

# STRATEGIES FOR MANAGING ELECTRIC VEHICLE CHARGING LOADS

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An assessment prepared for the Santa Delano Electric  
Company as an entry in the 2013 USAEE Case Competition

by

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## EXECUTIVE SUMMARY

This report analyzes several options for managing increasing electricity loads in the greater Santa Delano area due to electric vehicles (EVs) charging during peak demand. These options include 1) a “business as usual” (BAU) distribution infrastructure build out, 2) a controlled charging program for EV owners, 3) an energy storage program with large batteries, and 4) real-time pricing.

Our analyses indicate that the most cost-effective short-term strategy for meeting peak demand is to incentivize controlled charging and integrate batteries into the distribution system. In the long-term, we recommend the Santa Delano Electric Company (SDEC) leverage the information gained by deferring infrastructure build out with batteries to more optimally site and construct future infrastructure. If load growth approaches levels that would require transmission upgrades, then SDEC should collaborate with large commercial and industrial customers to construct ice storage systems to further reduce peak demand.

### Short-term recommendations:

- Controlled charging should be provided, free of charge, to all electric vehicle owners.
  - The cost to SDEC is between \$150 and \$200 per kW of peak demand offset – an order of magnitude lower than alternatives.
  - Controlled charging is not a stand-alone solution because of uncertainty in achievable peak reduction.
- Grid scale batteries should be installed in the distribution system if it allows SDEC to more optimally site future infrastructure.
  - Despite costing \$2,800 per kW of peak demand offset, batteries provide valuable information on where load is growing.
  - The cost of infrastructure upgrades combined with batteries is between 0% and 15% cheaper than infrastructure upgrades without batteries.

### Long-term recommendations:

- If EV adoption continues to rapidly grow such that transmission upgrades become necessary, then:
  - SDEC could reduce its infrastructure build out costs by 0% to 15% by installing batteries to improve siting decisions.
  - Collaboration with large commercial and industrial customers on ice storage systems can reduce peak loads at a cost of \$200 to \$500 per kW of peak demand offset – an order of magnitude lower than alternatives.
- Over the course of 15 years, implementing these strategies would cost approximately \$760 million to meet peak load compared to an expected \$1.3 billion in the BAU, a 42% cost reduction.

### Equity Concerns:

In addition to cost considerations, we find that non-EV owners may bear a large portion of costs due to EV charging. Therefore, we recommend two strategies to compensate for this equity disparity:

- Work with legislators to implement an annual EV registration fee.
- Implement a \$0.10/kWh tax on EV charging.

## 1 INTRODUCTION

In an effort to respond to recent increases in peak electricity load from new electric vehicles (EVs), the Santa Delano Electric Company (SDEC) is evaluating the feasibility and potential costs and benefits of several response options. The following specific proposals have been put forward: 1) a “business as usual” (BAU) distribution infrastructure build out, 2) a controlled charging program for EV owners, 3) an energy storage program with large batteries, and 4) real-time pricing.

The SDEC is particularly interested in meeting load at lowest cost. Therefore, we focus our analysis on the benefits and costs of these options on dollars per kilowatt (kW) of peak demand growth served. We also discuss the overall net effect of EVs on the SDEC system as well as equity issues surrounding spreading the costs of EV charging to non-EV owners.

## 2 EV CHARGING POWER DEMAND

### 2.1 EV Charging Load Model

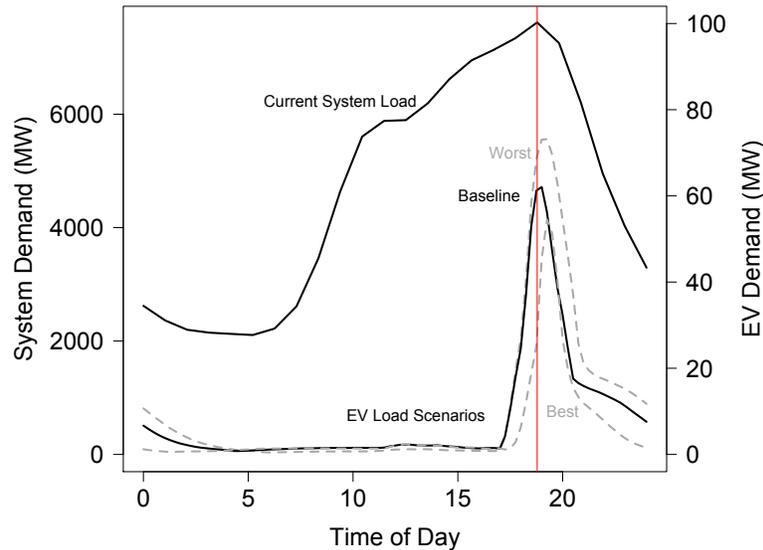
We develop a model to simulate the expected increase in power load throughout a day in a given year due to EV charging as a function the net increase in EVs added to the road that year. It is important to distinguish here that a *positive* net increase in EVs added to the road in any future year means more new EVs would be introduced than older ones retired.

All baseline parameters in the model are taken from the results of a phone survey of 100 EV owners in the SDEC area [1]. For each EV sold that year (both PHEVs and BEVs), the model draws a charging start time from a random distribution. For off-peak charging times (0:00 to 17:00 and 20:00 to 24:00), we use a uniform distribution; for peak charging times (17:00 to 20:00), we use a beta distribution with shape parameters 2 and 5, which is skewed towards 17:00 and was chosen because it closely matches the daily commute time distribution from the U.S. Census [12]. As a baseline, we assume 87% of the EVs start charging during this peak time period, while the remaining 13% start charging off-peak. How long an EV charges is based on the distance it was driven in a day, which is drawn from a lognormal distribution with a location parameter of 3.1 and a scale parameter of 0.26, which spans the range from 3 to 52 miles with a median of 23 miles. We assume efficiencies of 0.4 kW/mile for PHEVs and 0.3 kW/mile for BEVs, the respective efficiencies of the Chevy Volt, the top-selling PHEV, and the Nissan Leaf, the top-selling BEV [3].

Based on these efficiencies and the randomly drawn driving distance, the time required to charge a battery back to 100% capacity after a day’s drive is simply the distance driven times the efficiency divided by the charging power. Charging times for 4.5 kWh PHEVs and 16 kWh PHEVs were truncated at 3 and 10.6 hours respectively as limited by their battery capacities. We assume 20% of the EVs are charged both at home and at work, meaning that for these EVs the required home charging time is half of that otherwise required. Finally, to calculate the power demand at any given time in a day due to EV charging, we simply sum the power draw from each EV in the simulation at each instance in time from 0:00 to 24:00 based on each EV’s start and end charging times.

## 2.2 Model Sensitivity and Coincidence with System Peak Load

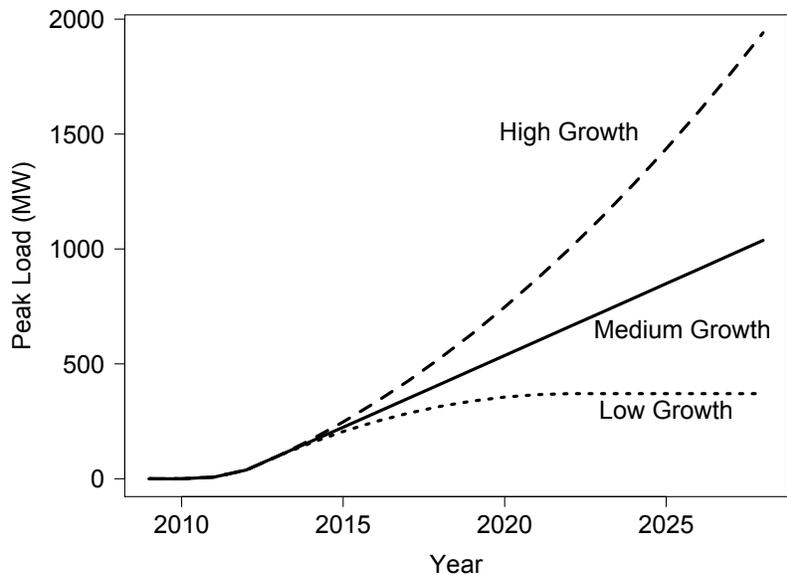
To examine the sensitivity of the model to its inputs, we run a best-case and worst-case scenario in addition to the baseline for all model inputs. Table 1 in the Appendix summarizes these scenarios. Figure 1 below illustrates the sensitivity of the assumptions on peak load. At the system peak load, the coinciding EV demand varies widely between the three scenarios, ranging from 25 to 73 MW from best to worst. Thus, the distributional assumption on the starting charge time during peak hours significantly changes the impact of EV charging on system peak load.



**Figure 1: EV charging loading coincidence with daily system peak load.**

## 2.3 Projections of Future EV Demand

In order to estimate associated costs from peak loads out to 15 years into the future, we develop a simple, linear model to project three scenarios of the net number of EVs added to the road each year out to 2028. Rather than base our projections on current or expected growth rates, we develop three scenarios (low, medium, and high growth) based on potential EV penetration into the vehicle market by year 2028. Using an estimated market size of 3 million vehicles, the three growth scenarios are 4%, 16%, and 30% market penetration, equating to cumulative net increases in EVs added to the road over 15 years of 120 thousand, 480 thousand, and 900 thousand. Each growth curve is simply a linear projection from the expected 2013 sales out to a calculated number of additional EVs in 2028 such that the integral under each respective curve is equal to 120 thousand, 450 thousand, and 900 thousand EVs.



**Figure 2: Expected peak in EV charging load for high, medium, and low EV growth scenarios.**

Figure 2 above shows the resulting cumulative increase in peak load from EV charging over time. The medium growth scenario is conservative and increases at a constant rate from 2013 to 2028. The high growth scenario is a result of a linear approximation to a typical “S” curve of EV adoption with initial high growth that decays over time. The low growth scenario represents a situation in which EV technologies (for any number of reasons) are not able to remain competitive in the market, resulting in rapidly decreasing sales over time. In this scenario, no EVs are added to the road after year 2024, and the resulting peak load from EV charging flattens.

### 3 “BUSINESS AS USUAL” (BAU) INFRASTRUCTURE BUILD OUT

#### 3.1 Modeling Method

Quantifying the cost of meeting peak demand growth requires two key pieces of information: the cost of new infrastructure and the increased cost of operating an electric grid with larger peak demand. In order to compare similar quantities, SDEC’s recommendation to increase 2001 prices by 20% is transformed into an annual cost escalation rate (1.5%). All infrastructure costs are brought to current (2013) dollars using this cost escalation rate. Two scenarios are created in order to bound the infrastructure required by SDEC to serve peak demand growth.

##### Transmission system model

The transmission system model estimates the embedded costs of operating the current transmission system and the marginal costs of investing in new transmission infrastructure. Embedded capital costs are estimated using SDEC’s estimate that transmission charges are equal to 21% of energy costs for residential consumers. This figure is then converted into an annual transmission investment per unit of peak demand (\$42,600/MW of peak demand). The cost of new infrastructure is quantified by multiplying the amount of new infrastructure needed by the infrastructure’s unit cost. As per SDEC’s guidance, no new transmission infrastructure is constructed until peak load grows by more than 5%. The assumed costs for each unit of distribution infrastructure are shown in Table 2 in the Appendix.

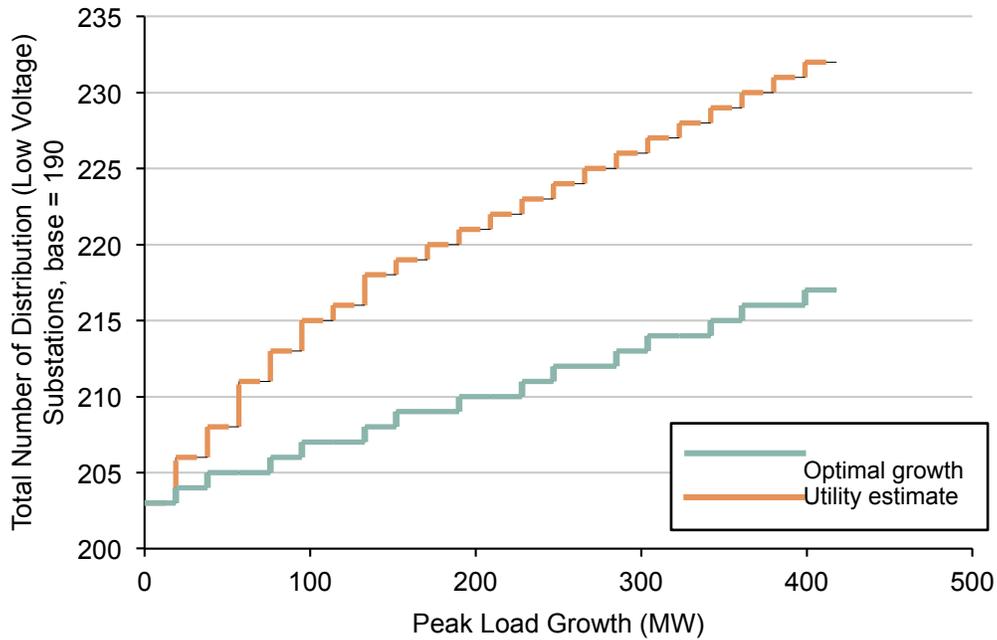
### Distribution system model

The distribution system model estimates the embedded costs of operating the current distribution system and the marginal costs of investing in new transmission infrastructure. Embedded costs are estimated using the utility's distribution charge data. An approximate value of \$170,000 per megawatt of peak demand is estimated [16]. It appears that Santa Delano has been able to maintain substantially below average distribution system investment costs (U.S. mean of \$340,000/MW of peak demand).

We estimate the infrastructure SDEC would need to construct as peak demand grows. We assumed that the relatively low voltage of the Santa Delano transmission system rendered the need for sub-transmission voltage level substations unnecessary. Additionally, PNNL [14] provided specifications for a "distribution" substation dropping voltage from 115kV to 12.5kV, similar to the drop in voltage SDEC would experience if voltage were dropped directly from transmission to distribution levels. According to NRECA [13], power lines of this voltage can transmit anywhere between 0.4 and 7 MW of power depending on the specific conductor utilized, a reasonably expected range for SDEC's distribution lines.

We estimate per unit construction costs for each type of infrastructure. We obtain two separate cost estimates for each of the two types of substations [14][9]. The two resources provided significantly different estimates for both the transmission and distribution substations, as shown in Table 2 in the Appendix. The cost estimates in bold are used for the baseline scenario, although using the other cost estimate did not influence our recommendations.

We calculate the infrastructure required to meet an arbitrary amount of peak growth. We produce two estimates of required infrastructure: 1) the utility's estimate of infrastructure growth at various levels of peak demand growth and 2) an "optimal" construction scenario. For the utility estimate, the highest infrastructure requirements occur at the first incremental units of peak load growth. In this scenario, additional units of infrastructure (or miles of power lines) are added annually per SDEC guidance. An "optimal" growth scenario is created by estimating the current amount of peak load handled by each piece of infrastructure (e.g. dividing the total number of distribution substations by peak load, or dividing total miles of power lines by the number of substations). The utility is then assumed to build infrastructure each year such that the peak load handled by each piece of equipment remained constant (or the miles of power lines per substations remained constant). This situation represents an "ideal" building out where the utility is able to fully utilize any previously constructed equipment before building new equipment – an unlikely scenario if peak load growth is sporadic and unpredictable, but more reasonable if the utility has information on where load needs to be served and can optimize the placement of infrastructure. Figure 3 shows how the utility's estimated infrastructure differs from the "optimal scenario" for distribution substations.



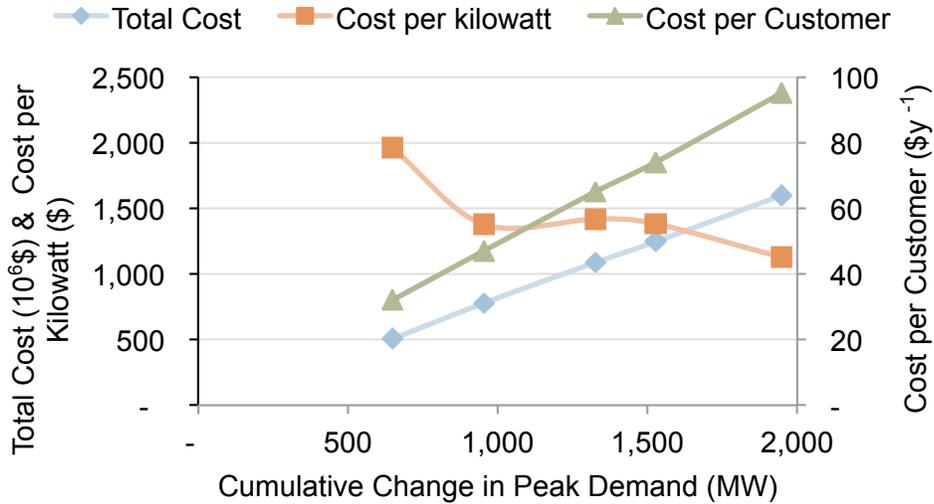
**Figure 3: The total number of distribution substations in the Santa Delano service territory as a function of peak load growth for the utility estimate and our “optimal” construction estimate.**

Finally, we calculate the cost of meeting peak demand. For each year, we multiply the infrastructure required due to load growth by the cost of the infrastructure in that year. We used the 1.5% cost escalation rate estimated earlier to inflate the cost of infrastructure over time. Net present cost is calculated by discounting future costs at a 4.3% annual discount rate, per DOE [19]. Embedded capital costs, calculated by multiplying cumulative load growth due to electric vehicles by the previously estimated embedded capital costs (\$170,000/MW) and discounting this number to present dollars, are then added to the infrastructure investment costs to find the total cost of meeting peak demand.

### 3.2 BAU Results

We present results for three important metrics: 1) incremental infrastructure costs, 2) costs per kilowatt of peak demand facilitated, and 3) cost per customer. Given the large uncertainty surrounding electric vehicle adoption and usage, we calculate utility costs for multiple electric vehicle scenarios. Finally, we perform an uncertainty analysis on key parameters such as the assumed cost escalation and discount rates.

Figure 4 shows the three cost metrics for five electric vehicle scenarios. Total cost is the net present cost of required infrastructure and embedded costs. Costs per kilowatt are calculated by dividing the cumulative peak load growth over 15 years by the total cost. Costs per customer are the annual payments (15 annual payments would be made by each customer) required by each of the ~1.8 million Santa Delano customers to cover the total cost. Although some economies of scale are achieved at large peak demand increases – the cost per kilowatt of peak demand fell from around \$1,500 to \$1,000 as peak demand growth changed from ~350 to ~1,700 MW – total costs and costs per customer scales nearly linearly with peak demand growth.



**Figure 4: Total cost, cost per kilowatt, and cost per customer versus the change in peak load.**

We estimate that annual system costs are approximately \$1.6 billion annually. Based on this estimate, meeting peak demand in the Mid penetration electric vehicle scenario would increase system costs by \$122 million annually (this was the required annuity payment given the net present cost of meeting peak demand, a 4.3% discount rate, and 15 annual payments), or by about 9%. New infrastructure investments make up approximately 1/3<sup>rd</sup> of the total net present costs. Thus, increasing peak load requires new infrastructure but also increases the embedded cost of operating the system significantly. Figure 11 in the Appendix shows both infrastructure and embedded costs over 15 years for the Mid penetration electric vehicle scenario. Initial peak demand growth causes a spike in infrastructure investment, but annual investments costs quickly become dominated by embedded capital costs, except for years where new transmission capacity was required.

Finally, we estimate the uncertainty surrounding the business as usual cost estimates. Our analysis shows that the most important assumptions are the cost escalation rate and the discount rate. Figure 5 shows varying the cost escalation rate impacts the net present cost of meeting peak growth by building infrastructure. As the cost escalation rate increases, the net present costs also increase. The change is more pronounced for the Mid and High EV penetration scenarios because these scenarios had previously benefitted from the cost of future infrastructure growing slowly. In the Low penetration scenario, less infrastructure was constructed in later years of the analysis, thus the cost escalation rate had less of an impact on total costs.

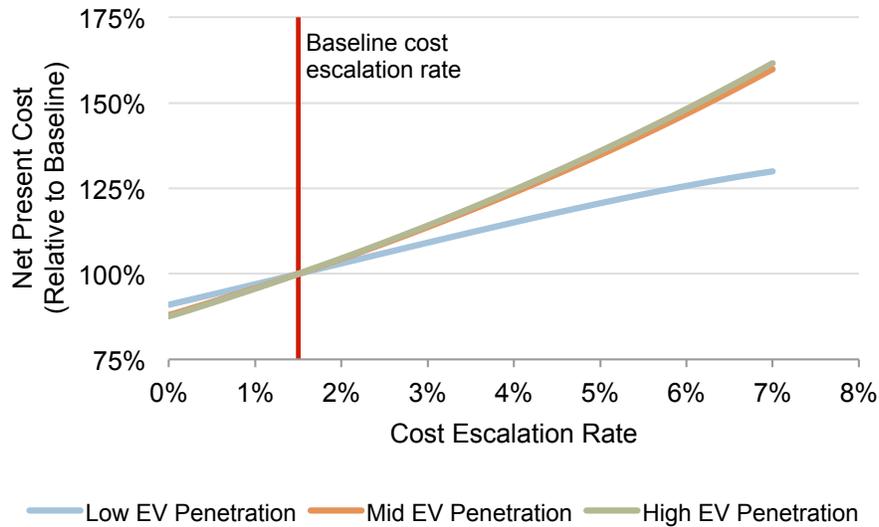


Figure 5: The impact of cost escalation rate on the net present cost of meeting peak electric demand.

#### 4 BATTERY COST ANALYSIS

We calculate the value of batteries as a tool for energy arbitrage and peak shaving and estimate the overall costs and benefits. First, we estimate the cost of a unit sized (1MWh) battery. Then, we calculate an upper bound on the potential energy arbitrage. We calculate the net present cost of the battery by adding all discounted revenue flows from energy arbitrage to the capital cost of the battery. Finally, we calculate the cost of offsetting one kilowatt of peak demand by dividing the net present cost of the battery by the peak demand offset (1/4<sup>th</sup> of battery capacity, assuming a 1 hour peak).

We estimate the cost of a 1MWh battery system using the costs provided by Santa Delano staff. Current battery prices (\$600/kWh) are used along with the conservative estimate that additional equipment would cost \$100/kWh and the assumption that initial systems would be housed within existing substations (\$20/kWh) for a **total capital cost of \$720/kWh (\$720,000/MWh)**. If battery prices decline as predicted by Aquarius Energy (\$300/kWh) and SDEC achieves economies of scale in the purchase of ancillary equipment for the batteries, reducing the price to \$50/kWh, the cost of batteries could potentially drop to \$370/kWh in the future.

We estimate energy arbitrage by calculating the maximum amount of revenue the 1MWh battery system generates assuming one discharge cycle per day and perfectly forecast prices. Given the single daily peak experienced by Santa Delano, one discharge cycle per day is reasonable. On the other hand, any error between forecast prices and actual prices would decrease revenues, thus the estimate is an upper bound on the value of energy arbitrage. Using the discharge time (C) provided by Santa Delano, \$8,700 would be the annual revenue generated by a 1MW battery. Using a battery life of 10 years and a discount rate of 4.3%, the net present value of arbitrage revenue would be about \$72,000 or 10% of the capital cost of the battery. Equation 1 below shows the annual energy arbitrage revenue calculation.

$$\sum_{day=1}^{365} \sum_{hour=1}^C (0.9 * price_{hour}^{highest,day} - 1.11 * price_{hour}^{lowest,day}) \tag{Equation 1}$$

Peak demand offset was then divided by the net present cost of the battery for a cost of \$2,880/kW of peak demand offset. The cost of offsetting peak demand drops to \$1,320/kW when the low capital cost numbers were used. One important note should be made regarding batteries: the discharge rating severely curtails the value of the battery – in order to offset one unit of peak demand, four units of batteries need to be purchased, which drives the cost of offsetting peak demand up significantly. A battery that could discharge 25% faster (31.25%/hour) would reduce the cost of offsetting peak demand by approximately \$620/kW, using today's battery prices.

A first order analysis indicated that batteries are an infeasible option for maintaining power during an outage. At the substation level, where up to 2MWh of batteries could be located, we estimate that consumer demand would be ~0.5MWh for a 60 second outage. A 2MWh battery can only discharge 0.5MWh of energy over the course of an hour, based on the stated discharge limit, thus could not prevent even a 60 second outage from occurring. At the household level, consumer demand averages around 1kW, but can be as high as 2.4kW. If household demand were at the average, unlikely given Santa Delano's statement that most outages occur during high demand summer hours, each household would be required to have 4kWh of batteries to maintain power (again, the discharge constraint was the limiting factor). Deployment of a 4kWh battery would not maintain power if household demand was above 1kWh, introducing significant risk that the "improved reliability service" would fail. Thus, current physical limitations on the operation of batteries make their use as an outage offsetting measure infeasible.

## 5 COMBINED STRATEGIES

### 5.1 Infrastructure + Batteries

One potential combination of solutions is the utilization of batteries to defer infrastructure investments. The optimal growth scenario discussed in the "Business as Usual" section is shown to require substantially less new infrastructure than SDEC's estimate of infrastructure needs. Unfortunately, with sporadic and unpredictable load growth, the utility is unlikely to be able to optimally site its infrastructure. However, if SDEC could utilize batteries to shave peak demand for a short period of time (e.g. one year), the utility would gain information on load growth location and potentially improve their ability to construct better infrastructure. We quantify costs by comparing the BAU scenario with the optimal growth scenario plus the cost of the batteries. Figure 6 compares the net present costs per kW of peak demand for the BAU scenario and for the battery installation + infrastructure build scenario. Even for the scenario where batteries do not provide the utility any information the total cost of meeting peak demand increases slightly. However, when the utility is able to derive sufficient information to build "optimally," costs fall between 0% and 15% per kWh of peak demand. This implies that batteries have the potential to cost effectively contribute to peak demand reductions at current prices, and if prices decrease, this investment option would look even more attractive.

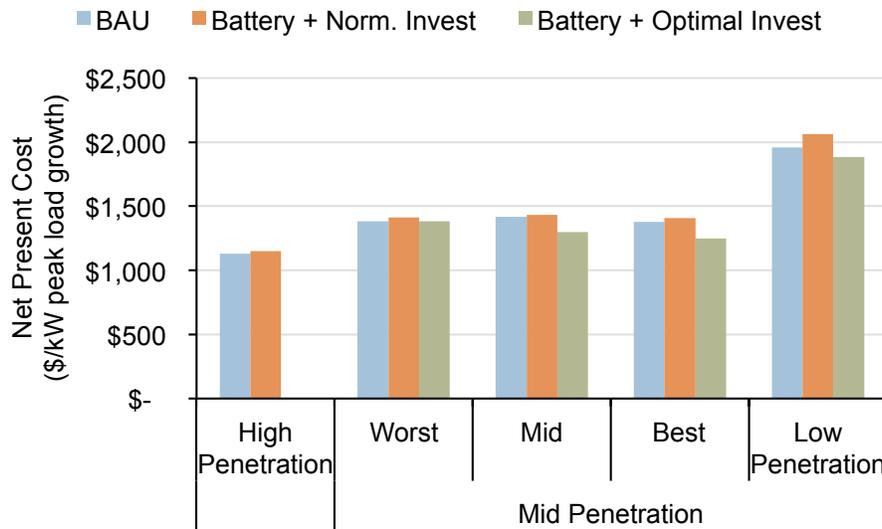


Figure 6: Comparison of the net present costs of meeting peak demand growth for multiple scenarios.

## 5.2 Ice Storage

When we examine the breakdown of total peak load, using the maximum possible electricity demand for residential customers and small and medium commercial customers, the minimum electricity demand for the 17 large commercial/industrial customers exceeds 80 MW. Given the enormous energy demand from these customers, SDEC should leverage this resource to avoid building new expensive transmission infrastructure to meet the growing EV energy demand. One potential resource that can be used to decrease energy consumption from these large consumers is energy storage technology, specifically ice storage which is a relatively cheap and effective resource for industrial settings [1][4][15]. At costs of \$200 to \$600 per kW of peak load reduction [10], utilities can provide ice storage systems to industrial users at a far cheaper cost than the cost of new transmission infrastructure costing approximately \$1,100 per kW. Given that large commercial and industrial customers are very likely to pay demand charges, ice storage would also help offset this cost. Therefore, it is likely that these large commercial and industrial customers would be receptive to utility programs designed to reduce peak loads in a cost effective manner.

## 6 DEMAND RESPONSE

### 6.1 Real Time Pricing: Analyzing Pilot Program

In order to understand the effects of real time pricing in the Santa Delano area, we conducted an analysis of consumer response to price signals. Using data provided by James Kuklos [17] in the demand response pilot program, we want to identify the potential for real time pricing to shift electricity usage throughout the day. The idea of this analysis is to be able to identify whether or not a similar program implemented throughout Santa Delano could incentivize electric vehicle owners enough to cause them to charge their cars at non-peak hours of the day. In order to measure consumer response to electricity price, we take a regression based approach from the provided data similar in structure to other real time pricing demand response studies in the literature [7][1][11][20].

The data from the pilot program provides information at an hourly resolution, every day, over the period of one year (though the pilot program is only for six months). It includes temperature at every hour, real time wholesale electricity prices, and the mean and standard deviation of energy consumption among four groups of people: single families and multi-families each with a treatment and control group.

Our first approach was to take the difference between treatment and control group means and examine whether the price differentials led to a change in consumption behavior. We developed a parametric fixed effects regression model:

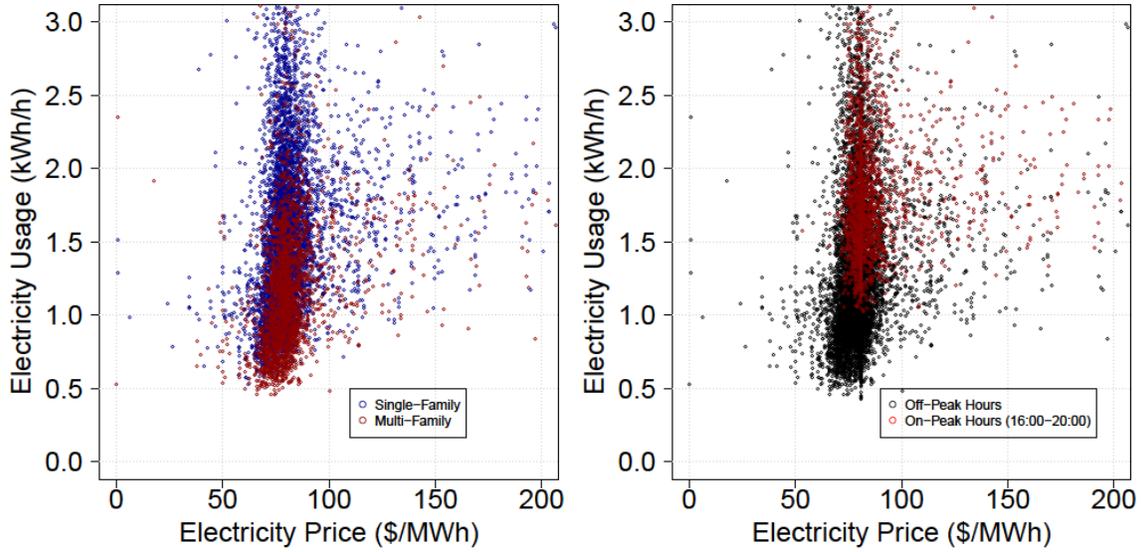
$$\overline{\Delta use}_{h,d} = \beta_0 + \beta_1 (weather)_{h,d} + \beta_2 (\Delta elec.price)_{h,d} + \eta_h + \varepsilon_{h,d} \quad \text{Equation 2}$$

Where:

- $h$  = set of hours in a day
- $d$  = set of days
- $\overline{\Delta use}$  = difference in average energy consumption between control and treatment groups
- $weather$  = average temperature in Santa Delano
- $\Delta elec.price$  = difference in electricity price between control and treatment groups
- $\eta$  = fixed error term
- $\varepsilon$  = error term

The method we use takes into account the effect of electricity price differences faced by the treatment group compared to the control group while controlling for weather and time of day effects. We find a statistically significant effect for electricity price, where a dollar increase in electricity price (\$/MWh) yields a decrease in energy consumption of about 0.00023 - 0.00028 kWh per hour per household for both single and multi-family homes. To verify the data properly fits the model formulation, we also conducted a non-parametric regression using a general additive model with the same specification as the fixed effect model to confirm the linear model.

Unfortunately, the initial analysis we conducted does not take into account variance in electricity usage across families. In order to fully take advantage of the provided data, we simulated energy usage for every individual household based on the provided mean and standard deviations using a lognormal distribution (to avoid negative energy usage). Over every hour of the year with approximately 600 households, we simulate approximately 5 million data points of energy usage. The tremendous variance in energy use across different households can be seen below in Figure 7 from simulated data:



**Figure 7: Simulated energy use versus electricity prices; layered as single-family and multi-family households (left); layered as off-peak hours and on-peak hours (right).**

Qualitatively, we see that single-family households have higher variance in energy usage than multi-family households. In addition, on-peak hours consume more electricity as expected. Note that 99% of the simulated points are between \$50-\$100/MWh with a large distribution in energy usage across these prices. We performed a regression analysis, similar to our first approach:

$$use_{i,h,d} = \beta_0 + \beta_1 (weather)_{h,d} + \beta_2 (elec.price)_{i,h,d} + \eta_{i,h} + \varepsilon_{i,h,d}, \tag{Equation 3}$$

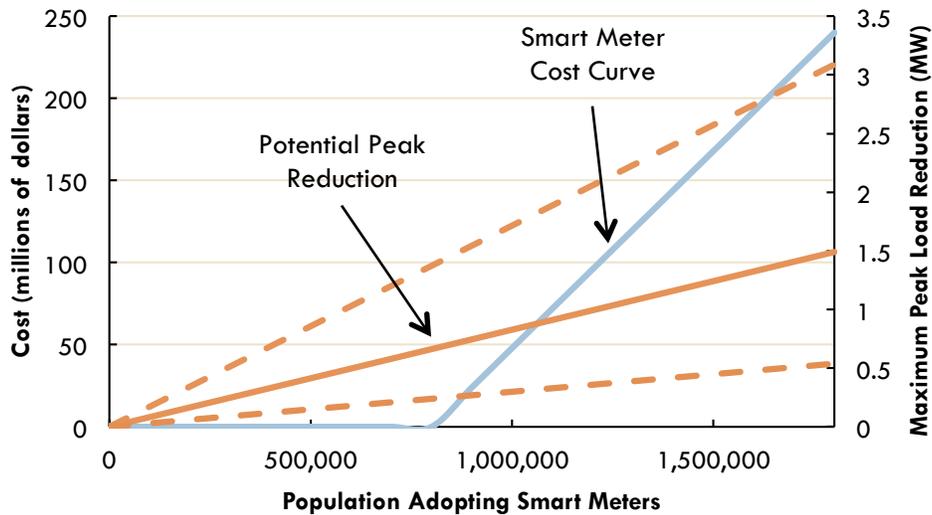
where the new subscript  $i$  represents each group of households (treatment/control and single/multi-family).

In the fixed effects linear model, the coefficient on electricity is no longer significant when using the simulated data. Due to the high variance in energy consumption, even when accounting for weather, time of day patterns, and household differences; the difference in electricity prices does not adequately explain changes in energy consumption behavior between different households. We can conclude from the analysis of real time pricing data that while there appears to be a difference on average between the treatment and control groups, once the variance between all households are accounted, electricity prices are not a good predictor for energy consumption.

## 6.2 Real Time Pricing Economic Analysis

In the following economic analysis, we examine the possibility of decreasing average daily peak load with real time pricing. We assume the best-case scenario of consumer response to electricity prices from our previous linear regression model. However, we note that in reality this optimistic scenario does not factor in the uncertainty from the high variance in energy consumption across different households.

For electricity price inputs, we used mean prices from 4 to 8 PM, only 6 PM, and only 7 PM to represent potential range of prices facing real time consumers during peak electricity use hours.



**Figure 8: Comparison of installation costs of smart meters with potential peak load reduction**

In Figure 8, the cost curve does not increase until approximately 900,000 users since half of the population in Santa Delano already own smart meters. The figure also reveals that even under full adoption in the population, the most optimistic consumer response to price, and the highest price differential with base rate pricing, a maximum of about 3 MW in reduction can be achieved with real time pricing. When considering cost in terms of \$ per kW of peak reduced, real time pricing ranges from approximately \$75,000 to \$450,000 – by far the highest cost of potential solutions to meeting an increasing peak electricity demand scenario from electric vehicles.

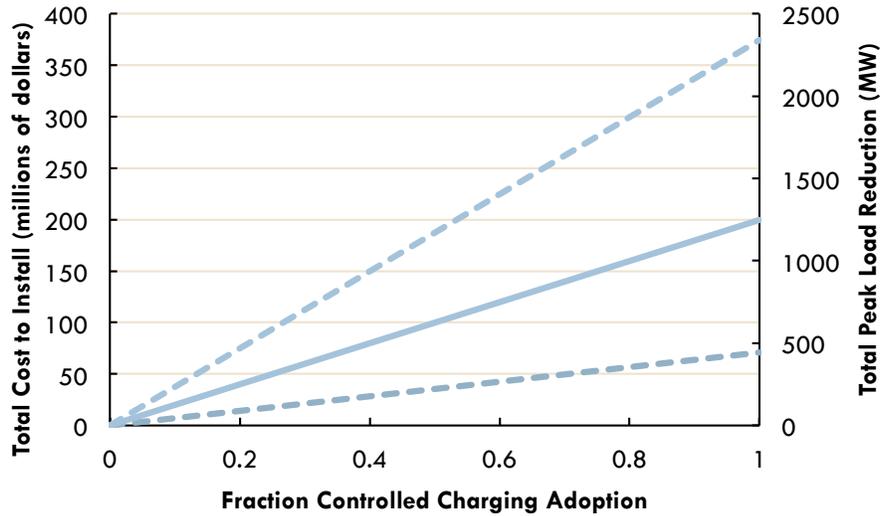
Unfortunately, real time pricing suffers deficiencies from both a practical and economic standpoint. Its reliability is highly uncertain due to variance of energy use among different households. We find that simulating the data drowns out any consumer responsiveness to price signals. However, even taking the most optimistic consumer response from our regression models, there is simply not enough potential to reduce energy consumption to address the increase from electric vehicle charging demand. From an economic standpoint, the relative ability to reduce peak demand load with real time pricing is a far more costly option than any other scenario by an order of magnitude with an estimated cost of \$160,000 per kW reduction in peak load.

### 6.3 Controlled Charger Analysis

The controlled charger is a type of automatic demand response where the plugged in EV does not automatically charge. Rather, the controlled charger can either be pre-programmed to charge later in the day/night or can interact with the utility to charge at optimal times under specific constraints.

In order to estimate the use-phase feasibility and economic viability of installation costs, we have to deal with the inherent uncertainty from demand response programs stemming from lack of information on consumer acceptance of the product. Rather than making assumptions about how consumers will adopt controlled chargers in future, we instead consider this value parametrically. Based on our previous estimates for adoption scenarios of electric vehicles, we are able to estimate the per car contribution to the peak load. Every consumer who has a controlled charger is assumed to offset their charging to a different period of time during the evening so that they no longer contribute to increased load during the highest peak hour of 7 PM.

The costs of the controlled charging infrastructure is \$200 per Level 1 charger and \$1,000 per Level 2 charger, with total costs scaling the number of each Level 1 and 2 charger by the number of PHEVs and BEVs adopted respectively.

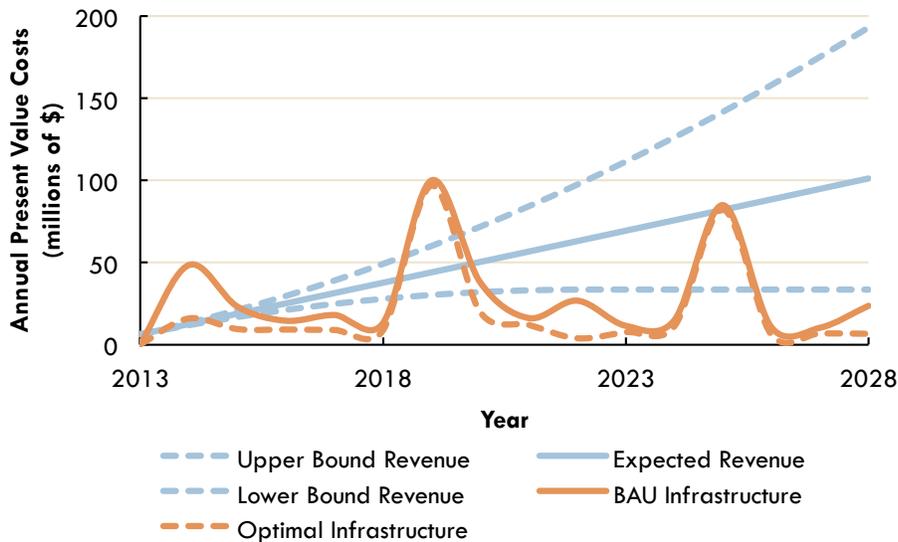


**Figure 9: Total installation costs of controlled charging with potential peak load reduction from 2013 through 2028, based on scenarios of low, medium, and high adoption rates of electric vehicles**

From an economic perspective, the cost of implementing controlled charging is more efficient than all other strategies at a range of \$150 to \$200 per kW reduction of peak load. Unfortunately, utilities face a large source of uncertainty in relying on controlled chargers to prevent peak load demand from increasing. While a full-scale adoption plan can theoretically completely offset all peak load such that no new infrastructure would need to be adopted, this would require an adoption rate of approximately 90%. Our calculations indicate that this amount is only on the order of \$15-\$30 savings per year – an amount that is not enough to incentivize consumers to purchase this technology on their own. Given that the cost is an order of magnitude cheaper than new distribution infrastructure rollout, we recommend that utilities offer this technology free of charge to consumers: PHEV owners would be eligible for a Level 1 controlled charger and BEV owners would be eligible for a Level 2 controlled charger. At the end of the day, this plan would promote higher adoption rates for consumers while offsetting distribution construction at a cheaper cost for utilities than if they meet peak load demand increases with new distribution infrastructure.

## 7 BENEFITS AND COSTS OF ELECTRIC VEHICLES

From the perspective of the SDEC, we find that even in incorporating uncertainty, the total net present revenue increase from the presence of EVs is roughly one to four times greater than the net present costs from a business as usual infrastructure build-out case (annual present value streams seen below in Figure 10).



**Figure 10: Annual revenue (with scenario sensitivity) and cost streams (for BAU and optimal build) facing utility company.**

Given that other strategy implementations suggested in this study will increase the revenue of the utility company relative to its costs, then the utility should theoretically promote EV adoption. However, depending on the utility’s willingness to face certain risks and their proclivity for expansion, this is not a hard and fast conclusion.

## 8 EQUITY CONCERNS

One of the primary concerns of meeting the increased peak load with any of the strategies discussed in our study is whether the costs can be distributed equitably. Under the BAU scenario of distribution infrastructure construction, the costs of this build out are passed onto consumers, which will increase their rates by 2% to 10%. However, these costs are being borne by the entire population of Santa Delano, while only EV owners see the benefits.

EVs have recently presented a different problem to state transportation departments throughout the United States. Revenues used to fund road maintenance and repair are drawn from a variety of vehicle fees, one of which is the state gasoline fuel tax. EVs contribute little to no revenue to this tax and in response several states have increased the annual registration fees (typically by a percentage of the retail price of the vehicle) to compensate. We recommend that the SDEC take an approach similar to the transportation departments’ strategy: work with the city by requiring an annual registration fee for owners of EVs to fund the various strategies required to meet the problem of increased peak load. Since this source of revenue will be directly proportional to the adoption volumes of EVs, the funding can be sourced directly from the beneficiaries (EV owners) at a flat annual rate of \$150 to \$200. This can be harmoniously combined with specific preferred strategies, such as promoting controlled charging by waiving registration fees for owners of controlled charging infrastructure. Taking this approach, the dilution of costs to non-beneficiaries of EV adoption can be avoided.

## 9 CONCLUSIONS

The cost of meeting the peak demand growth estimated for the Mid electric vehicle penetration scenario (Mid charging and usage assumptions) is \$1.3 billion dollars. Our calculations indicate that a combination of peak demand management strategies has a lower net present cost. The following strategies were combined:

- Approximately 25% of electric vehicle charging demand can be offset by a controlled charging program if free chargers are offered to all electric vehicle owners. The cost of this program (given that the utility subsidizes the cost of the chargers) is calculated to be between \$150 and \$200 per kilowatt of peak demand, for a total cost of approximately \$48 million.
- If Santa Delano partners with the large commercial and industrial customers and installs ice storage systems, peak demand reductions would reach 150MW (assuming air conditioning loads were 10% of the large customers summer peak loads and are completely offset with thermal storage) at a cost of \$50 million, or about \$350 per kilowatt of peak demand offset.
- Installing grid storage reduces the cost of meeting peak demand from \$729 million (after accounting for controlled charging and ice storage) to \$552 million at a cost of \$112 million.

The final cost of serving peak demand is \$762 million (~\$800kW of peak demand), a savings of 42% over the BAU case. The cost breakdown was \$552 million in infrastructure investments, \$48 million in controlled charging equipment, \$50 million in ice storage systems and \$112 million in batteries and associated equipment.

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APPENDIX

**Table 1: EV charging model inputs for baseline, worst-case, and best-case scenarios**

Scenario:	Worst-Case	Baseline	Best-Case
% of EVs charging during peak hours:	95%	87%	80%
% of EVs also charging at work:	10%	20%	30%
PHEV efficiency:	0.45 kW/mile	0.4 kW/mile	0.25 kW/mile
BEV efficiency:	0.45 kW/mile	0.3 kW/mile	0.25 kW/mile
Distributional form of starting charge time during peak hours <sup>1</sup> :	Beta(2,5)	Beta(2,5)	Lognormal(2.9, 0.03)

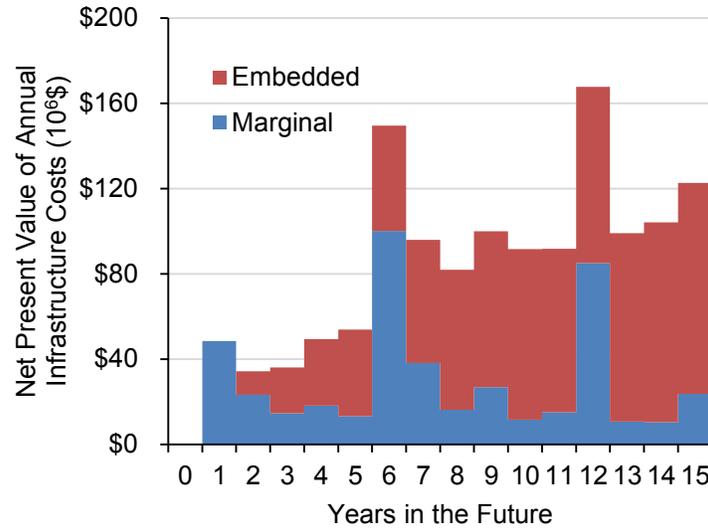
**Table 2: BAU model inputs**

		Idaho Power (2006) [9]	PNNL (1997) [14]	NRECA (undated) [13]	Fertig & Apt (2011) [6]	Hoppock & Patino (2010) [8]
Transmission Substation	(\$ each)	\$28,800,000†	<b>\$15,500,000</b>			
Distribution Substation	(\$ each)	\$2,200,000	<b>\$3,700,000</b>			
Distribution Lines	(\$/mi)			<b>\$17,300</b>		
Transmission Lines	(\$/mi, 400MW lines)				\$390 - \$1,740	<b>\$2,050 - \$7,190</b>

\*\*\* All estimates in 2013\$ based on a 1.5%y<sup>-1</sup> cost escalation rate

† This estimate was an upper bound on the cost

<sup>1</sup> The Beta(2,5) distribution puts a higher density of EV charging start times between 17:00 and 18:00, while the lognormal distribution spreads these out more between 17:00 and 20:00, thus resulting in lower maximum peaks.



**Figure 11: Infrastructure and embedded capital costs for each year in the Mid penetration electric vehicle scenario. The spikes in infrastructure investments are due to the addition of transmission capacity.**