportation such as walking, cycling, and public transit [5]. As a result, alternative vehicles are steadily making their way onto the roads and are growing in numbers. In fact, it is estimated that electric vehicles (EVs) will make up 35% of the light-duty vehicles sold in the United States by 2040 [2]. EVs may be a key technology in the movement towards a cleaner transportation sector. In order for this technology to become feasible and widely adoptable for both commercial and personal purposes, it needs to be economically desirable. This report explores the potential for an EV taxi fleet in San Francisco by developing a charging schedule dictated by time-of-use (TOU) electricity prices which will maximize profit while also limiting the fleets strain on the grid. TOU pricing is employed to address the "economic inefficiency" that currently exists in the electricity market due to retail prices that are typically time invariant, by establishing a distinct price for peak and off-peak hours, and as a result customers can readily understand and respond to it [6]. The peak hours in the model are specified by PG&E's Time-of-Use Plan from 3:00-8:00 PM [8]. The off-peak time period will be the remaining hours when there is less of a demand for electricity.

There are a number of barriers associated with electric vehicle fleets. Firstly, electric cars have a period of downtime where they are unusable due to charging, as it can take up to 8 hours for a full charge. This could be a complication for a car-sharing fleet of electric vehicles because there may be limits on how many cars are available at a particular time and the range in which the vehicles can be used. Secondly, the range of a typical EV is 50-75 miles on a full charge, which is significantly smaller than that of a gasoline vehicle. This means that recharging is going to occur a lot more frequently than the refilling of gasoline. As recharging requires a significant amount of time in proportion to a vehicle's hours of operation, knowing when exactly to charge an EV would have a direct impact on the profit margins of the service. Range anxiety turns out to be the primary hindrance hampering the proliferation of electric vehicles. EVs are also restricted to park at locations that have charging stations. If a city does not have the adequate infrastructure, or do not have enough charging sites, EVs would have to plan their routes even more carefully to avoid losing power before reaching a charging station.

Cucca, Gu, and Su's "A Study on the Battery Size and Optimal Charging Schedule of Electric Taxicabs in New York City", is a relevant project of interest where daily patterns of New York City (NYC) taxicabs were analyzed and then used to simulate a network of electric vehicles. The group sought to study battery sizes and optimal charging schedules, but due to time constraints was only able to provide conclusions regarding battery sizes. The NYC EV project approached their problem by attaining trip and fare data on taxicab trips from the New York Taxi & Limousine Commission, through a Freedom of Information Law (FOIL). It was decided to select only a few dates for thorough investigation due to the large data sets and time constraints. For these dates, a statistical analysis was performed: the pick-up and drop-off points were mapped out, operation times and downtimes were quantified for every hour, and other pertinent analyses were made in order to create appropriate daily profiles for individual taxicabs. The proper steps were then taken to properly formulate a model describing vehicle charge and discharge, as well as the evolution of power demand, which was then used to optimize both battery size and charging schedule. Ultimately, the group concluded that the optimal battery size for the given data set is 165 kWh, and developed a charging profile that brought the EV operational profile close to that of a gasoline-powered vehicle. This project will have a similar framework, therefore it is of interest to learn and adapt strategies and tools used in the NYC EV project to have a foundation from which the proposed project can be built around.

This literature review provides good background information for executing this project. What you didn't do, however, is review the state-of-art research. There are no research papers here. PhDs and PhD students have pursued your problem, and found some successes and failures. What are those?

## Relevant Literature

**The Impact of Climate Change on the Transportation Sector and the Need for Electric Vehicles:**

- "Sources of Greenhouse Gas Emissions- Transportation Sector Emissions"
  This Environmental Protection Agency page breaks down the sources of greenhouse gas emissions specifically from the transportation sector.
- "The Rise of Electric Vehicles: By the Numbers"
  This online article discusses the extent to which electric vehicles have been adopted around the world. The author also explores projections for future growth in electric vehicles as well as barriers to future growth.
- "Sustainable Mobility in the Periphery: Are Electric Vehicles the Answer?"
  This paper is a review of global electric vehicle technology and research by a group from Mid Sweden University. The authors discuss briefly some of the climate change issues influencing the search for sustainable transportation alternatives and explores the feasibility of electric vehicles.

The transportation sector is one of the primary contributors of greenhouse gas emissions, and it is a natural focus for climate change mitigation strategies. The EPA article outlines the impact of the transportation sector and describes the magnitude to which this sector influences climate change. One potential remedy to mitigating the carbon footprint of private vehicle travel is a transition from traditional combustion-engine vehicles to alternatives such as electric vehicles and hydrogen fuel cell cars. As this paper is focused on a fleet of electric vehicles, this literature review encompassed articles about electric vehicle technology and its projected adoptability.

**Past Studies Involving Electric Vehicle Charging Schedules:**

- "A Study on the Battery Size and Optimal Charging Schedule of Electric Taxicabs in New York City"
  This past CE295 project report serves as a starting point for the research explored in this report and provided an example on modeling a fleet of electric taxi cabs. The methodology and data used informed the development of the strategy for this project. This paper focuses on the impact of battery size on optimal charging schedule.

- "Online Optimal Charging Strategy for Electric Vehicles"
  This paper studies the optimization of charging schedules for an entire fleet and differentiates weekday and weekend charging prices. It explores coordinated vs. uncoordinated charging schedules, and the use of a charging window of 4 time steps ahead from the current step.

A number of past studies have explored electric vehicle fleets using datasets similar to the SF cab data utilized for this project. Electric vehicle charging schedules are important to consider in the process of modeling the cab fleet, and these studies provide insight on the different variables that impact an optimization of charging an EV fleet. This literature helped with the set-up of the dynamic model developed for this project. The first paper was primarily focused on electric vehicle battery size rather than charging schedules and electricity pricing; however, both papers provided information on the characteristics involved in modeling an EV fleet such as battery state of charge, discharge rate, etc. These two papers were a starting point for the development of system equations for the hypothetical SF EV taxi fleet model.

**Demand Response Electricity Pricing:**

- "Commercial and Industrial Demand Response Under Mandatory Time-Of-Use Electricity Pricing"
  This article evaluates the impact of large-scale field deployment of mandatory time-of-use (TOU) pricing on the energy use of commercial and industrial firms to determine whether or not TOU pricing should be implemented and if the concerns for mandatory TOU pricing are validated.

- "The Residential Electricity Time-of-Use Pricing Experiments: What Have We Learned?"
  This research conducts experiments to determine whether TOU pricing would produce significant enough changes in customer demand and justify the implementation of peak and off-peak electricity prices.

The heart of this project is the development of an optimal charging schedule to minimize the electricity costs of a SF taxi fleet. The literature in this section explored the concept of demand response systems and provided insight on how demand response affects operating costs and how effectively it shifted grid loads. In order for the developed project model to be representative of reality, it was crucial to develop a solid understanding of demand response and electricity pricing. The optimized charging schedule for the EV fleet takes into account the variation of electricity pricing based on PG&E time-of-use plan.

## <u>Focus of this Study</u>

The focus is to optimize the charging schedule for a fleet of electric vehicles such that the cost of charging the fleet is minimized. The optimization will primarily be a function of a time-of-use electricity pricing schedule and will reduce operating costs while additionally removing pressure from the electric grid during on-peak hours. This project's goal is encompassed within the overarching transition towards new methods of transportation and exploring the feasibility of a shift away from traditional combustion vehicles.

Sorry, but I take huge offense with this highlighted statement. Visualizing real-time data has been done for centuries. Science involves data collection. We have been visualizing this data since science began. Don't get sucked into this hype.

## TECHNICAL DESCRIPTION

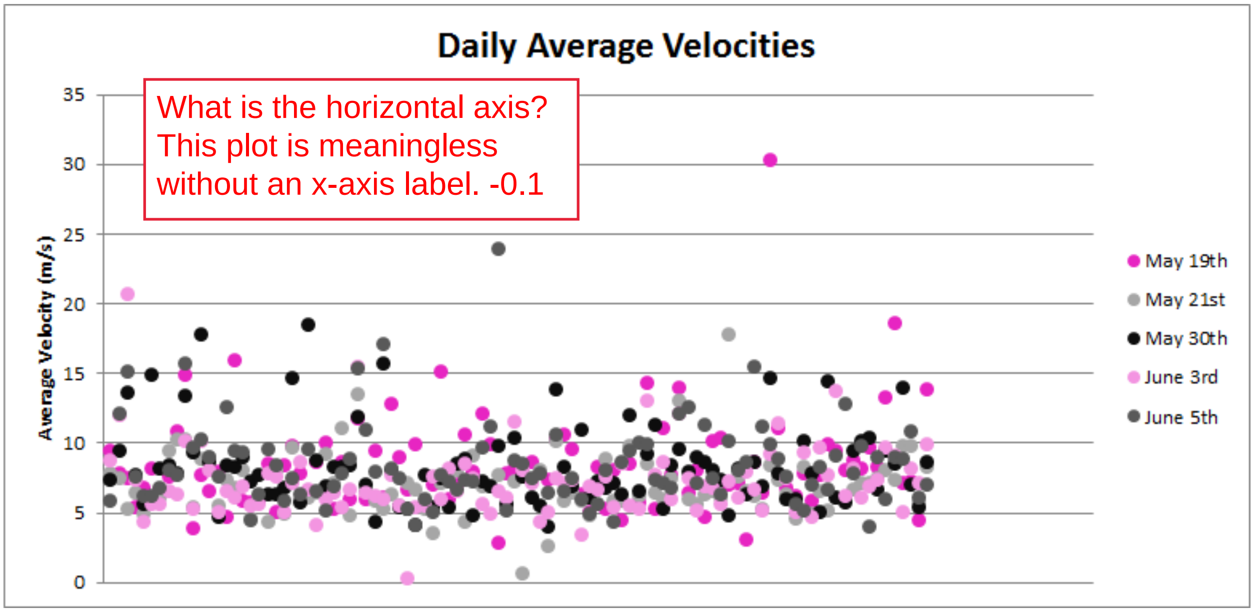
### SF Taxicab Data

The cabspotting dataset used for the cab simulation in this model is part of a research project called Invisible Dynamics, sponsored by The Exploratorium of San Francisco. It was noteworthy data when it was collected as it was one of the first real-time data sets used in any kind of visualization, namely, the aggregate mapping of cabs in San Francisco's streets. The resulting visualization piece was shown in the Design and the Elastic Mind exhibition at MoMA in 2008, as part of NighTime Dreamreal at the Shanghai Power Station of Art and is now part of the permanent collection of MoMA. Each mobility trace in the data set is displayed in a .txt file and is formatted as follows: each row contains [latitude, longitude, occupancy, time], where latitude and longitude are in decimal degrees, occupancy shows if a cab has a fare (1 = occupied, 0 = free) and time is in UNIX epoch format.

Each .txt file contains approximately 25 days of data. Aggregated over 500 taxi files, that is over 10,000 days and over 250,000 hours of data that need to be processed. Since time and labor are limited for this project, it was necessary to reduce this to a more manageable number. To perform this reduction, there were five days selected, where each one was representative of a day of the week, and only those days were used for the analysis/optimization. Dates near holidays were marked as "biased" and were excluded from the possible choices to ensure the data used was representative of a typical day. Ultimately, the five dates chosen were May 19, May 21, May 30, June 3, and June 5. In order to further reduce the data processed and entered into the model, a set of 100 taxis were randomly chosen from the data, given that the file contained all five of the dates of interest. This filtering process yielded a set of 500 days of data with over 180,000 total kilometers driven that was used in the dynamic program.

Great!

A MATLAB function was used to manipulate and reformat the information from the .txt files to be used in the optimization model. The function first broke up the data for each taxi by day. The function then used the two columns of latitude and longitude to determine the change in distance between two points using the Haversine method. The program calculated the difference in time stamp between the first entry (row) and the succeeding row in seconds and used this time difference with the calculated change in distance to find the average velocity between the 2 points. The function repeated this process for all of the rows of the .txt files, to arrive at a n by 10 matrix for each day for each cab, where n was the number of time steps that day for that particular taxi. The columns represented latitude, longitude, change in distance, change in time, cumulative time, time since midnight, velocity, acceleration, occupancy and time stamp from first data point. Only three of these columns (velocity, occupancy and time since midnight) were used in the model, but the rest of the columns were used for calculations about and analysis on the full data set such as average velocity each day and total distance travelled. Figure 1, below, displays the average velocities for all five days for all 100 taxi cabs.




What is the horizontal axis? This plot is meaningless without an x-axis label. -0.1

**Figure 1. Average Velocities of 100 Cabs For Five Chosen Days**

The primary purpose of Figure 1 is to display the trends in the data. Most of the cabs had an average velocity of between 5 and 10 m/s (11 to 22 mph). While this average velocity appears rather low, it is a result of calculating the average velocity based upon all of the time steps in a day. Since there are many times where the taxi cabs are stopped throughout the day, these periods of time where the velocity is zero bring down the overall average. It is also evident that although most of the data is clustered between 5 and 10 m/s, there are a number of outlying cabs that have extremely low or extremely high velocities. The only explanation found for these inconsistencies were errors in the actual .txt files. There were a few cabs in the subset selected that had changes in latitude and longitude between time step that were unrealistic. As a result, there were time steps where the average velocity seemed unrealistic because either the distance was much too high or the change in time was much too low. There was no good way to predict when this would occur during the period of selecting which cab data to use, so the resulting data was imperfect.

This is a good exercise in "data cleansing"

## Charging Location Data

In order to determine the closest charging station to the EV at any given time, a network of charging stations needs to be specified. Instead of developing our own, we decided to use an existing network and apply that in our model. The US Department of Energy has a database of fuel stations all across the United States. This database can be refined to show only data pertaining to electric charging stations. This is the data that was acquired for the project. The data for each location contains latitude and longitude in decimal degrees, which is the primary parameter of interest. These can be used to determine the minimum distance between a vehicle and all the charging stations in SF, which will then be input into the model.

Cool viz

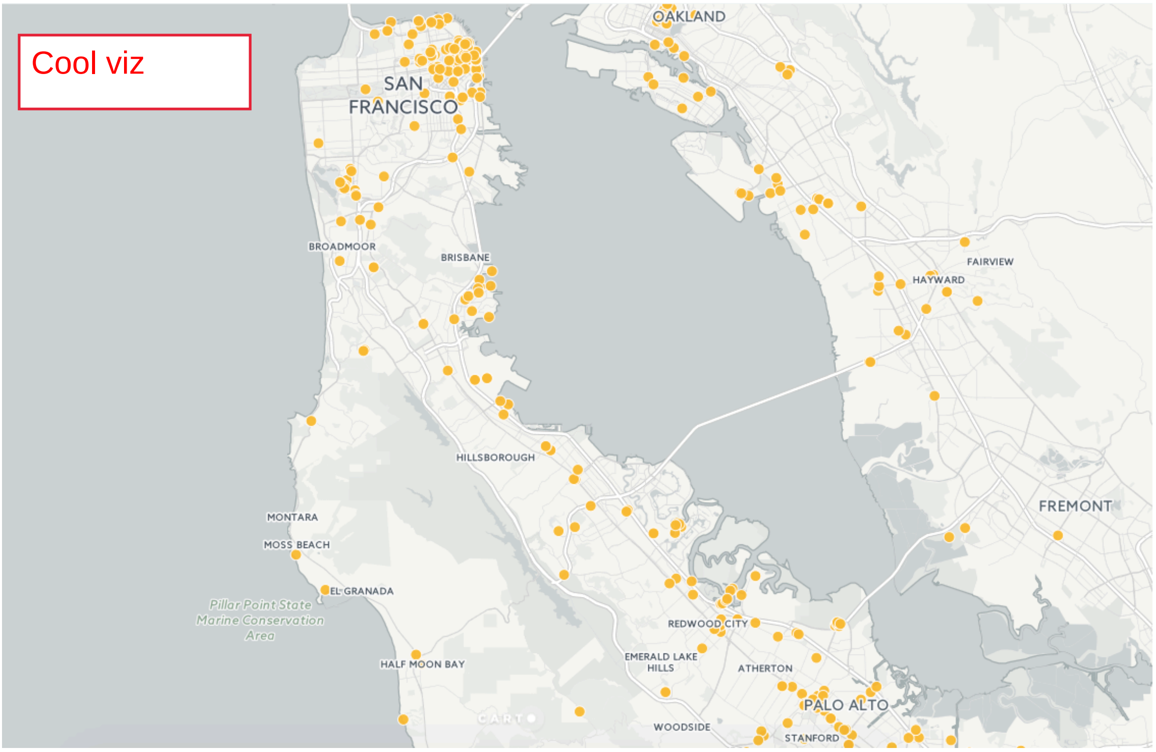



**Figure 2. Map of Electric Vehicle Charging Stations**

## Optimization Problem

For our project, we have chosen to focus on profitability. Hence, we would want to add the element of prices and factor in time-of-use electricity charges. Assuming that revenue patterns and profiles remain constant, we can focus on minimizing costs incurred to maximize the profit. Our setup is as follows:

$$min \sum_{i=1}^{N} \Delta t_i \cdot c_i u_i$$

This term should be u_i, not (1-u_i), right? -0.1 pts

$$(1)\ \mathrm{SOC}_{min} \leq \mathrm{SOC_i} \leq \mathrm{SOC}_{max}$$
$$(2)\ \mathrm{SOC_{i+1}} = \mathrm{SOC_i} + \Delta \mathrm{t_i} \cdot [\mathrm{u_i C_R} - (1 - \mathrm{u_i})\mathrm{D_R}] - (1 - \mathrm{u_i})\beta_i$$
$$(3)\ \mathrm{u_i} \in \{0,1\}$$
$$(4)\ \mathrm{w_i} \in \{0,1\}$$
$$(5)\ \mathrm{u_i} + \mathrm{w_i} \leq 1$$

**Table 1. Model Variables**

| Variable | Description | Units |
|---|---|---|
| i | Discrete Time Step | - |
| SOC | Battery State of Charge | % |
| $c_i$ | Cost of charging at particular time step | $ |
| $u_i$ | Charging Status | - |
| $w_i$ | Occupancy | - |
| $C_R$ | Charging Rate | %/s |
| $D_R$ | Discharge Rate (based on physical model) | %/s |
| $\beta_i$ | Distance Factor to nearest charging station | % |
| $\Delta t_i$ | Length of time step | s |

We have attempted to go a step further in reflecting geography and temporal-economic factors in our model. We added a cost factor $c_i$ that changes with the time of the day to penalize charging during peak demand periods. Additionally, a distance factor β which is scaled by the distance from the vehicle to the nearest charging station is included. This maintains that the vehicle would have enough charge to carry it to the charging station, as vehicles cannot plug in whenever they need or want to.

**Charging and Discharging**

$$D_R = \frac{P_D}{E_{max}}$$

$$C_R = \frac{P_C}{E_{max}}$$

**Table 2. Battery Charging and Discharging Variables**

| Variable | Description |
|---|---|
| $P_D$ | Power Demand |
| $P_C$ | Charging Rate |
| $E_{max}$ | Maximum Energy Capacity of Battery |

The SOC for the next time step depends on the charging and discharging rates. $P_D$ is calculated above, and $E_{max}$ would be a parameter decided by the specifications of the EV battery as specified below in Table 4.

**Table 3. Battery Characteristics**

| Vehicle Make | Vehicle Model | Cost | Full Charge Time | Range per Charge | Battery Size | Battery Degradation |
|---|---|---|---|---|---|---|
| Tesla [9] | 2016 Model S 60 | $67,200 | 8 hours, 42 minutes | 210 miles | 60 kWh | -2.3 miles/charge for every 10,000 miles driven [7] |

## Vehicle Dynamics

The discharge rate of the battery is related to the power the vehicle requires to maintain its velocity while overcoming resistive forces. The ones considered are friction and air drag. Additionally, it was assumed that the vehicle is travelling on level ground as we do not have the data to calculate angle of slope during the vehicle's motion.

Just FYI, elevation changes have a HUGE impact on energy consumption. I'm OK with this assumption, since you don't have elevation data. However, you should know it's an assumption that is unrealistic and will impact your final results.

$$P_D = mv\frac{dv}{dt} + f \cdot mgv + \frac{1}{2}\rho C_D A_f v^3$$

**Table 4. Vehicle Dynamics Parameters**

| Parameter | Description | |
|---|---|---|
| $m$ | Mass of vehicle | |
| f | Rolling resistance coefficient | |
| $\rho$ | Density of Air | |
| $C_D$ | Drag Coefficient | No units |
| $A_f$ | Frontal Area of EV | $m^2$ |

**Table 5. Vehicle Characteristics**

| Vehicle Make | Vehicle Model | Mass of Vehicle | Rolling Resistance Coefficient | Drag Coefficient | Frontal Area of EV |
|---|---|---|---|---|---|
| Tesla | 2016 Model S 60 | 2108 kg | 0.01 [4] | 0.23 [9] | 25.2 square feet [9] |

## Distance Factor

$$\beta_i = (\frac{P_{ave}}{E_{max}})(\frac{d_{min,i}}{v_{ave}})$$

**Table 6. Distance Factor Variables**

| Variable | Description |
|---|---|
| $P_{ave}$ | Average Power Demand of the car for the day |
| $v_{ave}$ | Average velocity of the car for the day |
| $d_{min,i}$ | Distance to nearest charging station at time step i |

The distance factor is computed using the average power demand and velocity for the car of that particular day. This gives an estimate on the amount of charge that will be depleted traveling to the nearest charging station.

## Dynamic Programming Setup

**Table 7. Dynamic Programming Variables**

| | Variable | Description | Units | Input Value |
|---|---|---|---|---|
| **Parameters** | $m$ | Mass of Car | kg | 2000 |
| | $f$ | Frictional Coefficient | - | 0.01 |
| | $\rho$ | Density of Air | kg/m$^3$ | 1.225 |
| | $C_D$ | Drag Coefficient | - | 0.23 |
| | $A_f$ | Frontal Area of EV | m$^2$ | 2.3 |
| | $E_{max}$ | Max Energy Capacity of Battery | kWh | 60 |
| | $SOC_{min}$ | Minimum SOC of Battery | - | 0.2 |
| | $SOC_{max}$ | Maximum SOC of Battery | - | 0.9 |
| **States** | $SOC_i$ | Battery State of Charge | - | |
| | $w_i$ | Occupancy | - | |
| **Uncontrollable Inputs** | $a$ | Acceleration | m/s$^2$ | |
| | $v$ | Velocity | m/s | |
| | $c_i$ | Electricity Cost | \$/s | |
| | $\Delta t_i$ | Time Interval | s | |
| **Controllable Inputs** | $u_i$ | Charging Status | - | |

i. **Value Function**

$\boldsymbol{V_i(SOC_i, w_i)}$ represents the minimum cost from time step $i$ to terminal step $N$, given that SOC in time step $i$ is $SOC_i$.

ii. **Bellman Equation**

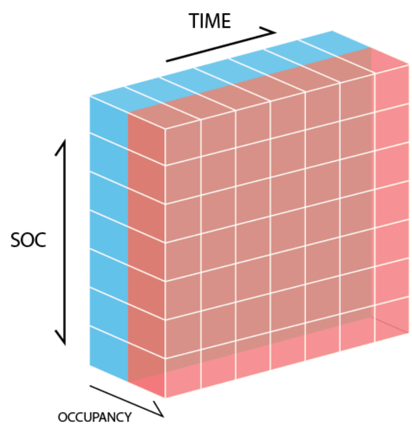
$$V_i(SOC_i, w_i) = \min_{u_i}\{c_i u_i \Delta t + V_{i+1}(SOC_{i+1}, w_{i+1})\}$$

$$where\ u_i \in \begin{cases} \{0,1\}\ if\ w_i = 0 \\ \{0\}\ if\ w_i = 1 \end{cases}$$

Excellent. A technical detail that you omitted are the w_i dynamics: w_{i+1} = w_i + \Delta w_i where \Delta w_i is the change in occupancy, and this is an uncontrollable but known input

$u_i$ can be 0 or 1 when the vehicle is unoccupied (i.e. $w_i = 0$). However, when the EV cannot be charged.

Boundary condition!? You have no boundary condition! You missed Step 3, and this step is very important! -0.2 pts



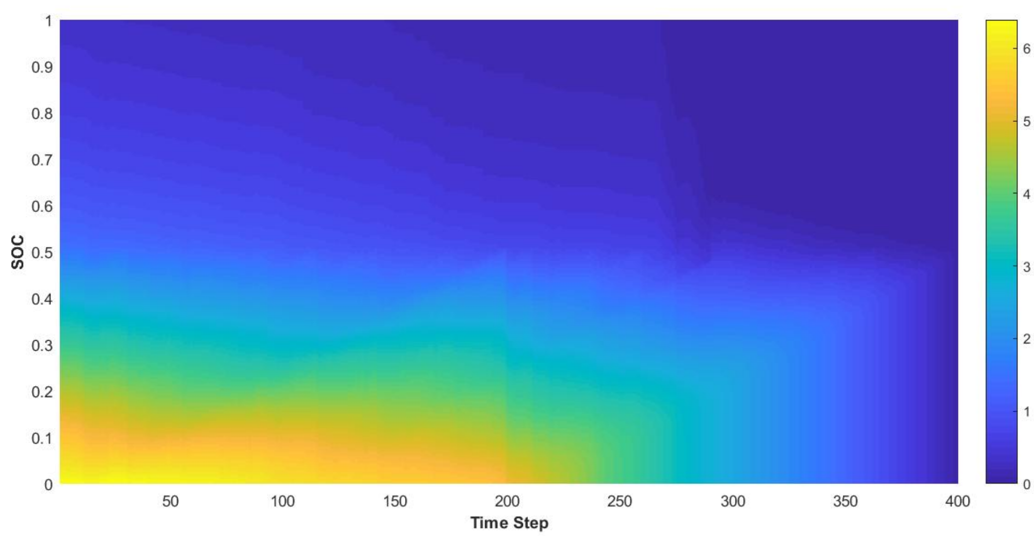

Great viz!

**Figure 3. Visual Setup of Dynamic Program, SOC and Occupancy as States**

The decision variable and Value Function matrices are 3 dimensional because of the presence of two states. These are then plotted for every time step.

## RESULTS AND ANALYSIS

The model was first simplified by setting $\beta_i = 0$ to make it easier for us to set up a working and running code that yielded sensible results. Figs. 4 and 5 show cross sections of the 3D matrices depicted in Fig. 3 for $w_i = 0$. In this case, the decision variable is allowed to take on both 1 and 0.




Another great viz! Your team project really stands out for the visualizations!

**Figure 4. Heat Map of $V_i(SOC_i, w = 0)$**

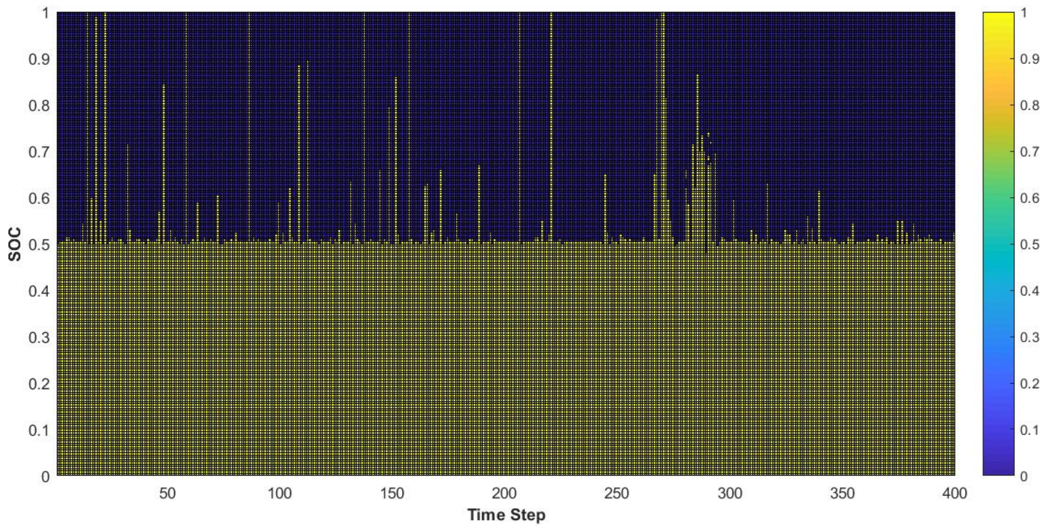



**Figure 5. Plot of $u_i(SOC_i, w = 0)$**

This is not a great viz. What do the light and dark blue mean? Also, is the left axis u? What does a u between 0 and 1 mean? Frankly, I am totally confused. -0.1pts

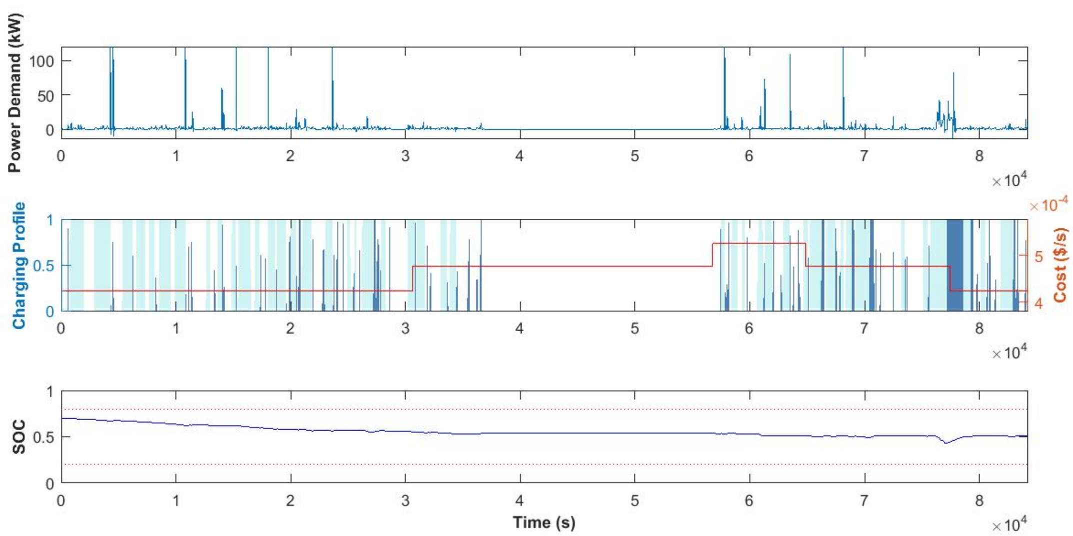



**Figure 6. Electric Vehicle Power Demand, Charging, and SOC Profiles Over Time**

Fig. 6 shows the power demand, charging profile and SOC plots for a single taxicab for the entire day. The large empty space in the middle represents the absence of data during that time period. It can be observed that most of the charging is centered towards the end of the timespan where charging prices are lower.

**Table 8. Comparison of Benchmark and DP Model Price**

| Day | Benchmark Model | DP Model | Percent Cost Reduction |
|---|---|---|---|
| **May 19** | $657.15 | $281.61 | 57% |
| **May 21** | $694.12 | $304.06 | 56% |
| **May 30** | $293.41 | $166.27 | 43% |
| **June 3** | $721.37 | $320.85 | 55% |
| **June 5** | $477.63 | $250.20 | 48% |

We ran our model for all 5 days with 100 taxicabs each against a benchmark model. The benchmark model follows the same occupancy and power demand profiles, but does not apply any optimization techniques and only charges when its SOC falls below the margin. It is also not allowed to charge when it is occupied. A comparison between our optimization model and the benchmark model that our model cuts the charging costs by 50% on average.

Impressive!

## Fine-Tuning of Model

Interesting. Your observation of unrealistic "spiky" charging is good. However, it means your model hasn't properly encoded something. Future work might examine these modeling details to more properly incorporate charging costs.

A problem with the model ... steps. These had little effe... correct this, we implemented two different methods aimed at recognizing that the costs of charging include more than just direct electricity usage.

Method (1) includes extra SOC depletion associated with the vehicle having to travel back to its path from the charging station. This managed to change some groups of closely bundled charging spikes into thick consistent bands which are more realistic.

Method (2) arbitrarily attaches a multiplier to the cost of charging value function. This means that the $\boldsymbol{V}$ value for $\boldsymbol{u} = \mathbf{1}$ is increased to capture economic costs of charging beyond the electricity cost. This may include opportunity cost of losing passenger pickups, and having to travel to the charging location. We used a multiplying factor This removed more charging spikes and still managed to keep the vehicle within the allowable SOC margins.

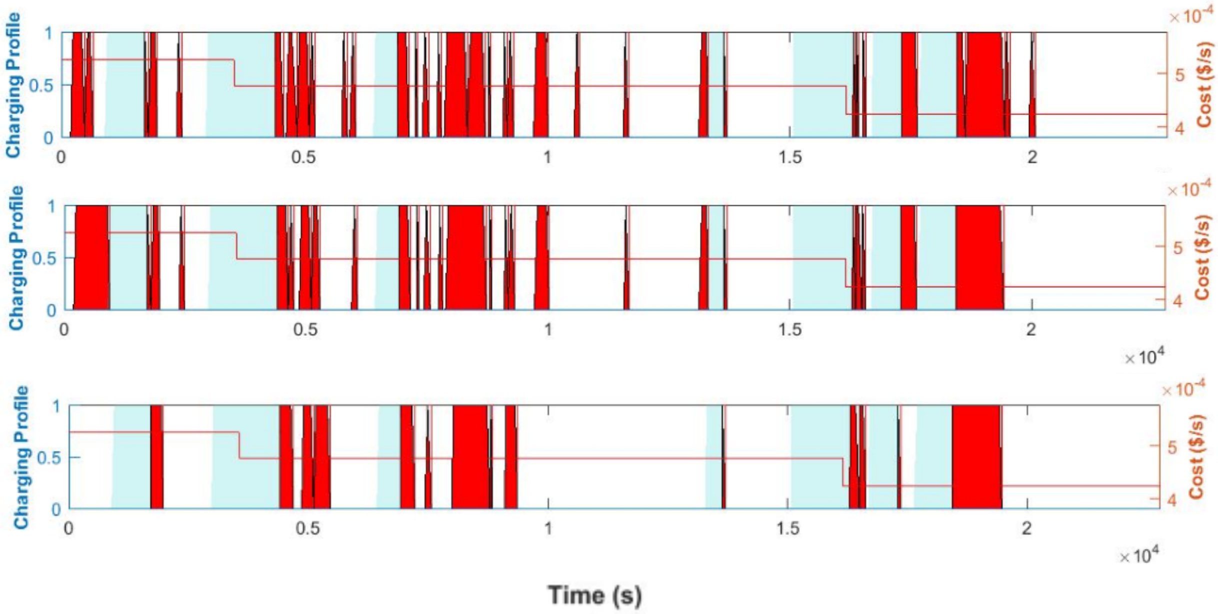



**Figure 7. Top: Unrefined Schedule, Middle: Implementation of Method (1), Bottom: Implementation of Methods (1) and (2)**

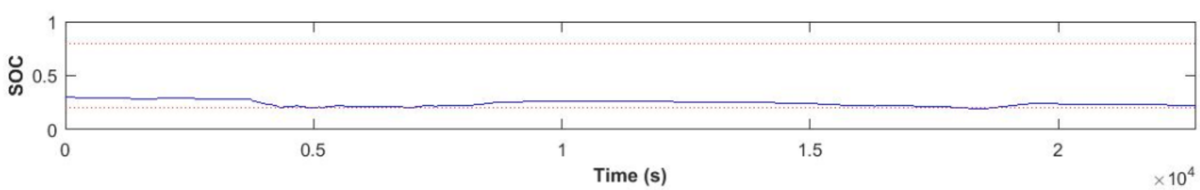



**Figure 8. SOC profile after implementations of Methods (1) and (2). Low initial SOC of 0.3 was used to serve as a better test**

## Including Distance Factor to Nearest Charging Station

We next reintroduced the $\beta_i$ term so that the model does not ignore the fact that the EV has to travel to the nearest charging station. This ensures that the vehicle's SOC does not fall below the minimum bound by the time it gets to the station. In general, this increased the frequency of charging in the schedule.

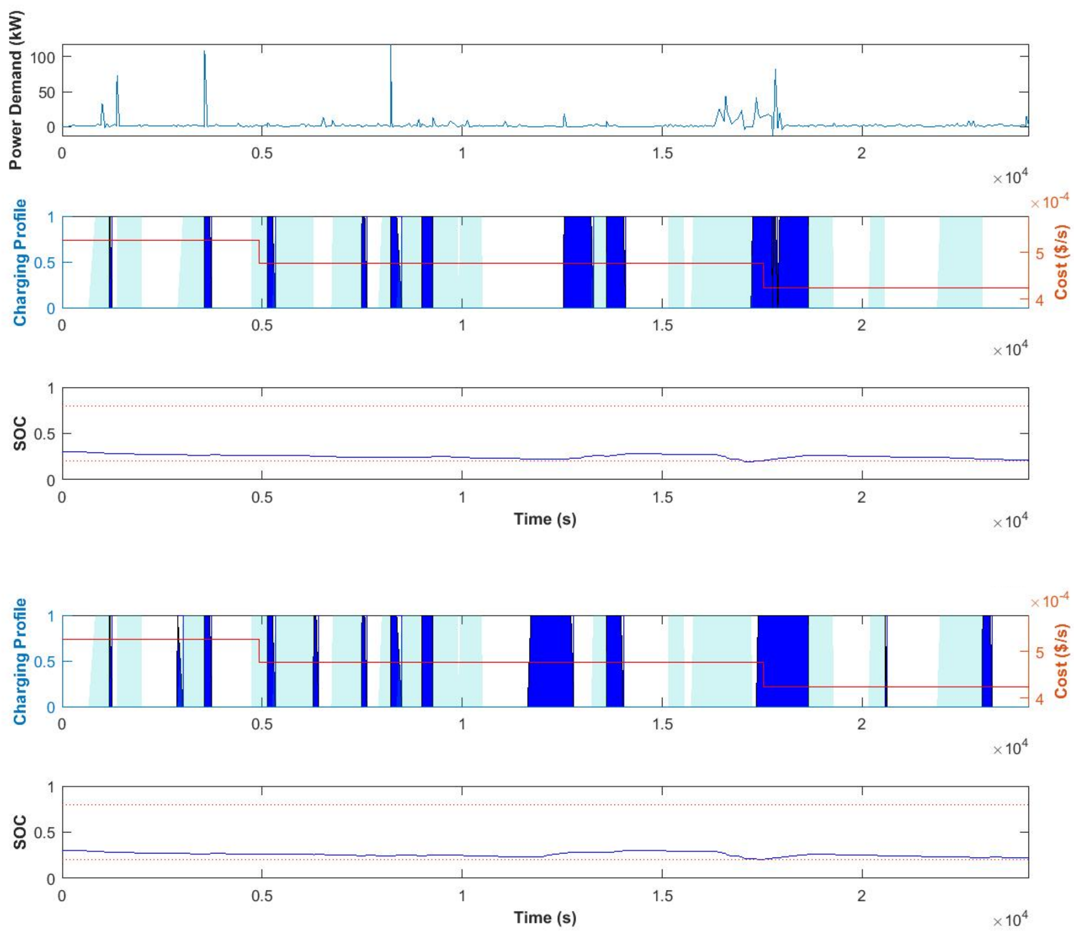



**Figure 9. Top Model: Does not include $\boldsymbol{\beta_i}$. Bottom Model: Includes $\boldsymbol{\beta_i}$**

It can be observed that towards the middle of the charging profile plots of Fig. 9, the model with the computed $\beta_i$ term shifted the charging band to the left. The minimum distance to a charging station is also lower during this period. This shows that the model successfully recognized that the vehicle was closer to a charging station during this period and responded accordingly. Refer to Fig. 10 for more details on minimum distance.

Very nice demonstration of successfully incorporating the distance-to-charger aspect. I'm glad to see you figured this out after the in-class presentation.

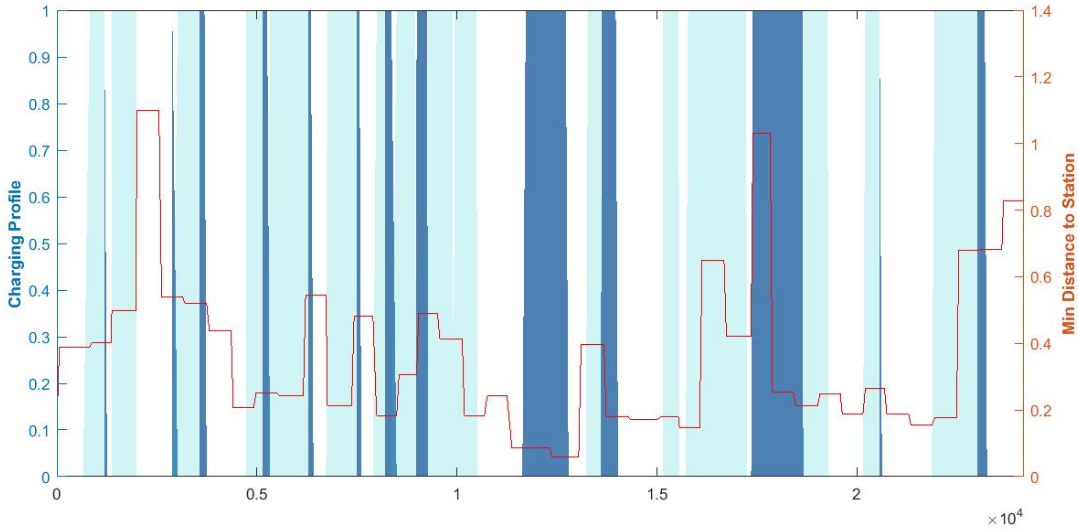



**Figure 10. Charging Profile for Bottom Model in Fig. 9 with minimum distance to charging station plotted**

Data quality issues are unavoidable in the real-world. Consider this good practice.

## SUMMARY

The objective of the project was to develop an optimized charging schedule for a fleet of electric vehicles that minimizes the operating costs of the fleet. Although there were initial issues with data quality which made it difficult to set up a realistic dynamic programming model, the final model yielded realistic and useful results.

Initially, the impact that traveling to a charging station has on SOC was ignored by making the assumption that the EVs would have the ability to charge on the spot as long as they were unoccupied. In order to quantify savings, a benchmark model was also developed. In this model, taxis were still constrained to charge only when the vehicle was unoccupied, but it did not take into acco electricity prices. The only thing driving decisions was a policy that if it was unoccupied, charge if its SOC fell below 50%. However, in the dynamic programming model, the taxi an optimized charging schedule, which balanced the need to maintain battery charge with electricity at different times. The results in Table 8 show that for all five days, the dynam model yielded average savings of about 50% from the benchmark model. However, this m a charging schedule that dictated that vehicles charge for few minutes at a time, and some vehicle's battery would die in the middle of the day. This is not a realistic result, so we so a model that considered the impact that traveling to a charging station has on SOC.

It would have been impactful to report how many vehicles are stranded using the baseline policy (50% threshold). Quantifying the avoided stranded vehicles is perhaps more significant than reducing operating costs

Due to time constraints, this final model was not run for the entire fleet. However, it succ generated more realistic charging schedules and increased the robustness of the model by to start with a low SOC and still satisfy consumer demand. Therefore, it is highly likely that the final model will perform better than the benchmark model and make significant reduction in operating costs from the initial dynamic programming model. Overall, the project objective was accomplished, though future considerations such as a comparison of vehicle models and stochastic demand profiles could make further significant reductions in operating costs.

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