

EVHomeShifter: Evaluating Intelligent Techniques for Using Electrical Vehicle Batteries to Shift When Homes Draw Energy from the Grid

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ABSTRACT

Time of use tiered pricing schedules encourage shifting electricity demand from peak to off-peak hours. Charging times for electric vehicles (EV) can be shifted into overnight hours, which are usually off-peak. EVs can also be used as energy storage devices, available during certain peak hours to power a house with electricity stored during off-peak hours. Studies suggest both techniques are practical, but were based on simulated demand patterns or large commercial fleets. To investigate feasibility on a per home basis, we collected data from 15 EV homes using the Lab of Things sensing infrastructure. We evaluate a scheme that powers homes with their car battery during expensive electricity periods and then charges the battery during cheaper periods. We show an average potential savings of \$10.91/month for shifting charging times, and an additional \$13.58/month for powering the home from the EV, even accounting for the inefficiencies of electric conversion.

Author Keywords

Sustainability; electric vehicles; home energy use; sensing; Lab of Things; load leveling; residential.

ACM Classification Keywords

J.7 [Computer Applications]: Computers in Other Systems: *Command and control*

INTRODUCTION

The stability and availability of electrical energy is a critical concern for many countries. Researchers have focused on understanding and reducing energy use in homes through the development of new sensing techniques and eco-feedback interfaces [e.g. 3, 7, 9, 10, 13, 26, 36]. In addition to reducing overall usage in the home, another important consideration

is shifting energy use, in particular reducing usage at peak times. The energy infrastructure must be provisioned to handle peak load, and methods for generating this extra capacity are often expensive, involving the use of less sustainable fuels that produce more carbon byproducts.

While the problem of peak demand is well known, the increase of renewable energy sources such as wind and solar has introduced a new challenge of intermittent energy production. Unpredictable production requires energy storage during periods of overproduction and flexible loads that can shift between storing energy during periods of high production and providing energy when the renewable source is not available [5, 16].

Energy companies already use a variety of strategies to encourage people to shift when they use energy in an effort to reduce peak demand or to shift to greener times of production. These include Time of Use (TOU) pricing, where rates are higher during peak times and lower during the non-peak, and demand response programs that offer savings to people who reduce energy use at certain times, typically with relatively short notice. Smart meters analyze energy use, and devices such as the Nest thermostat and other smart meters cooperate with electric companies to offer monetary incentives for participation in automatic energy reduction programs [30]. WattTime [44] attempts to monitor the grid in real-time to infer the source of energy production and provides a service to automatically shift appliance and device usage in the home to times of greener production as means to reduce overall carbon footprint.

Electric vehicles (EVs) are an interesting addition to the energy usage landscape. They are large energy consumers and their charging times may be shiftable. Moreover, their batteries can be used as home energy sources using a power inverter. Past research has explored the economic feasibility of vehicles providing energy to the grid [20, 21, 22, 40] and the length of time a car battery could power a home during an emergency [41]. EVs provide an interesting opportunity to “time-shift” energy use, thereby reducing peak demand, saving costs, and operating within green production times.

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ACM 978-1-4503-3574-4/15/09...\$15.00.

<http://dx.doi.org/10.1145/2750858.2804274>

¹ Research performed while author was visiting Microsoft Research

Using data collected from 15 homes with electric vehicles, this research quantifies the potential for shifting energy use away from peak times in two ways. First, we evaluate shifting electric vehicle charging to non-peak times to save car owners money and help with peak load leveling. Second, we evaluate the feasibility of powering the car owner's home from the battery in their electric vehicle during peak times and then recharging the battery during non-peak times to shift when energy is drawn from the grid.

We used the Lab of Things (LoT) platform [24] to log whole house energy use, car charging energy use, charging behavior, and car presence. We logged a median of 48 days per home, 113 days in one home, and 710 days in total. This real-world data set allows us to analyze the potential for energy shifting both to save the home owner money and shift peak demand. Unlike prior work, we are one of the first to empirically examine the use of EVs for shifting peak loads in the home by collecting actual EV usage data.

Our experiments show that we can indeed save money for a homeowner by shifting charging times and powering the house from the EV battery by taking advantage of TOU tiered electricity pricing that utilities offer to reduce peak demand. The simplest optimization of shifting charging times would save the homeowners on average \$10.91/month. For 98% of the 710 days in our dataset, the EV's battery had enough charge when it arrived home to power the home during the peak hours. Doing so would save homeowners on average an additional \$13.58/month, a 7.6% average savings on their monthly energy bill. Our primary analysis uses TOU rates from PG&E in California; additional analysis with other TOU pricing schedules shows similar results.

RELATED WORK

We describe related research on optimal charging schedules and providing power from an EV battery to the electrical grid or to a home.

Charging Electric Vehicles

The benefit of shifting electric vehicle charging has long been recognized. Many EVs offer simple timer mechanisms to configure charging to start at a certain time. An interview study conducted by Kurani et al. with 61 EV drivers in San Diego, CA showed that they were highly motivated to charge their vehicles during the super-off-peak period from midnight to 5 am [23]. This was due both to TOU pricing and their desire to be responsible citizens and not contribute to peak demand power issues which were well publicized in California. Davies and Kurani have also argued that models that assume one-per-day charging of EVs are overly simplistic, and given initial observations of variable charging behavior among EV drivers it would be better to use more complex models of EV charging. They stress the need to build a more comprehensive dataset of EV driving and charging [8].

More generally, managing and optimizing EV charging has long been a popular research topic. Anticipating the potential

of wide spread EV adoption to cause an overload of the power grid during periods of simultaneous charging, researchers have proposed a range of algorithms to coordinate charging. Some assume centralized control over fleets of EVs [e.g. 15, 37], and others are distributed control algorithms [e.g. 2, 14, 27]. Many of the distributed control algorithms assume signals about the condition of the power grid, either directly based on monitoring that would be installed [2] or indirectly through price information from a utility [15, 27].

While preventing wide-spread charging from overloading the power grid is an important topic, we focus on adjusting the charging schedule in individual homes to save money and reduce peak demand. We evaluate the potential savings using data collected on real usage, not with simulations.

Vehicle to Grid (V2G)

The University of Delaware Grid-Integrated Vehicle group has conducted research on the feasibility and economics of Vehicle to Grid power (V2G), where electric drive vehicles provide power to the grid when parked [e.g. 20, 21, 22, 40, 43]. Given the relatively small amount of power available from any single car, their analysis demonstrates the need for an aggregation service to create coalitions of 300 or more EVs to guarantee the 1 megawatt of capacity necessary to participate in the power regulation market [20]. Other researchers have studied the achievable power capacity of coalitions of EVs [17].

For utilities or companies that own fleets of vehicles, their analysis in four US regional markets showed that V2G could be profitable [40]. Additional research by the group demonstrates that the storage and discharge capabilities of V2G could help stabilize the intermittency of renewable energy generation (e.g. wind, solar) [22].

In our work, we empirically examine how households use power for homes and their EV charging. We focus on using the EV to minimize the cost of energy used at home by shifting when power is drawn from the grid, which does not require home owners to participate in V2G coalitions.

Vehicle to Home (V2H)

Companies and researchers have recognized the potential of EV batteries as direct energy sources for individual homes. One focus has been on their potential to power homes during emergencies when grid power is unavailable. In 2012, Toyota tested a V2H backup system using Prius cars in 10 homes in the Toyota City Project in Japan [12]. In early 2015, the company announced that the hydrogen powered Mirai arriving in late 2015 includes a port in the trunk that Toyota claims can be used to power a typical Japanese home for up to a week [35]. Other car companies are also testing V2H technology. In late 2014, Nissan deployed a test of Leaf-To-Home charging stations at dealerships in Japan [38], and in February 2015 Tesla announced it is working on a consumer battery pack based on batteries used in the Tesla car [34].

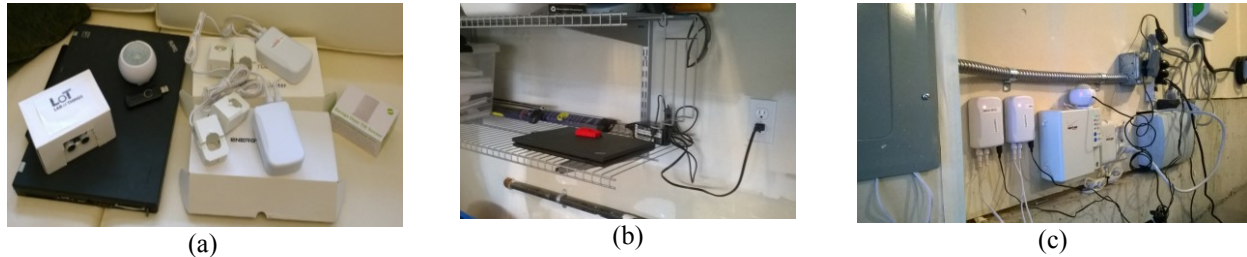


Figure 1. (a) Hardware deployed in Round 1 homes. In Round 2, two of the red beacons seen in (b) replaced the custom distance sensor, one was put in the car and the other in garage. (b) EV29's Home Hub and home beacon (c) EV26's garage wall with the two energy meters we added.

Research studies support the potential of EV batteries to power homes, particularly in emergency situations. Tuttle et al. [41] used residential energy data collected by the Pecan Street project [32] for 20 homes in Austin, Texas to analyze how long backup power could be provided by a battery electric vehicle (BEV) or plug-in hybrid electric vehicle (PHEV) alone, and in conjunction with rooftop photovoltaic solar panels. The BEV batteries sizes used in the simulations were 19.2 kWh and 32kWh, inspired by EVs available in 2012. Depending on the home energy use, their simulation showed BEVs could keep the home running on average between 10 hours (hot summer months in Texas) and slightly over 50 hours in the best case (large battery in March).

Our research differs from Tuttle et al. because we do not focus on emergency situations. Instead we use logged data to analyze the use of EV batteries to shift when homes draw energy from the grid to save consumers money and flatten grid demand during normal use. Also, many of our participants have EVs with larger batteries (60 and 85 kWh).

Tuttle et al. [41] used an 88% conversion efficiency for discharging energy from the battery to the home. This was based on measurement of a Chevrolet Volt battery during hot weather (≥ 92 °F, 33 C). The authors found a 93% conversion efficiency during cooler weather (67– 71 °F, 19 – 21 C), but opted to use the more conservative value. For our data, we analyze a range of conversion efficiencies to show how savings differ.

In their SmartCharge work, Mishra et al. compute the monetary return for individual homes to use dedicated rechargeable batteries for load shifting [28]. They develop a learned model for predicting a home's next-day electricity demand. Combined with next-day pricing data from electric utilities, they optimize the interplay between charging and discharging a home's batteries, showing a potential for a positive return on investment. In contrast, we propose using EV batteries instead of home batteries, which means the battery cost is absorbed as part of the vehicle cost, but the batteries may be away and not always available to power the house. A follow-up project by Mishra et al., proposes a peak demand surcharge to flatten demand and introduces PeakCharge, a peak-aware charging algorithm that would optimize energy use given the proposed surcharge [29]. We evaluate savings given existing TOU pricing schedules.

A project by Pedrasa et al. solves a complex optimization problem concerning electric energy costs and comfort for a home with a PHEV, electric water heater and space heater, pool pump, and other “must-run” electric services [33]. In this case, a demand pattern is assumed known in advance. Like us, they assume the home's vehicle can be used to power the house. Unlike our work, this work depends on a simulated demand pattern.

Finally, although not a focus of our research, for people with privacy concerns, other researchers have suggested that the use of rechargeable batteries to shift power usage can be valuable for hiding appliance usage information from non-intrusive load monitoring [19, 31].

STUDY METHOD

We gathered a data set of real-world home energy usage and car charging behavior from 15 houses using the Lab of Things research platform. Due to the amount of equipment required in each house, we conducted the study in two rounds. Round 1 occurred from July-September 2014 and collected data from six homes. Round 2 occurred from January-March 2015 and collected data from eight homes. One additional home participated in both rounds and as a long term testbed to bring the total to 15 homes. This section describes how we used LoT to collect data, the participating homes, changes we made to the LoT platform, and our study method to handle issues encountered during deployment.

LoT Research Platform

Lab of Things platform is a freely available, extensible research platform designed to enable deployments into homes of a range of connected devices for studies [24]. The LoT platform consists of a Windows computer called the Home Hub installed at the home and running the HomeOS client code to interact with devices [11], and a set of cloud services for remote access, monitoring, data upload, and remote updating. LoT code has been downloaded more than 8,000 times, used by more than 80 student developers in class projects, and enabled several research projects [25]. The first author co-leads the Lab of Things project.

LoT's goal is to change the scale and pace of research on connected devices in homes by enabling researchers to focus on their area of interest, e.g. building new technology or conducting studies, without needing to build out

ID	Valid Days	Car Type	People	Home Size (sq. ft.)	Median Charging Time per Session (minutes)	Median Charging Power per Session (kW)	Median Charge per Day (kWh)	Median Household Demand per Day (kWh)
EV2	26	Tesla	3	3000	29	17.6	8.5	26.9
EV3	113	Tesla	4	2400	105	8.6	17.4	15.2
EV4	15	Tesla	4	4700	43	13.6	6.6	61.5
EV5	21	Leaf	3	3100	114	3.5	5.1	31.2
EV6	48	Leaf	4	4390	438	1.4	10.7	59.1
EV7	63	Leaf	4	2800	123	3.4	3.0	55.0
EV8	68	Tesla	3	2700	38	18.0	7.0	37.5
EV22	42	Leaf	4	2900	548	1.4	11.9	15.7
EV23	42	Tesla-60	5	4000	51	8.5	15.6	34.6
EV24	50	Leaf	4	2900	150	3.5	9.4	26.7
EV25	50	Leaf	3	1790	68	5.1	7.4	12.1
EV26	49	Leaf	3	3300	39	5.9	4.4	13.0
EV27	27	Tesla	3	3000	146	7.4	14.1	23.5
EV28	48	Tesla	6	2100	90	4.3	17.0	45.6
EV29	48	Tesla-60	4	3000	121	6.5	12.1	19.9

Table 1: Households that participated in the study. Except for the two Tesla-60, all the Teslas had 85 kWh batteries. The Leaf battery is 24kWh. EV6 and EV22 used Level 1 Chargers (110 Volt circuit), all other homes had Level 2 (240 Volt).

infrastructure for field deployments. LoT's extensible platform already supports logging data from and actuating a wide range of sensors, including energy meters, cameras, thermometers, motion sensors, Microsoft Kinect, and custom sensors built with Arduino or .NET Gadgeteer. LoT can be extended as needed to interact with new devices by writing a small amount of code called a driver. For this field deployment, we extended the default LoT Sensor application with additional monitoring capabilities and also contributed a driver for Texas Instruments Bluetooth beacons.

Data Collection

We used the Lab of Things's Sensor Logger application to collect sensor readings and send them to cloud data storage for analysis. Figure 1 shows the hardware deployed in each house for data collection, including the Home Hub, an Aeon labs z-stick to communicate with zwave sensors, and the following sensors to collect:

1. Whole house energy use. We used an Aeon Labs Home Energy Meter connected to the LoT Sensor application to record data at 1 minute intervals. This two-clamp meter was installed by an electrician inside the home's electrical panel. In Round 1, a few homes had more than one electrical panel. In those homes, we installed multiple meters and combined the results to get total home energy use. In Round 2, we recruited for homes with only a single panel to enable deployment in more homes given our supply of meters.

2. Energy used for car charging. For homes that charge using a 240 volt circuit we used another Aeon Labs Home Energy Meter (13 homes). For homes that charged using an

110 volt outlet (2 homes, EV6, EV22) we inserted inline an Aeon Lab Smart Energy Switch which measures energy used by plugged-in devices. Both reported at 1 minute intervals.

3. Presence of the car at home. The car's presence at home determines the hours charging can be shifted and when its battery would be available to power the house. The energy signature of a charging car is trivial to detect, but after charging completes the vehicle is no longer detectable. Reliably detecting a car's presence at home was the most difficult sensing task of the study. We piloted many different approaches including placing motion sensors on the garage floor, which were destroyed by being run over, GPS trackers in the car which were deemed privacy invasive and expensive, and garage door sensors, which were not reliable due to double garage doors and opening of garage doors for other reasons.

For Round 1, we built custom distance sensors using Microsoft .NET Gadgeteer, one of which is shown in Figure 1. These were designed to be placed in the garage a short distance away from the car. The sensor reports a small distance when the car is parked and a longer distance when the car was not present. We also deployed the ECOLINK Z-Wave Garage Door Tilt Sensor as an emergency back-up. Unfortunately, we had not anticipated that a participant might park their car in several different places.

For Round 2, we extended Lab of Things with the drivers to enable Bluetooth Beacons and tracked car presence using the Texas Instruments CC2541 configured as beacons (Figure 1b). We deployed two beacons to each house, one for the car

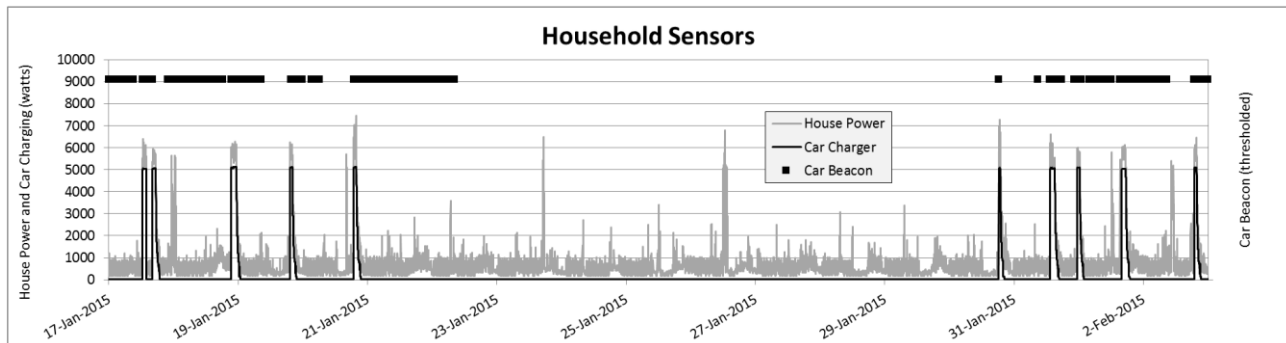


Figure 2: Processed household sensor values indicate the household electric demand, vehicle charging demand, and whether or not the vehicle is home. This vehicle was undergoing repairs from an accident for about nine days in the middle of the timeline.

and one for data validation to remain in the garage. Detecting the garage beacon meant that logging was still working and served as a check on the health of the beacon receiver. Again the Garage Door Tilt Sensor was deployed as back-up.

4. Temperature sensing. EV batteries are sensitive to temperature extremes [41], so we logged temperatures in the garages where the vehicles were parked using the Aeotec Z-Wave Multi-Sensor. In our moderate climate, we saw only a comfortable temperature range, from 54.2° F (5th percentile) to 80.9° F (95th percentile) and do not consider temperature impact on battery efficiency in our primary analysis. Note, Figure 5 shows potential savings using a range of battery efficiency providing insight into how savings would change for less efficient batteries due to temperature or other factors.

Participants & Install visits

We recruited households with a single, completely battery operated vehicle, either a Nissan Leaf (24kWh battery, 7 cars) or Tesla Model S (2 60kWh batteries, 6 85kWh batteries). To simplify analysis we selected drivers who charge their cars only at home with rare exceptions, drive more than 75 miles per week, and excluded hybrid vehicles. Homes ranged in size from 1790 – 4700 sq. ft. (median

3000). All homes had 3 to 5 residents with a mix of adults and children, and were located in Washington State, USA. Participants were recruited through a neighborhood mailing list and an EV enthusiast mailing list at our company.

Table 1 shows household demographics. EV2–EV8 participated in Round 1, EV3, EV22 – EV99 in Round 2. We visited each home twice, once to deploy sensors and once to remove them. We brought a licensed electrician to install or remove the clamp meters placed inside the home’s electrical panel. Participants received their choice of two software gratuities for participating in the study. EV2, EV3 are the homes of last author and first author respectively.

Representative Participants

We were interested in how representative our 15 homes were. We asked the main driver of each EV to estimate their average weekly driving distance. The results are shown as a box plot in Figure 3. (For drivers who gave us a range of distances, we took the midpoint of the range.) We compared this with data from the 2009 U.S. National Household Travel Survey (NHTS) [42].

The NHTS is a survey of U.S. household travel patterns. It includes vehicle data giving estimates of the annual miles driven. We filtered out vehicles that were not driven for work, commercial vehicles, and those that were not regular cars (*i.e.* not vans, SUVs, trucks, motorcycles, or golf carts). The survey did not ask if the vehicles were electric, but we surmise the vast majority were gasoline powered, given the relative popularity of EVs in 2009. We used the survey’s BESTMILE estimate of annual mileage, eliminating those values flagged as outliers and zero values, leaving annual mileage estimates for 86,193 vehicles. Dividing the annual numbers by the number of weeks in a year, the box plot for weekly mileage from NHTS is shown in Figure 3. We see that the two middle quartiles of our subjects generally fall within the third quartile of NHTS respondents, meaning our subjects generally drive farther than average, although not excessively more.

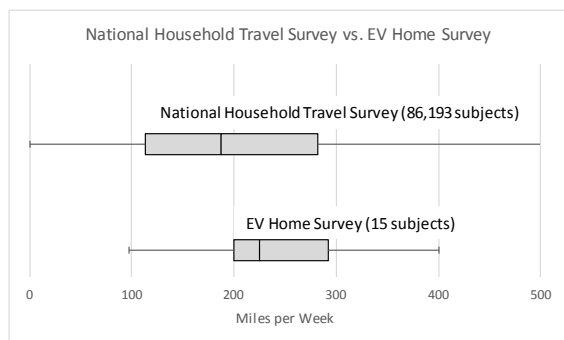


Figure 3: Our subjects generally drove more miles per week than drivers from the 2009 U.S. National Household Travel Survey.

A further comparison with other drivers is based on a 2012 survey of 1400 U.S. EV owners in California [6]. The survey

found that 91% of California owners lived in a single-family, detached home, and that 91% have installed a residential charger. Both these features were also true of all our study participants.

Monitoring to Reduce Real World Deployment Issues

Based on our own experience and that of other researchers [e.g. 18], we were aware that in-home sensor deployments invariably have challenges. We took several steps to detect sensor and data collection issues. First, we followed the online LoT study deployment instructions to make all hub interfaces remotely accessible and set up an email alert if any hub failed to send a heartbeat message for 15 minutes. We also extended the Sensor application deployed in each house with configurable monitoring per sensor and set up email alerts when no data was seen from the home energy sensor or home beacon for 30 minutes. Finally, at the end of every week we used the data export tool to download and plot data (see Figure 2) for each hub to check for anomalous values.

Using these methods we successfully detected numerous problems and either visited homes or worked with household members remotely to try fix them. However, the time to schedule revisits to homes and other issues led to lost data as shown in the valid data column of Table 1. In EV4, remote monitoring revealed the distance sensor was dropping off the home WiFi. Unfortunately even with visits and reinstalls we ultimately got only a few days of data from this home. EV5 parked the car outside the garage invisible to the distance sensor for several days. In EV27, we visited the home after detecting anomalous readings and discovered one of the electric clamps had slipped. In EV25, lack of car charging data was due to a car accident which put the car in the repair shop for several days. We also asked households about low energy or car charging readings and found several households went on break during a school holiday.

However, to make clear the realities of home deployments, we also want to report on two failed deployment sites not included in Table 1 or any analysis. In Round 1, the failed home (EV9) had multiple issues: a car frequently parked outside the garage out of range of the distance sensor and a low-bandwidth home WiFi connection that prevented remote monitoring so we could not detect sensor failures. Based on this home and EV5, we moved to beacons for car presence. In Round 2, the batteries in both beacons for EV21 failed three days into study. Remote monitoring alerted us to this, and we visited and replaced them. However, due either to hardware problems with the beacons or the distance the car was parked from the house, the car beacon data ended up having significant gaps that we deemed too unreliable to use for analysis, and we had to drop this house, despite our recovery efforts.

Even though two homes had deployment problems, overall the existing monitoring of LoT combined with the additions we contributed to the platform helped us catch and respond to many problems or detect when home-owners' behaviors had changed so we could check-in with them (about

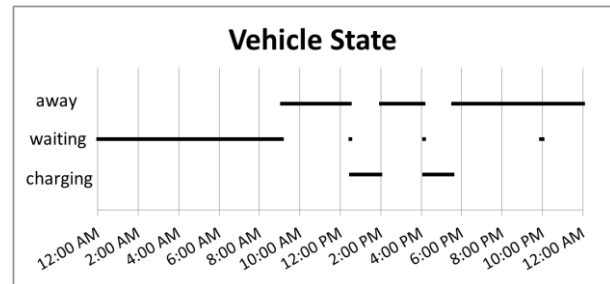


Figure 4: This shows the computed state of the vehicle from Figure 2 on Saturday, 17 January 2015. The vehicle was waiting at home from midnight until it left at approximately 9 a.m. It arrived home again around 12:30 p.m., was briefly in the “waiting” state, and then almost immediately plugged in for charging until about 2 p.m. Then the vehicle was driven away again for another two hours, parked at home, and charged starting around 4 p.m. The vehicle left home shortly before 6 p.m., came home briefly around 10 p.m. and then left again.

vacation, etc.). We hope the additional monitoring options we added to the platform are valuable to future researchers deploying studies.

DATA ANALYSIS

With raw data gathered as described above, we processed it into clean, meaningful signals to support our analysis of charge shifting and vehicle-to-grid. Specifically, we needed to know household electricity demand, vehicle charging electricity demand, and whether or not the vehicle was parked at home.

The raw sensor data was stored in log files as tuples giving the sensor name, a time stamp, and a sensor measurement for each sensor reading. For each household, we built configuration files that mapped the specific sensor names to the actual signals we were trying to measure, such as household power demand and vehicle charging demand. These configuration files were useful for abstracting away the household-specific sensor names and to account for when a sensor was renamed or replaced during the course of the study. This was also how we accommodated homes with multiple electrical circuit breaker boxes, which led to multiple household power sensors that had to be summed to measure whole-household demand.

After reading each sensor log and de-duplicating identical time stamps, the sensor data was concatenated according to the configuration files into four different raw time series:

- Household electric power demand
- Vehicle charging electric demand
- Vehicle distance from depth sensor
- Vehicle beacon signal strength

The household power demand values were normally stable and thus required no further processing. The vehicle charging values sometimes showed brief, unrealistically large spikes, so we smoothed them with a 20-minute wide symmetric median filter, extending 10 minutes prior and 10 minutes after the value being smoothed. As explained above, we measured vehicle presence with either a depth sensor or a beacon. We discovered the depth sensor produced very noisy values, so we smoothed it with a 30-minute wide symmetric median filter. The four resulting time series supported not only our subsequent analysis, but also served as a convenient way to discover problems with our logging system (such as a sensor going off-line) or unexpected behavior from our study participants (such as a vacation).

An example of these time series is shown in Figure 2. Note that the household power demand is always larger than the vehicle charger demand. This is because the household demand includes the charger demand. For this particular household (EV25), the participants' vehicle was undergoing repairs from an accident that occurred on 21 January, which explains the approximately 9 days of vehicle absence in the middle of the timeline.

After this processing, we produced a clean, interpolated summary log for each household with evenly sampled values at 1-minute intervals consisting of:

- Household electric power demand in watts
- Vehicle charging demand in watts
- Vehicle state from {away from home, waiting at home (not charging), charging (at home), unknown}

We considered the vehicle charging whenever the smoothed charging demand exceeded a manually set threshold. We considered the vehicle at home whenever the smoothed depth sensor measurement was below a manually set threshold (indicating the vehicle was close to the sensor) or whenever the vehicle's beacon was detected. Note that we included an unknown state for the vehicle to account for those times when the depth sensor was not reporting and no charging was occurring. An example of the vehicle state from the first day of the household in Figure 2 is shown in Figure 4. In our data analysis algorithms as described next, we err on the side of caution and filter out any data with an unknown state from our computations of savings and cost benefits.

ID	Valid Days	Median Household Demand per Day (kWh)	Car Charging Shifted to Cheaper Tier		Car Powers Home During Expensive Tier		
			Avg. amount saved per month (\$)	% Savings on monthly bill	Avg. amount saved per month (\$)	No. of days car charge insufficient	% Savings on monthly bill
EV2	26	26.9	11.71	7.2	7.76	0	4.8
EV3	113	15.2	13.59	4.9	1.81	0	0.6
EV4	15	61.5	0.00	0.0	5.76	0	6.2
EV5	21	31.2	5.52	5.1	10.11	0	9.4
EV6	48	59.1	4.88	1.7	18.91	10	6.6
EV7	63	55.0	6.22	2.9	22.73	3	10.5
EV8	68	37.5	0.00	0.0	35.32	0	18.1
EV22	42	15.7	3.01	2.0	16.59	1	10.9
EV23	42	34.6	28.22	9.7	20.44	0	7.0
EV24	50	26.7	15.06	7.5	10.94	0	5.5
EV25	50	12.1	10.63	10.6	3.45	0	3.4
EV26	49	13.0	10.60	11.8	10.72	0	11.9
EV27	27	23.5	26.96	24.8	8.17	0	7.5
EV28	48	45.6	19.73	6.1	24.48	0	7.6
EV29	48	19.9	7.46	4.6	6.54	1	4.0
Average	47.3		10.91	6.6	13.58		7.6

Table 2: (Left) Average amount saved per month and % savings on monthly bill for shifting car charging to cheaper tier. (Right) Additional average amount saved per month and % savings on monthly bill for car powering home during expensive tier with a 90% battery efficiency model. Also shown are number of days for which the car's battery had insufficient charge to completely offset the home's power demand during peak pricing tier. PG&E TOU tiered pricing assumed.

CHARGE SHIFTING

One of the optimizations to save energy costs in a TOU tiered pricing structure is to shift the use of energy to cheaper tiers. That is, instead of the car being charged as soon as the homeowner plugs it in, the charging is scheduled to happen during the cheapest tier. We analyze the savings as a result of such shifting by computing the energy used by the car's charger per household during peak demand period for each 24-hour period. This is accomplished by isolating the car charger's power data during the expensive tier and computing the energy consumed. We then apply pricing from each tier to estimate the energy costs.

Analyzing TOU tiered pricing for various states across the US, one notes that the peak demand period is often between 1 p.m. and 8 p.m. For our analysis, we made use of the PG&E TOU pricing where the base price per kWh is \$0.143 and peak demand pricing is \$0.336/kWh between the hours of 1 p.m. and 7 p.m. PG&E serves California, even though our subjects were all in Washington State. Because Washington does not offer TOU pricing to consumers, we chose PG&E as a nearby electric utility that does offer TOU pricing.

For this analysis, we computed the effect of delaying the start of charging until 7 p.m. when the vehicle was at home in the evening. Table 2 (left) shows the average dollar amount saved per household as a result of charge shifting. Over all 15 households, the average monthly savings is \$10.91. Also shown are the total dollar savings during the entire duration of the study. In every case, the EV was available the next morning with a full charge.

It is important to note that because these households are located in an area that currently does not have TOU charging, there is no current financial incentive for the households themselves to use features provided by car manufactures to delay EV charging to cheaper times during the late night. In fact, in our dataset only two homes, EV4 and EV8, did not charge their cars during peak hours. Our data shows in the absence of TOU pricing, most homes did not shift their charging away from peak periods.

We showed earlier that our EV drivers drove more than most drivers in the National Household Travel Survey. Because more driving means more electricity use, absolute savings for vehicles driven less would be reduced.

Though a straightforward optimization, simple shifting of charging schedule is only the first step in making use of the car's battery and TOU pricing to save energy costs. Savings could be further maximized by offsetting the home's power consumption (in essence shifting the home's power) during peak demand tiers, which we examine next.

POWERING HOUSE WITH THE CAR (V2H)

Several constraints must be taken into account to assess the economics of using the EV's battery to offset a home's power demand during peak pricing times. First, the car's battery should be charged during a cheaper pricing tier. In our dataset we observed the typical office hour's schedule

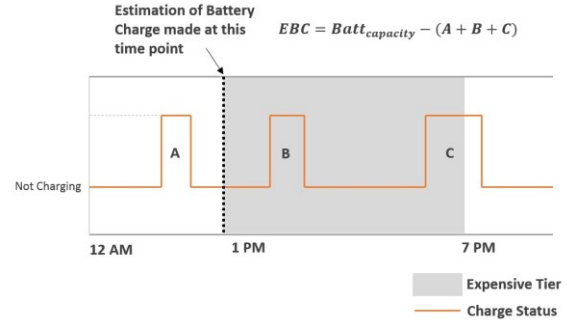


Figure 5: Estimation of battery charge (EBC) that can be used to offset the home during the expensive tier is made at the start of the tier. EBC is computed by summing energy consumed by all car charging events following the estimation point for the day up until the start of the next day's expensive tier.

where the car was left charging overnight, ready to be driven the next morning to work.

Use the PG&E pricing schedule as an example, the first constraint mandates that the car's charging period be shifted out of the 6 hour expensive segment. In our analysis, we assume this is the case and verified that the duration of non-peak hours provides sufficient time for all cars in our study to be fully recharged. This is also important for the second constraint: if the car's battery is depleted as a result of powering the house, there should be sufficient time left in the non-peak segment for the car's battery to be fully charged.

We analyzed the dataset in segments of 24 hour periods with cost computation performed on a per-minute granularity. For each day, we estimated the residual charge of the battery that could power the home during the expensive tier. This estimation is performed at the beginning of the expensive tier, with the proviso that during the expensive tier the car cannot be charged and can only power the house. This estimation is performed by looking ahead in time (up until the start of the next day's expensive tier time point) at all the car charge events. Figure 5 illustrates this process.

The net kilowatt hours of these charge events is computed and subtracted from the car's total battery capacity to estimate the amount of charge available to power the house. It should be noted that it is possible to have multiple distinct charge events with the car being driven in-between. However, by only subtracting the net energy of charge events from the total battery capacity, we compute a *conservative* estimate. Additionally, losses during battery charging (efficiency factor) are taken into account. The following equation summarizes how we compute the estimated battery charge available to power the home.

$$EBC = BATT_{CAP} - \left(EFF_{CHG} * \sum CHARGING_{KWH} \right)$$

where, EBC = Estimated Battery Charge

$BATT_{CAP}$ = Battery Capacity

EFF_{CHG} = Charging efficiency factor

$CHARGING_{KWH}$ = Energy (kWh) used per charge event

Next, the usable battery charge (UBC) is computed that takes into account the inverter and the battery’s chemical to electrical conversion inefficiencies. This is computed by multiplying the EBC with the discharge efficiency factor: $UBC = EFF_{DSCH} * EBC$. For our analysis, it was assumed that the charging and usage efficiency factors were the same, i.e. $EFF_{CHG} = EFF_{DSCH}$. As described later, we run our analysis for a variety of efficiency factor values ranging from low to high. This allows us to model the economics of offsetting home power demand using a car battery without explicitly considering complex battery models to predict efficiency factors that depend on its chemistry, temperature, discharge rate, humidity etc.

Once an estimate for the UBC is computed, we segment out the home’s power usage during the peak expensive tier that can be offset by the car for potential savings. We compute the total energy in kWh that the home consumes in this period with the condition that the car be present. In particular, if the car status is away or unknown, we do not sum the energy for those periods to the expensive tier’s home energy use as it cannot be offset by the car.

Finally, we compute how much of the expensive tier energy can be offset by the car and the resulting price for that energy. It should be noted that a corrective factor that takes into account the battery charge-discharge inefficiencies is used to compute the effective price per kWh for energy used from battery to offset the home. That is, for every 1 kWh used from the battery, we use $1/(EFF_{CHG} * EFF_{DSCH})$ from the grid. If the UBC is less than the total energy used by a home during the expensive tier, then a deficit results which is charged at the expensive tier rate.

Table 2 shows the average savings in USD and percentage during peak pricing tier when an electric vehicle is used to offset the home’s power needs, assuming an efficiency factor of 0.9 for battery charge and discharge. The average savings per household is \$13.58/month. Also noted in Table 2 are number of days for each house where the UBC was less than the total energy a home consumed during the expensive tier. That is, the car’s battery did not have sufficient charge to bring about maximum savings. Out of the 710 days in our dataset this occurred 15 times (2%), and primarily in one household EV6 (10 days). Thus 98% of the time, the EV battery had sufficient charge to fully power the house during the expensive tier.

Break Even Point at Low Battery Efficiency

As discussed previously, the battery and inverter efficiency can vary based on a large number of parameters. To better understand how the savings from car powering the home vary with battery efficiency, we ran our analysis on efficiency ranging from 45% to 95%. Figure 6 shows that the break-even point is around 65%, which is far worse than modern battery technology.

This is a significant observation as it opens up making use of used but still functional EV batteries for home power

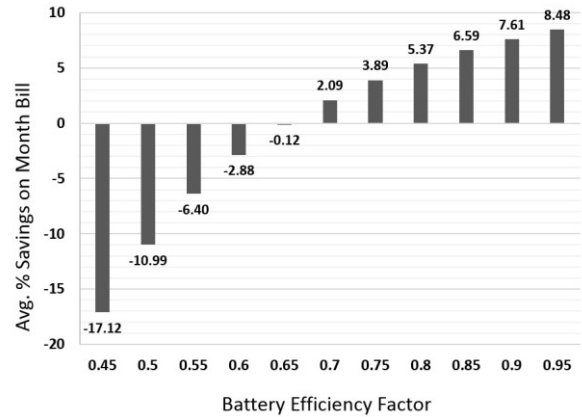


Figure 6: Average monthly percentage savings during peak pricing tier when using the car’s battery to offset the home power consumption as a function of the battery efficiency. Notice that the cost benefit break-even point is around 65%, i.e., using battery of efficiency lower than

management. For instance, a modern Li-Ion battery nearing end of life for EV use still performs at about 75-80% capacity and efficiency [1]. Such second-use in energy storage system for residential peak demand flattening has been an active area of research, particularly from the perspective of understanding a battery’s capacity fade model and making the most out of a second-use battery. Our results based on real power usage further bolsters the argument for using “spent” EV battery for home power.

DISCUSSION

Other Pricing Schemes Have Similar Savings

Though we make use of the PG&E TOU tiered pricing plan for our analysis, the results extend to other tiered pricing plans as well. In particular, it is important to have a sufficient difference in the expensive tier and base tier so that battery inefficiencies do not matter. If this is the case, the homeowner will benefit by powering their home with their car’s battery. To validate this, we ran our analysis using pricing for Baltimore Gas and Electric and Wisconsin Public Services and found an average monthly saving across all households of \$13.36 and \$13.50 respectively for powering the house from the EV.

Prediction Unnecessary With Current TOU Pricing

When we started this research, we anticipated we would need to learn participants’ commute patterns and use prediction to ensure the shifting algorithm would start recharging in time to guarantee enough battery charge for the following day’s driving needs. However, we found for all homes in our study that the off-peak pricing tier lasted long enough to fully charge the EV battery, even when the battery was discharged to power the home during the most expensive pricing tier. Thus with current Time of Use pricing schedules, learning and prediction of user’s commute patterns is not needed. Utilities would need to shorten their off-peak pricing times for prediction to become relevant.

Risk of Uncharged Battery

There is some risk that delaying the start of charging until later, or using the EV's battery for powering the house, may leave the EV with insufficient charge for an unusual trip. We see two simple solutions to this potential problem. First, chargers could be equipped with an override button, allowing an owner to easily indicate that the vehicle should be ready for another trip soon, ignoring the charging/discharging algorithms we proposed above. Offering manual override, or more generally the option to manually control charge shifting, would be valuable in future studies to investigate whether EV owners are comfortable with automated shifting or prefer manual control. A study of time of use pricing for mobile data found participants preferred to manually control their usage [39]. Our expectation is that automated shifting will appeal to EV drivers who currently leave their cars charging for long periods, but it may take time for people to develop trust in shifting algorithms and would be interesting to study.

Another way to decrease the risk of an uncharged battery is to impose a rule that the EV battery can never be discharged below some predefined capacity (e.g. 20%) to account for an unanticipated trip. In our analysis using the aforementioned PG&E tiered pricing, we found that in general there was sufficient time to re-charge the car completely after being used to offset energy in the expensive tier. It is unlikely, but possible that undercharged events may happen with the 110V slower chargers, especially when attempting to fully charge a completely depleted battery.

Scaling to Even Larger Deployments

Using LoT we collected a dataset containing 710 days of data from 15 houses. To scale to hundreds or thousands of homes, based on our experience, the biggest challenge would be designing the in-home sensing infrastructure so that it could be installed by the home owner independently. Pragmatically, there is also the cost of provisioning sensing hardware to consider, but this is a trade-off between money and time: as we did in our study, a limited number of hardware kits can be rotated through homes to deploy in a larger number of sites over a longer period of time.

Choosing sensors that can be installed by home owners comes with trade-offs, and we considered some of these approaches in our study design. For example, plug-in GPS trackers are available for cars, which would be a simple alternative to our vehicle presence sensor. But with GPS, the participant must agree to have their car location tracked all the time rather than only sharing when they are home. Also, we wanted real-time data in order to detect data collection issues as soon as possible, which requires a data service plan for each tracker. This increased the potential cost beyond what was feasible for our study.

To sense energy use without an installation visit, we could have limited our participant pool to homes that have smart connected meters. We could have then inferred EV charging data from the whole house data with some loss of accuracy

or recruited participants that charge their EV's using 110 volt outlets who could self-install inline smart energy switches. These constraints might be an acceptable trade-off for future large scale studies, but for our initial study we wanted fine grained whole house energy use, separate sensing of car energy use, and EV's charged using 240 and 110 volt outlets.

These real-world challenges do not mean as a community we should give up on the goal of scaling field deployments. One advantage of using LoT is that we contributed our software driver for Bluetooth beacons back to the platform so that sensor can be easily used by others. As discussed in [4], another way to facilitate larger deployments is collaborating across research groups to deploy studies in pools of homes recruited by other research groups (and vice versa). This would increase the size of deployments and add geographic diversity while preserving a local contact for the home owners to help with installation or other issues.

CONCLUSION

As peak electricity demand becomes more acute, power companies are encouraging a shift in demand to off-peak hours. Electric vehicles offer the chance to shift when they are charged and to store electricity from less expensive, off-peak hours for use during more expensive times. We outfitted 15 EV homes with sensors to record home electricity use, EV charging, and vehicle presence. We developed a fairly simple schedule of using the car battery to power the house during peak hours and charging the vehicle during non-peak hours, effectively reducing peak demand and saving money with tiered pricing.

Using our recorded data, we showed that the batteries in EVs could power the homes during the expensive tier during 98% of the days in our dataset. Doing this would save homeowners money. At a 90% conversion efficiency, the average monthly savings from simple shifting of EV charging would be \$10.91. The additional savings from powering the house from the EV would be \$13.58/month. The conversion efficiency would have to drop to an unrealistically low 55% before the cost savings went to zero for powering the home from the EV. Powering the home from the EV would allow an average 7.6% savings on the monthly electric bill. An advantage of this approach is that the home would not have to pay for dedicated home batteries, but could use EV batteries for both transportation and home power, without any changes in their driving habits.

ACKNOWLEDGMENTS

We thank all of the households that participated in the field study. We thank the members of the Lab of Things project for their support.

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