

Electric Vehicles:
Cost and Emissions Analysis for CA Electric Grid

by

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Table of Contents

Abstract.....	3
Introduction.....	4
Literature Review.....	5
Scope.....	6
Envisioning a V2G System.....	7
Batteries.....	9
Data and Methods.....	9
Handling Model Weaknesses.....	13
Formulation.....	13
Results and Analysis.....	15
Conclusions.....	19
Appendix.....	21

Abstract: Electric Vehicles:

Cost and Emissions Analysis of Vehicle to Grid Services in the CA Electric Grid

Electric vehicles have been suggested as one of the primary possible solutions to fuel dependency and emissions reduction, but hesitation has been expressed as to the actual emissions reductions that electric vehicles would bring as well as the cost impacts on the individual vehicle owner.

This Masters Project analyzes the impacts of various scenarios of the integration of a passenger electric vehicle fleet into the California electric grid through Vehicle to Grid Services (V2G). The central focus of this analysis was to determine what percentage of vehicles can complete their standard driving behavior with an electric vehicle based on different assumptions of charging availability as well as battery and charging technology assumptions. To accommodate a range of possible future grid situations, three technology scenarios were conducted. Using these three grid scenarios the model was also able to show what the approximate cost would be per vehicle-week and vehicle-mile of using electric charging.

The data showed that even the pessimistic technology baseline demonstrated superior costs and emissions as compared to conventional vehicles. All three scenarios reduced emissions by more than three-fold and the cost per mile was found to be an eighth of the conventional vehicle cost. The cost differences result from lower electricity “fueling” costs as compared to gasoline fueling costs, as well from the earnings the vehicles received from selling their electricity to the grid through V2G.

At maximum, a total of 65 vehicles out of 841 vehicles “failed” meaning that the model could not find a way to allow them completion of their driving. This has significant implications as many concerns exist as to the feasibility of electric vehicles for the majority of drivers, but this data demonstrates that less than 8% of the employed population in CA has driving unfit for electric vehicles. The remainder of the population, 92%, could complete their driving under an aggregator controlled V2G scheme.

These conclusions imply that a reasonable amount of investment into Level 2 chargers and Vehicle to Grid infrastructure, could result in savings for the consumer, increased frequency regulation for the grid, and significant emissions reductions.

Introduction

The transportation sector features prominently in discussions of emissions reductions and global climate change mitigation due to the magnitude of its contribution to annual emissions; in 2003, the transportation sector accounted for about 27 percent of total U.S. GHG emission.ⁱ Of that 27 percent, 62 percent of the emissions are attributable to passenger cars and light duty vehicles.ⁱⁱ

With measures like Corporate Average Fuel Economy Standards, the government has indicated its interest in pushing for cleaner vehicles, and with their purchasing shift towards more fuel efficient vehicles Americans have demonstrated their interest in paying less at the pump and driving green. One of the many possibilities to this energy and transportation issue is the deployment of a large fleet of electric vehicles. The Obama administration stated its goal to have 1 million electric vehicles on the road by 2015.ⁱⁱⁱ

This paper analyzes the impacts of various scenarios of the integration of a passenger electric vehicle fleet into the California electric grid through Vehicle to Grid Services (V2G). The central focus of this analysis was to determine what percentage of vehicles can complete their standard driving behavior with an electric vehicle based on different assumptions of charging availability as well as battery and charging technology assumptions. To accommodate a range of possible future grid situations, three scenarios were run which will be explained in detail later in this paper. Using these three grid scenarios the model was also able to show what the approximate cost would be per vehicle-week and vehicle-mile of using electric charging.

Literature Review

The topic of vehicle to grid integration has not been very thoroughly researched yet, as there are still many steps in technological development and cost scaling that must occur before any cost effective and large scale system is viable. However, some researchers have conducted analyses of what the future of this space may look like. Kempton, et al. from the UC Davis Institution of Transportation Studies, estimated the potential costs of electric vehicles on the CA grid estimating between 30-45 cents/kwh for the charging costs of electric vehicles; they based their analysis on 2001 price data and driving assumptions from CARB standards for electric vehicles.^{iv} Guille and Gross' paper addressed the idea of aggregation from a technical and conceptual framework to consider what controls systems may be needed to run such a system.^v A Colorado State University Group conducted an analysis of grid infrastructure adjustments needed for viability of electric vehicles and determined that an aggregator control scenario is preferable.^{vi}

Electric vehicles also have positive implications for public health because the negative effects of near road pollution would be reduced dramatically by a significant electric vehicle presence on our roads. The Clean Air Scientific Advisory Committee (CASAC) performed an analysis of near-road NO₂ because the EPA "recognized that roadway-associated exposures account for a majority of ambient exposures to peak NO₂ concentrations."^{vii} The CASAC study also noted a linkage of NO₂ exposure with emergency room visits. NO₂ is just one of the many pollutants that are produced by vehicles, and electric vehicles would help mitigate this health impact of pollution by shifting the sources of pollution away from the roadways to more rural areas at plants that can be more centrally monitored and controlled.

Utilizing electric vehicles also reduces the nation's reliance on crude oil, which has important national security implications. There has been a long-standing effort by many countries to move away from energy dependence upon other countries so as to not have their hand forced in other decisions because of an energy stranglehold that a major oil producer has on them. With electric vehicles, the source of power is electricity which can be acquired from a number of different technologies and inputs, and thus no single country or region would have a monopoly over the products needed.

Scope

This analysis was initiated by Adam Langton of the CPUC to determine whether or not the claims made by electric vehicle manufacturers and vehicle charging station providers are accurate. The project has grown significantly in scope since the initial foray into the topic, but as a result of that initial direction, the data and hence the analysis is specifically California-focused. As there is not a significant amount of data available publicly on California regulation markets and it is unclear how the pricing would work if there were a vehicle fleet bidding into the ancillary services market, some assumptions were made as to what payment the vehicles would earn for their frequency regulation services.

The data gleaned from this analysis also allowed us to answer several other questions as well with either no or minimal further calculations: What would the carbon emissions be based on each of these scenarios as compared to conventional vehicle emissions? What percentage of drivers require a larger charging infrastructure with quick charging stations or battery swap to accommodate their current driving behavior?

Envisioning a V2G System

A large scale V2G system would require a significant amount of infrastructure and strategic planning. Chargers would have to be installed within residential parking areas but also at shopping areas, schools, and offices. There are three types of chargers, Level 1 (in-vehicle chargers), Level 2 (wall mounted chargers, commercial chargers), and Level 3 (commercial chargers). The Level 1 charger requires no installation or permitting because it is a standard 120 Volt outlet and it delivers 3.3 kW. A Level 2 charger requires permitting before installation and can require a transformer upgrade when installed in a residential area; it can deliver 6.6 kW.^{viii} A Level 3 charger, also known as a DC Fast Charger, is the highest rate of charge and delivers upwards of 10 kW; due to the cost and energy demand of this it is likely to only be used on a commercial scale.

The model discussed in this paper assumes that all charging locations are equipped with level 2 chargers, but it is likely that when V2G becomes widespread, all three levels of chargers will exist at different locations depending upon customer preferences as to cost of charger, rate of charge needs, regulations, electric grid capability, and location. A Level 2 charger may be ideal for a local store or restaurant parking lot, but along a long stretch of highway, a Level 3 charger may be necessary to allow a quick charge at a rest stop; for a customer who only uses their vehicle a few times a day and does not want to invest in the wall-mount charger, a Level 1 charger may be the most practical and lowest-cost solution.

Envisioning the integration of electric vehicles into the electricity market is also complex. Although utilities can bid in the power from their power plants to the appropriate Regional Transmission Operator (RTO) or Independent System Operator (ISO) it is impractical to

have thousands or potentially millions of vehicles sending in their individual bids to buy and sell power. Thus the most likely future scenario, and the one utilized in this model, is that of an aggregator who controls an accumulation of vehicles and makes the buy/sell electricity decisions on behalf of the vehicles and also submits bids to the RTO/ISO for these aggregated vehicles. For this aggregator to be effective, he needs to have information ahead of time about the driving and parking behavior of the people he will be bidding on behalf of. Hence predictable drivers, such as employed people who go to and return from work at a fairly constant time each day, are the ideal people for such a system. Using the data these drivers submit to the aggregator about when and where they will be parked and how far they will be driving, the aggregator can make bidding decisions for purchase and sale of electricity in the same way that any other electricity generating or consuming entity would in. Then the aggregator would determine which vehicles would charge and when, while allowing them to complete their driving needs and minimizing costs.

The total cost is calculated as the sum of the cost of all charging events subtracted by the sum of revenue from all the discharge events. One thing that this modeling effort did not take into account that must be considered when actually planning such a V2G system, is the fact that the revenue from the discharge events is a function of the price of regulation services. If a sufficient number of vehicles subscribe to a V2G service, they may flood the market with frequency regulation ability and result in a lowered price, thus decreasing the revenue component and hence increasing the total cost. This model however, assumed that the aggregator was a price taker and that the volume of frequency regulation that is bid in does not affect the market price.

Batteries

A discussion of batteries would require an entire paper to itself, but I will touch briefly upon some characteristics of batteries that are relevant to the analysis. Much of this information was gleaned through informal discussions with BMW. Battery impacts are one of the biggest concerns with electric vehicles and especially with V2G. The concern is that every battery has a certain number of cycles, deep and shallow, that it can go through before it is so severely impacted that is essentially unusable. If V2G was utilized in the full sense of charge and discharge capability, there would be an increased number of cycles as the discharge-charge cycles would occur in addition to standard drive-time discharging. The impacts of rapid v. slow discharge also need to be analyzed with respect to batteries to understand whether there is a better rate of discharge for these batteries so as to minimize the adverse impacts of each cycle.

Data and Methods

This section qualitatively describes the data, data sources, and analytic methods used. At the end of this section I provide definitions of variables and the primary equations used in the analysis.

The data was obtained from the National Household Travel Survey database.^{ix} The data includes information on start and stop times of individual driving trips, the distance traveled, the start and stop locations of each of those trips described as “home,” “work,” “school,” etc, and demographic information about the household that owns that vehicle.

The data required a great amount of manipulation. The first step in adjusting the data was to select which entries would be most appropriate for our analysis. Because we wanted to pick out repeatable data for California drivers – as per the discussion of predictable driving

behavior needed for the aggregator to be effective – we extracted driving data specific to California and specifically weekday worker data; hence, weekends and non-workers were excluded. This was done in part because NHTS data is provided in single day snapshots of household driving so this allowed us to select out the most “replicable” data, as employed people tend to have more regularity to their schedules than the unemployed, and then repeat that snapshot across 5 days to get a one work-week profile of driving. Furthermore, employed people are more likely to participate in V2G services, since some knowledge of driving patterns is needed ahead of time to bid into the Day Ahead Market, or potentially on an even longer time horizon.

After the inapplicable entries were removed, a random group of entries were selected from the remaining data, and the number of entries was determined primarily as an issue of practicality; we wanted as large of a data set as possible to represent a range of drivers and behaviors, but a small enough data set to make calculations and manipulations manageable for the average computer. Hence, we settled on 841 vehicles. You will notice that the final analysis only includes 810 vehicles, because as we went through the analysis, 31 unique vehicles’ driving patterns – 4% of our data set – were found to be completely unmanageable even under the optimistic electric vehicle scenarios that we were forecasting. For example, our battery had a range of 125 miles/vehicle, so a vehicle that completed more than 125 miles consecutively without stopping was completely impractical for this analysis. The implication is that about 4% of workers would not be good candidates for electric vehicles under our assumptions with level 2 chargers regardless of what charge-discharge strategy is taken, until the technology undergoes significant improvement.

The data was presented as a series of single trip entries associated with unique home id numbers. Instead of these individual trip rows of data, I combined all the data from each individual vehicle into one row of data that had data on how far each given car drove in each 15 minute time intervals across a day. Hence, for each day there were 96 intervals. If the vehicle did not drive in a particular hour the value was 0. Furthermore, each individual car id was combined with the household id to create a unique id for each vehicle.

So for example, vehicle 39865031, car 1, would receive the ID of 398650311. If it was driven 30 miles from 2:45pm-3:15pm then for 2:45-3:00 it would have 15 miles, and 3:00-3:15 showed another 15 miles. If the timings were less perfectly in particular time slots, such as 6:23pm-7:16pm, then the full driving distance would be represented within the slots that it rounded into; hence in that case, if there were 45 miles of driving on that trip, 15 miles would be entered into each 6:30-6:45, 6:45-7:00, and 7:00-7:15. This clearly creates some small distortion of the actual timings of the driving, but it was the most efficient way to handle the data for our 15 mile intervals. All of this conversion and time slot allocation was done with a series of excel formulas so it was systematic and consistent throughout the data set.

In a similar 15 minute interval fashion I also created a table to show if a particular vehicle was at or not at a charging location at any given moment. This was based upon the location data provided in the NHTS database, and a set of assumptions: 100 percent of homes were assumed to have chargers, 50 percent of workplaces, and 10 percent of “other” locations.

All of this data was then replicated 4 times, so that I had 5 consecutive days’ worth of repetitive driving behavior, and hence 480 time periods of data for each vehicle for the workweek. The assumption in doing this was that on average, weekday commuting would be

“repeatable” especially since we had selected out retirees and youth and focused upon the working population. Even though there were likely some aberrations from a normal driving pattern within our 810 vehicles, on average it should represent a standard week. This allowed us to optimize the charging to minimize cost to the drivers and maximize the number of vehicles that can complete their full charging across the course of a five day week. The inherent assumption in that is that cars are able to get to a full state of charge over the weekend, as we start the week with full batteries and end the week with only semi-full batteries. For the price component, I then obtained Day Ahead Market prices from the OASIS database of the California Independent System Operator.

The vehicles were then aggregated as if one “aggregator” or operator was controlling the charge and discharge of these vehicles. Every car started full at the beginning of the week and was allowed to drive, charge, and discharge through the 5 day work week. The model was made in such a way as to assume that the aggregator was aware of market prices, and aware of future vehicle driving behavior, simulating a scenario in which vehicles would let the aggregator know their planned driving for the next day. Of course, there was a minimum charge window built into this analysis to assure that this aggregated vehicle never went below 20% charge.

It was also assumed that at all times the aggregator bid in 77.64% of the available plugged in charge, and that a randomly generated 5% of times they would be called to discharge. When such a discharge was called, we modeled that the aggregator was obligated to provide the power they had bid in.

Handling Model Weaknesses

To then assure that there were no “stragglers” due to the aggregation – meaning cars that used a disproportionate portion of charge compared to other vehicles and thus the aggregation scenario may leave them stranded – an analysis of individual vehicles was then completed. Although modeling each individual vehicle was ideal, that was too complex a scenario from the perspective of computing power as that would require 480hours*800 cars*2 data sets just for the input data of charger availability and miles driven, and then an additional 480hours*800 cars of variable cells to keep track of each car. Although the input data was manageable, having over 350,000 variable cells was not an option.

The alternative method that was then used was to create another model to mimic the aggregators actual decision making process. Multiple methods were tried for this, and finally the best viable method was to break each day into 4 time periods: night, morning, peak, workday. Within each of these time periods the charging was distributed different to three different categories of vehicle charge state low, middle, and high. Hence at any given time period the total charge decided by the main model was distributed in this secondary model to each vehicle based on its state of charge and the presence of a charger at its parking location

Formulations:

Variables:

i = identifier for vehicles in data set [1,810]

t = time periods in 15-minute intervals across one work-week [1,480]

p_t = time of use price at time t (\$)

v_i = vehicle number i

o_t = binary for whether ancillary services are called at time t

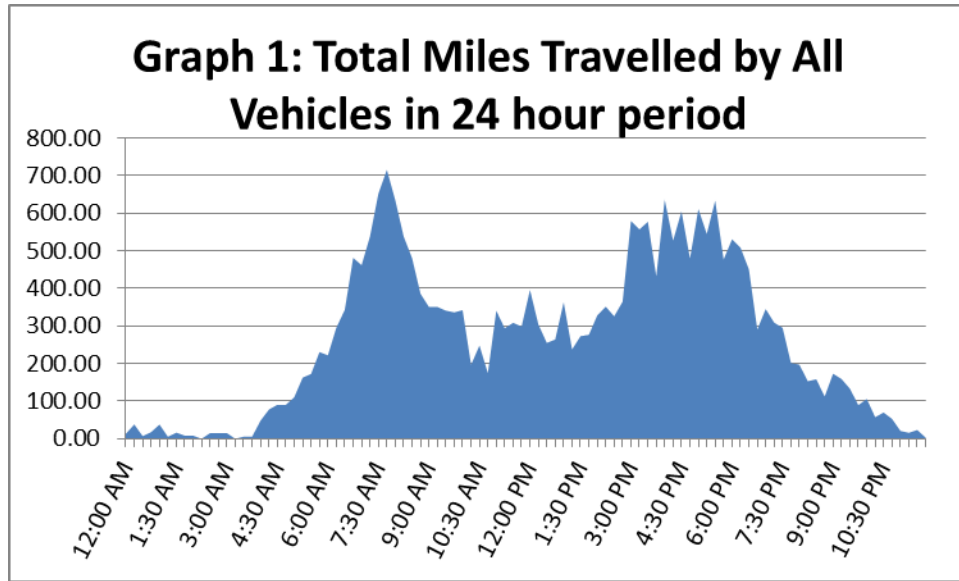
g_t = amount of discharge requested by utility = amount bid in (assumed that when discharge is called, the full amount that was bid in is actually called) (kwh)

e_t = energy price paid for selling back to the grid at time t (\$/kwh)

r_t = regulation price for being available at time t (\$/kw)

$m_{i,t}$ = distance traveled by vehicle i at time t (miles)

d_t = cumulative distance driven at time t defined as $\sum_{t=0}^{810} m_{i,t}$ as shown in Graph 1



z_t = amount of cumulative charging at time t (kwh)

Given

r = range of a single vehicle (miles)

R = range of total vehicles = $\sum_{i=1}^{480} r_i$ (miles)

C = miles/kwh of charge

L = loss factor when discharging

Primary Constraint:

Total Driving + Total Discharge \leq Total Initial charge + Charging

$$\frac{\sum_{i=1}^{810} \sum_{t=1}^{480} m_{i,t}}{c} + \sum_{t=1}^{480} g_t o_t \leq \frac{R}{c} + \sum_t z_t$$

Other Constraints:

Discharge in a single period does not exceed maximum discharge

Charge in a single period does not exceed max charge rate.

Objective Function, minimization:

Cost of purchasing electricity – Gain from providing ancillary services – Availability payment

$$\text{Minimize } \sum_{t=0}^{480} (p_t k_t - o_t g_t e_t (1 - L) - r_t g_t) \forall v_i$$

Results and Analysis

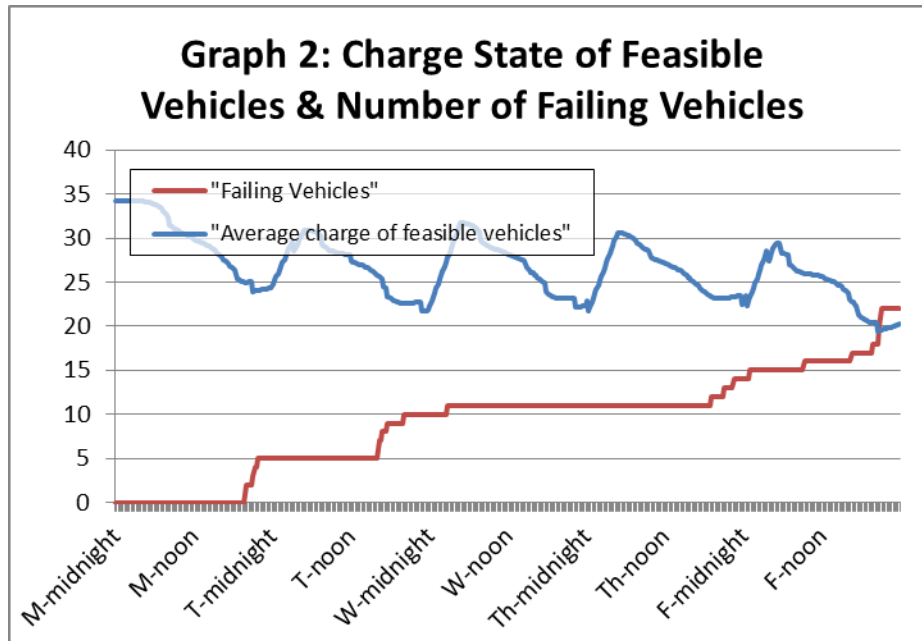
One Scenario is explained in detail, graph by graph below, followed by a comparative discussion of the other scenarios.

Scenario 1

Optimistic Scenario

Assumptions	
Range (miles/vehicle)	120.00
Minimum charge %	20%
Max Charge Rate (kwh/hr)	6.60
Loss Factor (during discharge)	10%
Miles/kwh, conversion factor	3.50
Outputs	
Number of failed cars	22.00
Total Cost	\$ 730.20
Average Cost per car per day	\$ 0.18
Average Cost per mile	\$ 0.01
Week Total (tonnes CO2)	10.94
grams CO2 per mile	89.85

Considering the costs and specifications of Nissan Leaf’s 100 mile range, the Tesla Roadster’s 250 mile range, the Tesla Model S’s 160 mile range, and the BMW mini-E’s 109 mile range, we picked an initial range estimate for our model of 120 miles that seemed reasonable technologically and likely affordable to many consumers. The 6.6 kwh/hr charge rate is based upon the assumption that at a point in the future, level 2 chargers would be available in 100% of homes, 50% of workplaces, and 10% of other locations



Based on that assumption as well as several others, we determined that 4% of vehicles were completely inappropriate for EV driving because they exceeded the entire range within one trip or within a very short time span so recharging sufficiently was impossible with a Level 2 charger. Those 4% were removed from the model. As shown in Graph 2, 22 additional vehicles, or 2.7% of the remaining vehicles were still unable to complete charging under our model. This may be a weakness in our model rather than the reality, since our model did not optimize charging for each vehicle but rather for “buckets” of vehicles, hence we still kept these vehicles in. Even if we are to count these, cumulatively less than 7% of the random selection of weekday driving that we selected would not be feasible under this scenario, meaning 93% would be feasible.

assumptions were made for regenerative braking technologies, which would in fact make costs even lower.

As far as emissions, based on the EPA estimates, there are 8.8 kg of CO₂/gallon of gasoline of gasoline, and 23.9 miles/ gallon for average passenger car, hence approximately 368 g CO₂/mile are emitted by a traditional vehicle. Hence the 99 g CO₂/mile estimated by our model are significant emissions reduction. Obviously this depends on the energy mix of the area under discussion, but in the CA region that we considered, EVs could have a major emissions reduction impact.^x

Scenario Comparison Table

Assumptions	Optimistic	Intermediate	Pessimistic
Range (miles/vehicle)	120	100	100
Minimum charge %	20%	20%	20%
Max Charge Rate (kwh/hr)	6.60	6.60	6.60
Loss Factor (during discharge)	10.00%	10.00%	10.00%
Miles/kwh, conversion factor	3.50	3.50	3.00
Outputs			
Number of failed cars	22.00	32.00	34.00
Total Cost	\$ 730.20	\$1,207.18	\$1,852.50
Average Cost per car per day	\$ 0.18	0.30	\$ 0.46
Average Cost per mile	\$ 0.01	0.01	\$ 0.02
Week Total (tonnes CO ₂)	10.94	10.79	12.84
grams CO ₂ per mile	89.85	92.32	110.68

More detailed graphs of each scenarios can be found in the appendix.

As a baseline for comparison, for conventional vehicles of model year 2010 the EPA projects average CO₂ emissions to be 394 grams per mile.^{xi} The EPA estimate for the cost of driving a traditional vehicle is \$0.16 per mile.^{xii}

Industry estimates of standard electric vehicle charging are around \$0.03 per mile, and because this model allows additional flexibility and earnings due to discharge, the calculated values align with other estimates.^{xiii}

Compared to these conventional vehicle baselines even the pessimistic technology baseline has superior costs and emissions, with the cost per mile being lower by 14 cents and the grams of CO₂ per mile being lower by 284 grams. All three scenarios reduce emissions by more than three fold and the cost per mile is also significantly lower. The cost difference is a result of electricity costs being lower than gasoline costs, as well as the earnings the vehicles get from being part of V2G.

The cost component here does not include maintenance costs of owning and operating a vehicle, but electric vehicles are known for having lesser maintenance costs than conventional vehicles due to the existence of fewer moving parts and hence even including these costs would not change the relative costs comparison of electric vehicles and conventional vehicles.

Another notable point is that at maximum only 34 vehicles were unable to complete their driving. In addition to the 31 vehicles that were omitted pre-analysis because of their driving patterns, that equals 65 vehicles out of 841 vehicles failing. This has significant implications as many concerns exist as to the feasibility of electric vehicles for the majority of drivers, but this data demonstrates that less than 8% of the employed population in CA has driving unfit for electric vehicles. The remainder could complete their driving under an aggregator controlled V2G scheme.

Conclusions

The qualitative understanding that can be gleaned from this analysis is that over 90% of drivers can complete their weekly driving behavior under standard electric vehicle assumptions using a level 2 charger, which suggests that the need for quick chargers, battery swapping stations, or other varied charging strategies is only needed for the remaining 10% of the

population. This suggests that our current charging infrastructure with slight modifications to handle Level 2 chargers, is sufficient to support a large electric vehicle fleet.

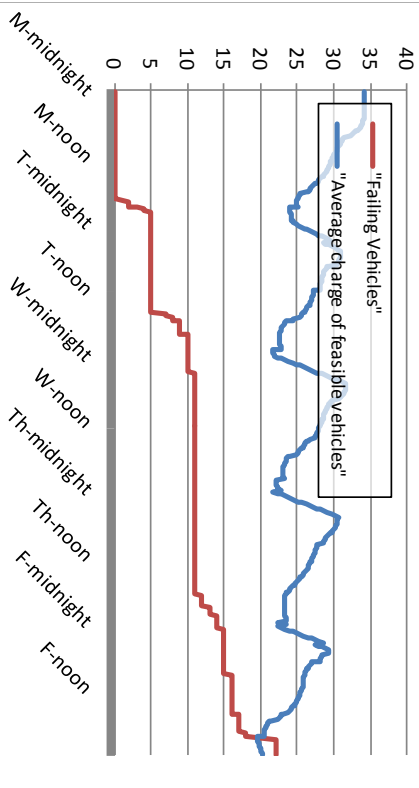
The analysis also shows that utilizing V2G can allow for near break-even costing with respect to charging the vehicle and that electric vehicles variable costs in California would be significantly lesser than those of a conventional vehicle. This implies that if we can create the infrastructure to facilitate V2G it could motivate people to purchase electric vehicles due to gasoline fuel cost savings, it could provide a meaningful ancillary service to the grid, and by subscribing to V2G the customer could further mitigate his costs of electricity. Of course, this does not take into account that a very large vehicle fleet would flood the ancillary services market, potentially swamping some of those initial cost gains, but the gains should still provide some momentum to get the V2G services started.

The emissions implications are very clear. Regardless of technology growth assumptions, in the CA electric grid, electric vehicles provide a definite and notable emissions reduction.

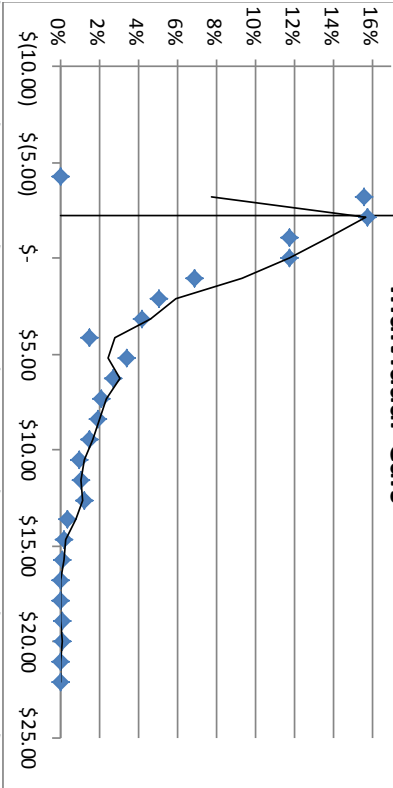
These conclusions imply that with a reasonable amount of investment into mid-range chargers and the creation of an infrastructure for vehicle to grid, savings could be created for the consumer, increased frequency regulation could be provided for the grid, and significant emissions reductions could be made.

Appendix

Graph 5: Charge State of Feasible Vehicles & Number of Failing Vehicles



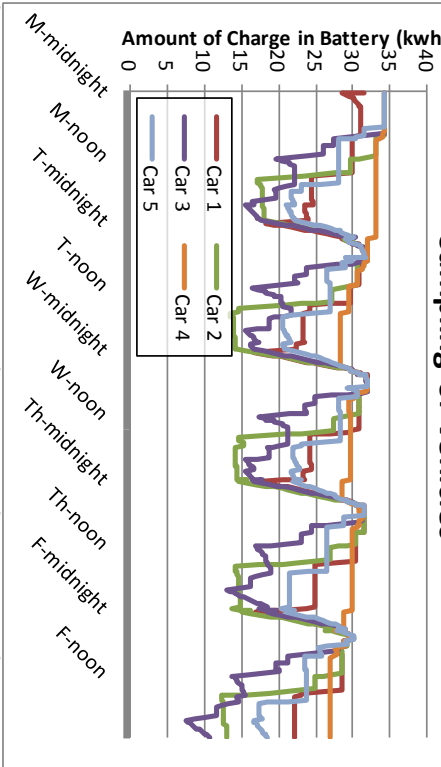
Graph 6: Distribution of Cost to Individual Cars



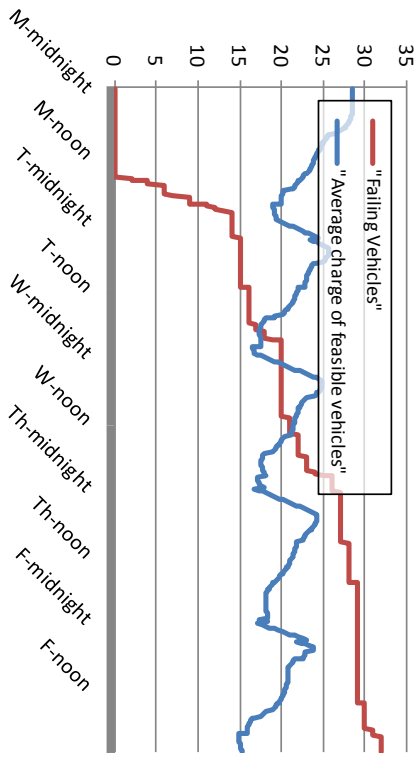
Optimistic Scenario

Assumptions	
Range (miles/vehicle)	120.00
Minimum charge %	20%
Max Charge Rate (kwh/hr)	6.60
Loss Factor (during discharge)	10%
Miles/kwh, conversion factor	3.50
Outputs	
Number of failed cars	22.00
Total Cost	\$ 730.20
Average Cost per car per day	\$ 0.18
Average Cost per mile	\$ 0.01
Week Total (tonnes CO2)	10.94
grams CO2 per mile	89.85

Graph 7: Battery Charge State of a Sampling of Vehicles



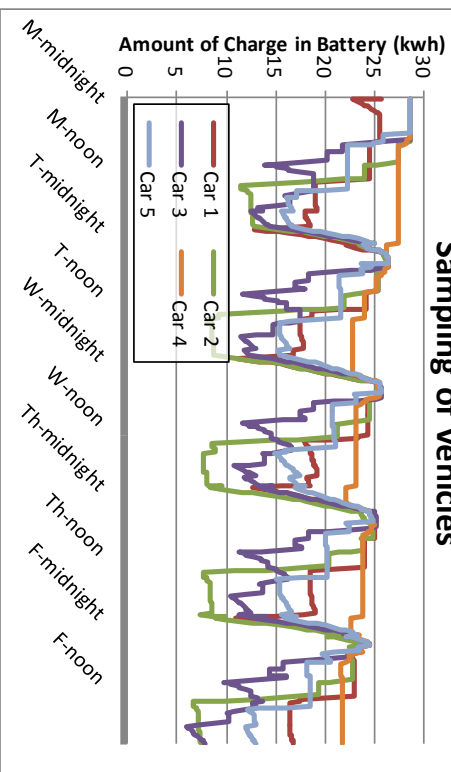
Graph 8: Charge State of Feasible Vehicles & Number of Failing Vehicles



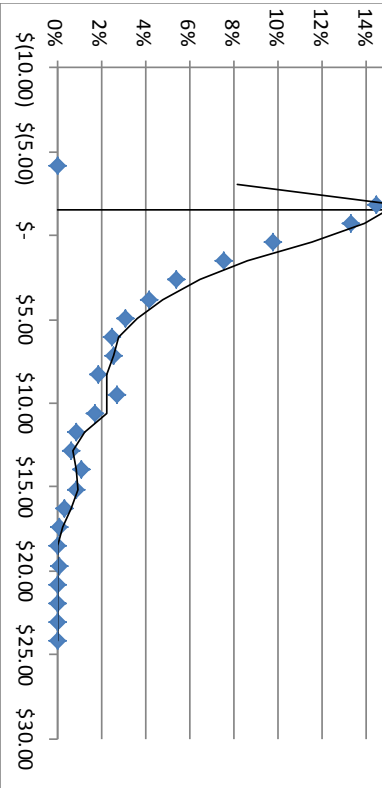
Intermediate Scenario

Assumptions	
Range (miles/vehicle)	100.00
Minimum charge %	20%
Max Charge Rate (kwh/hr)	6.60
Loss Factor (during discharge)	10%
Miles/kwh, conversion factor	3.50
Outputs	
Number of failed cars	32.00
Total Cost	\$ 1,207.18
Average Cost per car per day	\$ 0.30
Average Cost per mile	\$ 0.01
Week Total (tonnes CO2)	10.79
grams CO2 per mile	92.32

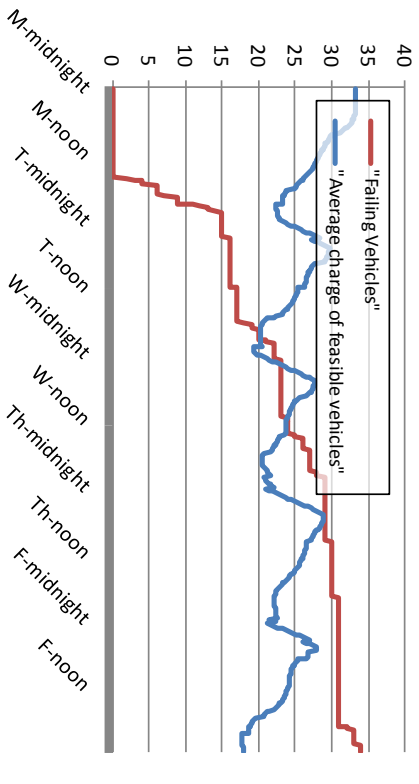
Graph 10: Battery Charge State of a Sampling of Vehicles



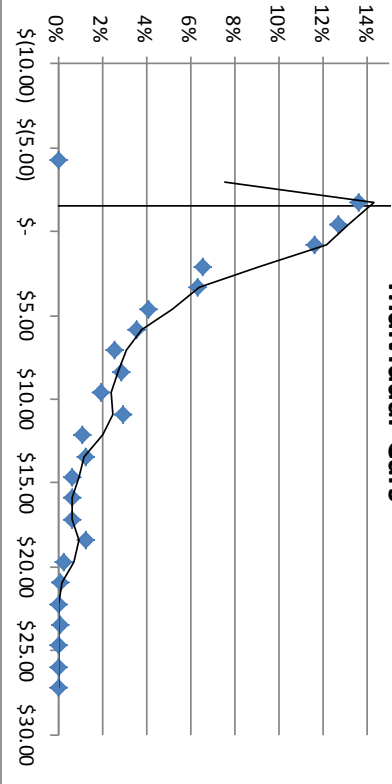
Graph 9: Distribution of Cost to Individual Cars



Graph 11: Charge State of Feasible Vehicles & Number of Failing Vehicles



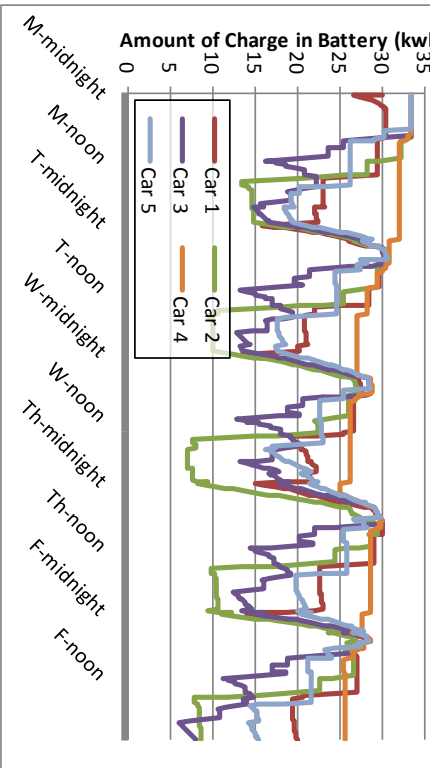
Graph 12: Distribution of Cost to Individual Cars



Pessimistic Scenario

Assumptions	
Range (miles/vehicle)	100.00
Minimum charge %	20%
Max Charge Rate (kwh/hr)	6.60
Loss Factor (during discharge)	10%
Miles/kwh, conversion factor	3.00
Outputs	
Number of failed cars	34.00
Total Cost	\$ 1,852.50
Average Cost per car per day	\$ 0.46
Average Cost per mile	\$ 0.02
Week Total (tonnes CO2)	12.84
grams CO2 per mile	110.68

Graph 13: Battery Charge State of a Sampling of Vehicles



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