Cornell Vehicle Charging Plan

SYSEN 5300 Six-Sigma Project Report

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Introduction

Emission of large quantities of carbon dioxide (CO_2), mainly due to anthropogenic activities such as using fossil fuels for transportation has raised serious global concerns because of its greenhouse effect. According to a study *(Energy Information Administration, 2016)*, the transportation sector consumed 71.4% of all petroleum in the United States. The overall transportation emission of Cornell University is about 62000 metric tons, accounting for 26% of total CO_2 emissions. Consequently, a carbon neutrality imperative in the transportation sector has been suggested, both at micro level on campus and at macro level in the outside world, to address the environmental and behavioral complexities. Announced by the U.S. Department of Energy (DOE) in 2011, massive implementation of Electric Vehicle (EV) Systems and emphasizing on harness of renewable energy has become one of the most advocated approaches. Combination of EVs, infrastructure and ecosystem is an essentially fundamental part of the suite of prospective solutions to address the challenges of providing sustainable, affordable, environmental-friendly, secure transportation, in strong contradiction to the continuous massive deployment of conventional internal combustion engine vehicles powered primarily on gasoline and diesel. EVs are powered at least in part by electricity, generated from domestic, diverse, secure energy sources. With the rapid development and popularizing of EV technology and ecosystem, the new alternatives have been proving to travel further, faster, more reliable, and at overall lower lifetime costs, despite higher initial costs and drawing considerable amount of electricity during charges.

As one of the kernels contributing to realize Cornell's Climate Action Plan to achieve carbon neutrality by 2035, substantially reducing the emission by Cornell's fleet of vehicles is of utmost priority. This makes it extremely necessary to carry out a study to establish the basis of reliable and effective execution in the few years to come. In this study we are focusing on providing robust engineering evaluations and optimization methodologies to come up with an optimal strategy to empower Cornell University Center for Transportation, Environment and Community Health. To provide them with strategies to use in future decision making of building and enhancement, the team utilized the knowledge of the course Systems Engineering Design and Operation of Reliable Systems.

The objective of the Six-Sigma Project on Cornell Vehicle Charging Plan is to provide data-oriented, reliability and optimization-based decision making tools to the staff working on Cornell EV plan.

Cornell transportation's performance in energy demand and emission would be generally improved, tracing the guidelines of the overall carbon neutral initiative if the decision makers are confident empowered by quantitative methods to take charge of their plans. EV infrastructural support, in the scope of this project, battery charging and parking, is crucial to the EV penetration inside Cornell and Tompkins County. Our goal is to provide easily applicable and realistic mathematical models on Site Selection of EV charger parking spaces, Capacity Management of supporting electric grids supporting the chargers and Cost Recovery of EV vehicle investment/return with respect to conventional combustion vehicles, in serious attempt to assist in the swift future implementations of an EV Cornell.

Background

1.) Electric Vehicles (EV)

Traditionally, the term EV referred to hybrid electric vehicles which had both an internal combustion engine and an electric motor powered by a battery which would be charged whenever the vehicle dissipated its kinetic energy while braking. There was no way to externally charge the batteries in the initial stages development of these vehicles.

In recent years, under the context of rapid advancements in EV and related technology, a new category of electric vehicles known as plug-in electric vehicles (PEVs) is introduced to be mature. These are vehicles that can be plugged into an electric terminal to charge the battery.

Initially this was an extension of the hybrid vehicle concept resulting in plug-in hybrid electric vehicles (PHEVs) with both internal combustion and electric motors but these have the provision to externally charge a battery that is bulkier compared with a regular HEV (some variations known as extended range EVs). Companies have recently been promoting their new product vehicles running solely on battery known as battery electric vehicles (BEVs). A conventional estimate of BEVs is that they travel between 60 and 300 miles on a single charge and takes at least 30 minutes to recharge. In comparison, gasoline vehicles can run 300 to 500 miles on a full tank and it takes less than 5 minutes to refuel. PHEVs have ranges similar to all gasoline vehicles but typically run only on electricity for 10 to 40 miles.

2) Charging stations

Charging stations' classification is based on the charging rate they deliver and the form in which they output the energy (AC or DC). Although to be exact, the exact charging time for each vehicle would depend on the state of the battery, its capacity and the power electronics in the charging circuit *(NYSERDA, 2017)*. The following are the most common types of charging stations, their technical details and approximate cost (not including installation)

Table 1: Classification of Charging Stations

Type	**AC Level 1**	**AC Level 2**	**DC Fast Charge**	**Wireless Charger**
Voltage Requirement	120 V	240-280 V	480 V	Induction of charge
Range of Charging	2-5 miles	10-20 miles	35-40 miles	10-20 miles
Model	3 prong household plug	Standalone station		
Cost	$1000	$450-5000	$7,000-40,000	$3,000

3) PEV Market Growth

It is important to realise the popularity of the PEVs in the past and expected market share in the future. This will help us be confident in our decision to invest in the technology. The numbers PEVs account for less than 1% of the vehicles in use worldwide and future adoption rates have a strong dependence on battery technology, government policy and consumer preferences. This introduces a great deal of uncertainty about the future growth prospects. To deal with this uncertainty the Energy Information Administration divided the future penetration into three scenarios: High Penetration, Low Penetration and the reference case. In all three cases there will be a significant reduction in the petroleum consumption for transportation needs and an increase in the electricity consumption by transportation. And this is a crucial thing for energy security because the US imports about one fourth of the petroleum it uses (24% in 2015 according to the US Department of Energy) and three fourths of its petroleum consumption is accounted for by transportation *(EIA Energy outlook, 2017).*

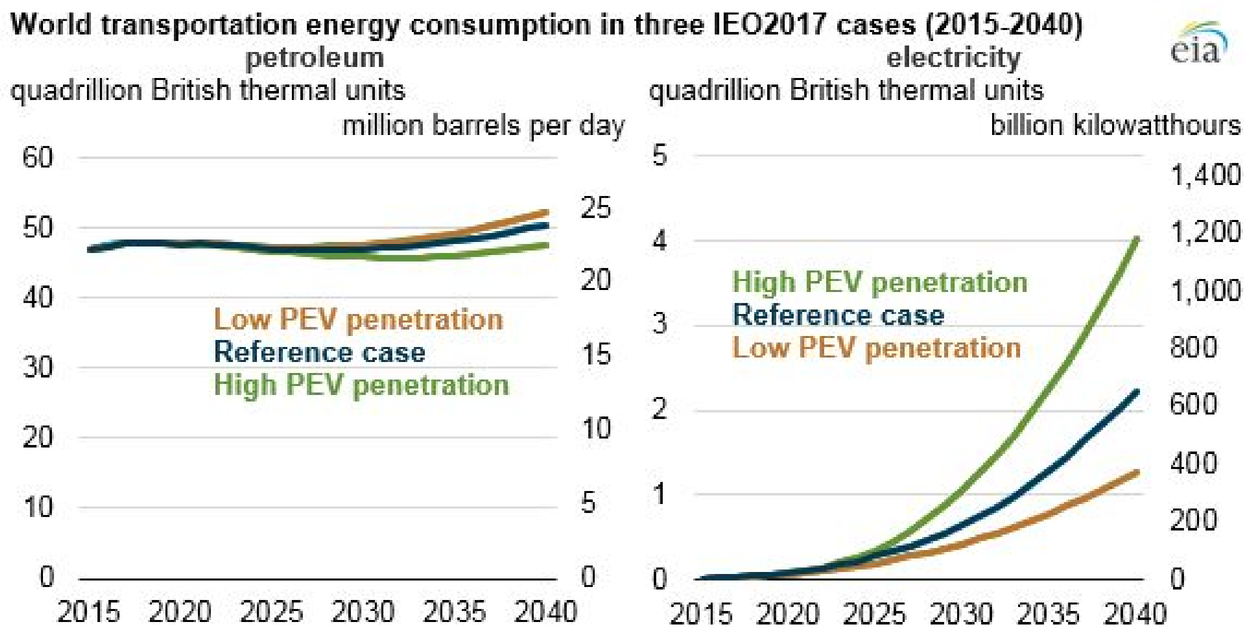

Fig 1. Electric Vehicle Penetrations

As with any infrastructure planning problem this can be segmented into three key sub-problems as shown below:

1) **Site Selection**

   The decision of selecting specific locations for putting up charging stations is a crucial element of the whole infrastructure planning process. It has to be close enough that the distance is not a deterrent because one of the things foremost on the mind of a PEV owner is anxiety related to the vehicle's range. This is more commonly known as 'Range Anxiety'. And it also has to be far enough to make sure that it is not a small fixed set of people who benefit from it but rather the charging station caters to a wide variety of users from a number of locations. However, specifically looking at Cornell, given that we we are just starting our journey on the EV path is that we need to be pragmatic in our choice of sites for installing charging stations. For this reason we felt the most important thing to look at, for any decision maker would be the ability to tell whether the current grid infrastructure at a location is sufficient to bear the peak loads. If it is not, then it is better to look at alternatives because upgrading the grid infrastructure would be a considerable added cost. These alternatives could be installing fewer than planned number of charging stations at the site under consideration with the remainder installed at a nearby location or choosing an entirely new location that would not need any additional investment.

2) **Capacity Management**

This is another key activity that comes in after the locations for the charging stations have been finalized. To ensure a good experience for the user we need to make sure that the charging stations have access to enough power to withstand even the peak loads when all the charging stations are in use at the same time. This will ensure that the charging stations do not become unusable at any point during the day by planning for the maximum possible load. As a best practice we should plan for about 1.2 times the anticipated peak loads.

The key difference between this section and site selection is that here, the model determines the hour to hour loads in much more detail to make sure that we have concrete points to discuss with the distribution company in terms of load distribution throughout the day.

3) **Cost Recovery Model/Pricing Strategy/Business Model**

The third key element of this infrastructure planning problem is designing a good pricing strategy. This is a very crucial part of the EV infrastructure planning problem because this provides the economic incentive for users to recover the relatively higher initial cost of a PEV and it also helps the equipment owner to recover their cost. And if designed correctly this could also motivate higher penetration levels for PEVs and thus reduce gasoline consumption. So any good model will balance all three aspects in an optimal way and this aspect will be discussed in greater detail in later sections.

We will be discussing these three parts in greater detail with regards to their significance for Cornell and any additional constraints that Cornell's mission places on these problems. However, at a very broad level the majority of research that is being done in the area of PEV infrastructure planning is focussed on problems of a scale much larger than our current project. In our current setting we are looking at a smaller number of charging stations and that too mostly in parking lots. The problem becomes much more complicated when planning a public PEV charging network for highways and at a city level and require more sophisticated models. The complexity of models that we have chosen may seem to be a little high for the current scale of infrastructure that we are planning but we believe by choosing a slightly more complex model we can equip the Cornell transportation team to tackle this planning exercise better when in the future it expand its charger network to better serve the increased number of PEVs on campus.

We will be explaining the rationale behind the choosing a specific model and the data required for drawing accurate inferences using these. Due to the unavailability of data we will be assuming/simulating the data to demonstrate the efficacy of the chosen models and also guide anyone who uses this study to plan Cornell's EVSE infrastructure in the future. We will also be making recommendations as to the data that Cornell Transportation should collect so that any decision maker can tackle this problem on a larger scale and come up with sound decisions backed by data.

Literature Review

1.) Site Selection:

There have been a number of studies that work towards determining the methodology for optimum site location of the EV charging stations. One of these studies focus on using the 30,000 personal trip records in the Puget Sound Regional Council's 2006 household travel survey to develop an algorithm that minimizes the user's access cost while penalizing any unmet demand *(Chen et al 2013).* The researchers claim that the resulting model is applicable to any location in the World although no sound quantitative basis is provided for the same. The researchers first use regression models to predict factors like the parking demand in terms of various measures and then use these as an input to a mixed integer programming problem that would then assign optimal locations for EV charging stations. However the models used in this paper are for a much more complicated problem such as planning the charging station locations, for instance a city. Our study draws heavily from this paper in terms of concepts but does not use the mathematical models.

Another paper draws from the study above but focuses on assessing the feasibility of BEVs for the general population considering the heterogeneous travel habits of people. They use genetic algorithms to show that the usage of electric vehicles can be promoted a lot by installing chargers in popular destinations without large investments *(Dong et al 2014)*. We have used concepts used in this paper to develop our own ideas and models.

2.) Capacity Management:

There have been several studies on modelling the effect of electric vehicles charging on the power grid. They have studied this using a set of statistical clustering algorithm to identify a set of feeders for the electric utility system *(Fluhr et al 2010).* They have developed a stochastic model using about 167,000 data points and also address the urgent need for intelligent charging strategies to avoid additional peak loads. Some studies have looked into the effect of public EV charging on the electric grid by developing a stochastic model considering the Initial State of Charge and start time of charging *(Qian et al 2010).* This study is the most relevant to our case and we have chosen this study as a base to develop our calculations on.

Additionally, several papers have worked on the concept of “Vehicle to Grid” (V2G), to manage capacity. This concept focuses on how EV can support the power grid as storage and/or generation resource. There have been several studies on this concept. This opportunity was first identified in 1997 *(Kempton et al 1997)*. Following this there have been studies that have demonstrated the applicability of this concept in a practical setting successfully *(Brooks et al 2002)*. However, the absence of data and the complexities arising from this concept due to the increased number of interactions would make the modelling for this extremely cumbersome. Another recurring trend in the literature on capacity management is the focus on cities or metropolises covering large areas. The models developed in these literatures cannot be directly applied to Cornell due to the following reasons:

1.) Most faculty and student owners of EV live in the vicinity of the campus. Thus, the distances travelled would be much smaller than that travelled in the cities.
2.) Traffic issues in Ithaca are significantly lower than the metropolises. Also, the number of EVs that are in Ithaca are lower due to the lower population density in Ithaca.

To overcome this, we made a few assumptions and slightly modified the model chosen to make it suitable for our requirements. This has been explained in detail under the methodology section.

3.) Cost Recovery:

There have been several studies that look to determine the optimum strategy to recover the cost of investment of owning an EV for the consumers and the cost of setting up charging stations for the service providers. A study developed a method that integrates indirect costs (externalities), including emissions and time losses with direct total cost of ownership. Life cycle emissions and time losses were converted into costs for three representative urban light duty vehicles: internal combustion, hybrid and electric vehicle. The results were based on vehicle technology characteristics and transportation impacts on environment *(Peterson et al 2013).*

Another study talks about the cost-effectiveness of increased battery capacity vs. non domestic charging infrastructure installation for PHEVs for cars in the U.S. Wide range of charging scenarios, age and efficiency of vehicles, annual vehicle loan payment, distance travelled by cars, charging infrastructure cost estimate etc. were analyzed to get the Lifetime Cost Premium. The model could be used universally to get the cost recovery for the system, where negative lifetime cost premium values would indicate lifetime savings. We have used this paper for our studies as it was more comprehensive than the other ones reviewed *(Mitropoulos et al 2017) .*

Measure and Design/Model development

1.) Site Selection

To simplify the process of site selection we have carried out simulations to estimate the State of Charge (SOC) that would trigger range anxiety in an EV user. We did this by using a lognormal distribution to model the distance travelled by a car after its last charge and then using that to calculate the SOC of an EV parked at the location. We then modelled the probability of a vehicle being plugged in by using the fact that the load on the grid would be distributed in the same way as the number of vehicles plugged in at any given time. This allowed us to simulate the probability of an EV being plugged in from the distribution of loads throughout the day which is a Normal distribution as per our literature review. This allowed us to calculate the expected SOC value of a plugged in car at any given time which came out to 17% and our interactions with a few EV users verifies this value.

We then created a multi-day simulation of SOC's of cars parked at charging stations and if they were below the 17% threshold we assumed that they would be drawing 6.6kW from the grid. Although literature suggests that the power drawn is not constant it usually stabilizes to the maximum value of 6.6kW within 15 minutes of being plugged in. This cannot be ignored if evaluating a DC fast charger where the total charging time (~45 minutes) is comparable however for Level 1 and Level 2 (currently being considered by Cornell Transportation) the total charging time is approximately 6–8 hours so an assumption of a flat load for the batteries is justified.

The assumptions we made based on our conversations with various EV users, literature review and other research are as follows:

1. The distance travelled by an EV car between two charges is a lognormal distribution with a mean of 22 miles and a standard deviation of 11 miles. The average time between charges is taken to be 2 days.
2. The load curve for a charging station follows a normal distribution with its peak at 2pm and a standard deviation of 4 hours.
3. The maximum load the grid can bear at any point throughout the day is 22kW.

Capacity Management:

With the expected increase in EVs in the Cornell community in the coming future, it would be necessary to understand the effects of incremental charging load on the grid. The need to be aware of the rising number in EVs and planning for additional capacity investments to avoid grid failures due to overload has become imperative. Although current EV numbers do not pose immediate threats to the grid, the rising number of EVs in the future could shift peak demand (both peak magnitude and peak time *(Nelder et al, 2016).*

In an approach to analyze the possible impacts, the following factors needs to be considered:

- **EV Penetration**

  Predicting EV penetration in the future is not an easy task since EV as a technology is still at its nascent stage.There have been quite a few case studies on forecasting EV penetration, the predictions were in a wide range varying from 5-100%. However, majority of them expected the penetration to be around 20% by 2030 in the United States *(Zamorano, 2017).*

- **Spatial Distribution of Vehicles During Charging**

  The distribution of charging lots around the campus can be obtained quite easily by compiling the planned locations of EV charging stations. Moreover, the number of charging stations allocated to each selected site should be proportional to the expected energy demand at each location

- **Time in the Day of Vehicle Charging**

  Since most staff, professors and students are in the campus only during the day, the 8 am-4 pm slot of day would be the period of maximum usage of the charging stations. This could also be affected by variable pricing based on peak grid demand. In the model to determine load on the grid, this is taken to be a random variable with pdf f(t), described by normal distribution *(Wang et al, 2012).*

- **Energy Consumed Per Charge**

  Most conventional EVs consume about 6-10 kw*hr per full charge *(Hadley et al, 2008).* However, this depends on the initial State of Charge of the battery whose distribution can be assumed to be represented by the probability density function h(E). This pdf depends on the distribution of vehicle driving distance before charge which could be derived with lognormal distribution in most settings.

- **Charging Rate**

  Most chargers in the campus are Level 2 and would be charging at the rate of 2.8-15 kw. Level 1 and Level 2 chargers have the following characteristic ranges:

  a) Level 1: 120 Volts, 1.2-2.0 kW

  b) Level 2: 208-240 Volts, 2.8-15kW

To model the load due to EV, we could follow the procedure shown below *(Qiang et al, 2011)*

If X_1, X_2, X_3 ….X_n be a sequence of n independent random variables with the same distribution, each having mean and variance. If X_i stands for the charging power demand of the ith EV charging station and n be the number of EV charging stations active, from central limit theorem (CLT), as n becomes sufficiently large, the means of the sequence tend towards a normal distribution, with mean equal to the summation of individual means of the sequences.

From the probability of the charging load operating at power P_j at any time instant t, which can be expressed as follows:

$$\Phi(P_j, t) = \sum_{k=1}^{t} f(k) h\left(E_{j-(t-k)}\right) \tag{1}$$

Here f(k) is the probability distribution function of the normal distribution modelled for the charging start times. And h(E) represents the distribution of state of charge among different cars, it can be obtained as follows:

$$h(E;\mu,\sigma) = \frac{1}{\frac{d_R}{\alpha}(1-E)\sqrt{2\pi\sigma^2}} \times e^{-\frac{\left[\ln(1-E)-\left(\mu-\ln\left(\frac{d_R}{\alpha}\right)\right)\right]^2}{2\sigma^2}} \quad (2)$$

h(E) was obtained using the assumptions of normal distribution modelling of distance travelled, g(d) and linearity of relation between SOC drop and distance travelled. These two assumptions can be mathematically expressed as:

$$g(d;\mu,\sigma) = \frac{1}{d\sqrt{2\pi\sigma^2}} e^{-\frac{(\ln d-\mu)^2}{2\sigma^2}} \quad (3)$$

$$E_i = \left(1 - \frac{\alpha d}{d_R}\right) \times 100\% \quad (4)$$

From equation (1) we can write,

$$\mu(P) = \sum_{j=1}^{n_c} P_j \Phi(P_j, t). \quad (5)$$

From equation (5) and central limit theorem, the load on the grid, when multiple EVs charge at various locations can be described as:

$$P_n = \sum_{i=1}^{n} \sum_{j=1}^{n_c} P_j \cdot \Phi(P_j, t) \quad (6)$$

Equation (6) can be used to determine the load on the grid at various points of time. This in combination with the knowledge of spatial distribution of charging stations in the campus, can be used to determine if any additional capacity investments or modifications to the grid would be necessary to meet the demand of a possible surge in the number of EVs in the campus.

The above approach to determining the load on the grid can be simplified to a large extent by making some some assumptions that would not compromise the accuracy of the predicted model to a great extent but would simplify the computations. Also, the absence of usage data with Cornell transportation necessitates the need to make certain assumptions in order to simulate the data. The following assumptions are made:

1.) Charging happens at 6.6kW throughout the period of charge. All EVs have a trapezoidal shaped charging curve, with a initial rise to 6.6kW where it stays constant for the rest of the period and falls to 0 once the charging is complete. This would be a valid assumption because the periods of increasing and decreasing charging loads are very small (~15 minutes) which can safely be ignored.
2.) Time of day of charging is assumed to follow a normal distribution with a mean of 12pm and standard deviation of 4hrs. Since the charging stations are located in and around Cornell, most of the usage would be during the working hours of the university by the professors and students between a time frame of 8 am- 4 pm with significantly lower usage during other times of the day . This fact makes the assumption a reasonable one.
3.) Distribution of distance travelled is obtained by assuming a lognormal distribution with a mean of 22 miles and a standard deviation of 12 miles. This would be a reasonable estimate of the distance travelled in the scenario of Cornell.
4.) To calculate the state of charge, it was assumed that the driving range of an EV is 100 miles and the users charge the cars once in three days. Since most modern EVs have driving ranges of about 100 miles and with most towns in Tompkins county being well within this distance from Cornell, it would be a reasonable assumption to make.

Using these assumptions, we have simplified the model described above to make computations very convenient. The simulations were carried out on MS- Excel and can be found with the Excel sheet attached with this submission.

1.) State of Charge was calculated from distance travelled as described in the "Location selection" section.

2.) Time of the day was listed in the Twenty-four hour format at 1 hour intervals.

3.) A Cumulative Distribution Function (CDF) for time of day of charging using the NORM.DIST function taking on values from the time of the day column with a mean of 12 pm and standard deviation of 4 hours.

4.) The CDF was used to find the probability of a charging station being in use at a given 1 hour time interval. This probability is to be multiplied by the number of charging points (assuming 20 charge points for the purpose of calculation), with each charge point drawing 6.6 kW. Thus the power demand is given by:

    Power demand (in kW)= (Probability of a vehicle charging at a charging point)*(6.6)*(20)

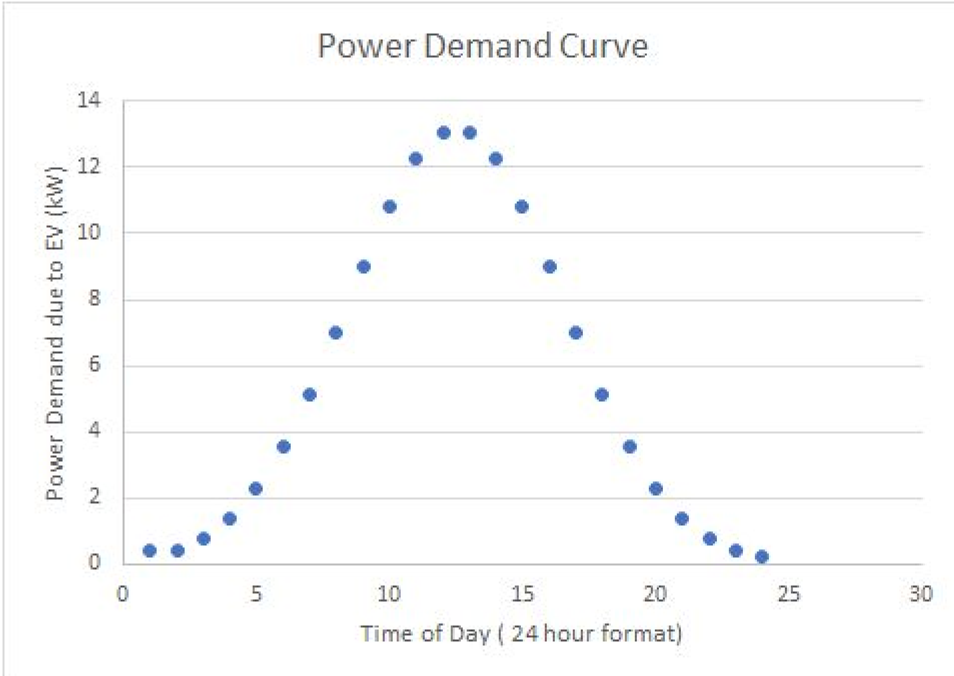

Fig 2- The power demand curve at various times of day

The above curve in figure 2 can then be used to consult with Cornell utilities to determine the need to increase capacity and by how much. This curve can be matched with the existing power generation cycles at Cornell utilities to come up with a generation plan that matches the curve shown.

Cost Recovery:

For estimating costs and gasoline savings, we could follow the model as mentioned by S. B.Peterson et al., 2013. Firstly, gasoline and electricity use by PHEVs of varying battery capacity could be calculated from *(Eq. 7 & 8)*

Total electricity use

$$f_c^{\mathrm{ELEC}}(\beta,\gamma,L) = \sum_{a=1}^{L} f_{ca}^{\mathrm{ELEC}}(\beta,\gamma) \qquad (7)$$

Total gasoline use

$$f_c^{\mathrm{GAS}}(\beta,\gamma,L) = \sum_{a=1}^{L} f_{ca}^{\mathrm{GAS}}(\beta,\gamma) \qquad (8)$$

where,

j indexes the vehicle driving profiles (day trip file)

$J_{a,c,WE}$ and $J_{a,c,WD}$ are the set of vehicle profiles of age a and class c surveyed on a weekend and weekdays, respectively

$|J_{a,c,WE}|$ and $|J_{a,c,WE}|$ are the number of vehicles of age a and class c surveyed on a weekend and weekdays, respectively

$\eta^{CD\text{-}E}$, $\eta^{CD\text{-}G}$, and $\eta^{CS\text{-}G}$ are the vehicle's electrical efficiency in CD mode, gasoline efficiency in CD mode, and gasoline efficiency in CS mode, respectively

d_j^{CD} and d_j^{CS} for computing the distance that a vehicle would travel in CD mode and CS mode,respectively

charging scenario γ

L is the vehicle life

$$f_{ca}^{\mathrm{ELEC}}(\beta,\gamma) = 104\,\frac{\sum_{j\in J_{a,c,\mathrm{WE}}} d_j^{\mathrm{CD}}(\beta,\gamma)}{|J_{a,c,\mathrm{WE}}|\,\eta_c^{\mathrm{CD-E}}} + 261\,\frac{\sum_{j\in J_{a,c,\mathrm{WD}}} d_j^{\mathrm{CD}}(\beta,\gamma)}{|J_{a,c,\mathrm{WD}}|\,\eta_c^{\mathrm{CD-E}}} \qquad (9)$$

$$f_{ca}^{\mathrm{GAS}}(\beta,\gamma) = 104\left(\frac{\sum_{j\in J_{a,c,\mathrm{WE}}} d_j^{\mathrm{CD}}(\beta,\gamma)}{|J_{a,c,\mathrm{WE}}|\,\eta_c^{\mathrm{CD-G}}} + \frac{\sum_{j\in J_{a,c,\mathrm{WE}}} d_j^{\mathrm{CS}}(\beta,\gamma)}{|J_{a,c,\mathrm{WE}}|\,\eta_c^{\mathrm{CS-G}}}\right) + 261\left(\frac{\sum_{j\in J_{a,c,\mathrm{WD}}} d_j^{\mathrm{CD}}(\beta,\gamma)}{|J_{a,c,\mathrm{WD}}|\,\eta_c^{\mathrm{CD-G}}} + \frac{\sum_{j\in J_{a,c,\mathrm{WD}}} d_j^{\mathrm{CS}}(\beta,\gamma)}{|J_{a,c,\mathrm{WD}}|\,\eta_c^{\mathrm{CS-G}}}\right) \qquad (10)$$

Secondly, the necessary charging infrastructure to enable each charging scenario could be estimated by calculating the total number of charges per vehicle in different charging case. Method described by *Dogget et al., 2011* could be used to calculate the infrastructure cost.

Finally the Lifetime cost premium could be estimated from *eq. 11*

$$\text{Lifetime Cost Premium} = C^{\text{NPV}}_{\text{PHEV},\,c} - C^{\text{NPV}}_{\text{CV},\,c} \quad (11)$$

$$C^{\text{NPV}}_{\text{PHEV},\,c} = D + \sum_{a=1}^{L} \frac{f_{\text{PMT}}(C_c - D, i, L) + p_a^{\text{ELEC}} f_{ca}^{\text{ELEC}}(\beta,\gamma) + p_a^{\text{GAS}} f_{ca}^{\text{GAS}}(\beta,\gamma)}{(1+r)^a} + C_{\text{CH}} \quad (12)$$

$$f_{\text{PMT}}(C_c - D, i, L) = \frac{(C_c - D)i}{1-(1+i)^L} \quad (13)$$

$$C^{\text{NPV}}_{\text{CV},c} = \sum_{a=1}^{L} \left(\frac{\sum_{j \in J_{a,c}} d_j}{|J_{a,c}| \eta_c^{\text{CV}}} \right) \left(\frac{p_a^{\text{GAS}}}{(1+r)^a} \right) \quad (14)$$

Where,

NPV is Net Present Value

D is the vehicle down payment

f_{PMT} is the annual vehicle loan payment

d_j is the total distance that NHTS vehicle profile j drove on the day surveyed

η_c^{CV} is the efficiency of the conventional vehicle in miles per gallon.

p_a^{ELEC} is the price of electricity a years after 2015

p_a^{GAS} is the price of gasoline a years after 2015

r is the discount rate

f_{PMT} is the annual vehicle loan payment

C_c is the additional cost of a plug-in vehicle of class c over a CV of class c

i is the vehicle loan's interest rate

L is loan period in years

Due to the unavailability of data we will be assuming/simulating the data to demonstrate the efficacy of the chosen models and also guide anyone who uses this study to plan Cornell's EVSE infrastructure in the future. We will also be making recommendations as to the data that Cornell Transportation should collect so that any decision maker can tackle this problem on a larger scale and come up with sound decisions backed by data.

Analysis and recommendation for improvement and Conclusions

We found that the simulations we carried out based on the chosen distributions happen to be in agreement with the experience of our client with Cornell transportation. The developed models seem promising in their usability in providing decision support for EV infrastructure planning.

Our recommendations to Cornell Transportation are as follows:

1. The following data needs to be collected to make actual calculations in place of the simulations and making real use of the presented models:
    a. The SOC of an EV when it is plugged into a charging station
    b. The SOC of an EV when it is plugged out
    c. Number of EV's on campus
    d. Number of days between battery charges (survey)
    e. Grid supply curve
    f. Time of the day at which the EV is plugged into a charging station
    g. Efficiency of vehicles in CD and CS mode
    h. Distance that a vehicle would travel in CD mode and CS mode
2. Once a site is chosen and number of EV charge points are decided, the site selection model can be used to quickly check the soundness of the decision

3. If a site is suitable, the load generated by the EV charging stations can be modelled to enable discussions with the distributions company to make sure they can match it.
4. Once the capacity has been planned and there is a proposed pricing model the cost recovery model can be used to check if the pricing model would result in a lower lifetime cost premium for the EV as compared with a regular gasoline vehicle.

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