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GreenCharge: Managing Renewable Energy in Smart Buildings

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***Abstract*--Distributed generation (DG) uses many small onsite energy harvesting deployments at individual buildings to generate electricity. DG has the potential to make generation more efficient by reducing transmission and distribution losses, carbon emissions, and demand peaks. However, since renewables are intermittent and uncontrollable, buildings must still rely, in part, on the electric grid for power. While DG deployments today use net metering to offset costs and balance local supply and demand, scaling net metering for intermittent renewable to a large fraction of buildings is challenging. In this project, we explore an alternative approach that combines market-based electricity pricing models with on-site renewables and modest energy storage (in the form of batteries) to incentivize DG. We propose a system architecture and optimization algorithm, called GreenCharge, to efficiently manage the renewable energy and storage to reduce a building's electric bill. To determine when to charge and discharge the battery each day, the algorithm leverages prediction models for forecasting both future energy demand and future energy harvesting. We evaluate GreenCharge in simulation using a collection of real-world data sets, and compare with an oracle that has perfect knowledge of future energy demand/harvesting and a system that only leverages a battery to lower costs (without any renewable).**

Keywords: Distributed Generation(DG),Green Charge, Smart Charge

I.INTRODUCTION

Buildings today consume more energy (41%) than either of society's other broad sectors of energy consumption industry (30%) and transportation (29%) [1]. As a result, even small improvements in building energy efficiency, if widely adopted, hold the potential for significant impact. The vast majority (70%) of building energy usage is in the form of electricity, which, due to environmental concerns, is generated at "dirty" power plants far from population centers. As a result, nearly half (47%) of energy use in residential buildings is lost in electricity transmission and distribution (T&D) from far-away power plants to distant homes. An important way to decrease both T&D losses and carbon emissions is through distributed generation (DG) from many small on-site renewable energy sources deployed at individual buildings and homes. Unfortunately, in practice, DG has significant drawbacks that have, thus far, prevented its widespread adoption. In particular, DG primarily relies on solar panels and wind turbines that generate electricity intermittently based onus controllable and changing environmental conditions. Since the energy consumption density, in kilowatt-hours (kWh) per square foot, is higher than the energy generation density of solar and wind deployments at most locations, buildings must still rely heavily on the electric grid for power.

Distributed generation (DG) uses many small onsite energy harvesting deployments at individual buildings to generate electricity. DG has the potential to make generation more efficient by reducing transmission and distribution losses, carbon emissions, and demand peaks. However, since renewables are intermittent and uncontrollable, buildings must still rely, in part, on the electric grid for power. While DG deployments today use net metering to offset costs and balance local supply and demand, scaling net metering for intermittent renewables to a large fraction of buildings is challenging. In this project, we explore an alternative approach that combines market-based electricity pricing models with on-site renewables and modest energy storage (in the form of batteries) to incentivize DG. We propose a system architecture and optimization algorithm, called GreenCharge, to efficiently manage the renewable energy and storage to reduce a building's electric bill. To determine when to charge and discharge the battery each day, the algorithm leverages prediction models for forecasting both future energy demand and future energy harvesting. We evaluate GreenCharge in simulation using a collection of real-world data sets, and compare with an oracle that has perfect knowledge of future energy demand/harvesting and a system that only leverages a battery to lower costs (without any renewables). We show that GreenCharge's savings for a typical home today are near 20%, which are greater than the savings from using only net metering.

II. GREENCHARGE ARCHITECTURE

A. *Objective of Project*

The objectives of green charge is to develop an alternative approach that combines market-based electricity pricing models with on-site renewable and modest energy storage (in the form of batteries) to incentivize DG (Distributed Generation). We propose a system architecture and optimization algorithm, called Green Charge, to efficiently manage the renewable energy and storage to reduce a building's electric bill. To determine when to charge and discharge the battery each day, the algorithm leverages prediction models for forecasting both future energy demand and future energy harvesting.

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B. Layout and Schematic

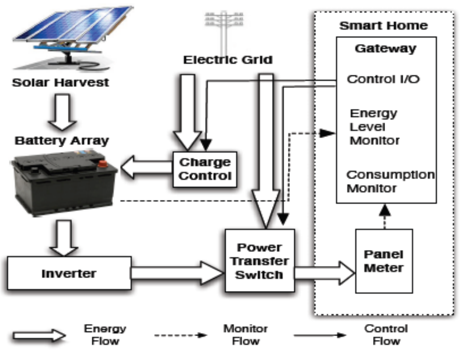

Fig.1. GreenCharge's architecture

Green Charge's architecture, which utilizes a power transfer switch that is able to toggle the power source for the home's electrical panel between the grid and a DC-AC inverter connected to a battery array. On-site solar panels or wind turbines connect to, and charge, the battery array. A smart gateway server continuously monitors 1)electricity prices via the Internet, 2) household consumption via an in panel energy monitor, 3) renewable generation via current transducers, and 4) the battery's state of charge via voltage sensors. Our SmartCharge system, which we compare against in this work, utilizes the same architecture, but does not use renewable. Before the start of each day, the server solves an optimization problem based on the next day's expected electricity prices, the home's expected consumption and generation pattern, and the battery array's capacity and current state of charge, to determine when to switch the home's power source between the grid and the battery array. The server also determines when to charge the battery array when the home uses grid power.

C. Network Communication and Sensing

One challenge with instantiating GreenCharge's architecture is transmitting sensor data about energy consumption, energy generation, and battery status to GreenCharge's smart gate way server in real time. The simplest way to measure energy consumption and generation is to wrap current transducers(CT) around wires in the building's electrical panel. CTs must be installed in the panel, since this is the only place in the building that has the incoming grid lines exposed for sensors. Since electrical panels are often in remote corners of a building, transmitting readings wirelessly is difficult. While wired Ethernet is an attractive option, it requires running an Ethernet cable from Green Charge's gateway server to the electrical panel. Multiple types of power line-based communication protocols exist. The most common are X10, Insteon, and HomePlug.X10 is by far the oldest protocol, having been developed in1975; it is primarily used for controlling applications, which only requires sending brief, short control messages.
Unfortunately,X10 has severe bandwidth limitations (a maximum of 20bps) and reliability problems, which make it undesirable for continuous real-time sensing. Further, power line noise caused by switched mode power supplies results in substantial losses with X10 in most buildings. Insteon is an improvement to X10 that includes acknowledgements, retransmissions, and optimizations to overcome power line noise. However, Insteon still has bandwidth limitations that, in practice, reduce its maximum rate to near 180bps. While useful for controlling devices via the power line, it is still insufficient for continuous real-time sensing of multiple data sources. Thus, in our own prototype we chose a power meter that uses the Home Plug Ethernet-over power line protocol. Unlike Insteon and X10, Home plug was initially designed to stream high definition audio and video data from the Internet to televisions. As a result, it was designed from the outset to support high-bandwidth applications. Home Plug modems exist that are capable of transmitting up to 200Mbps.

D. Market-based Electricity Pricing

Most utilities still use fixed-rate plans for residential customers that charge a flat fee per kilowatt-hour (kWh) at all times. In the past, market-based pricing plans were not possible, since the simple electromechanical meters installed at homes had to be read manually. However utilities are in the process of replacing these old meters with smart meters that enable them to monitor electricity consumption in real time at fine granularities, e.g., every hour or less. To cut electricity bills, GreenCharge relies on residential market based pricing that varies the price of electricity within eachday to more accurately reflect its cost. We expect many utilities to offer such plans in the future. There are multiple variants of market-based pricing. Figure 2 shows rates over a single day for both a time-of-use(TOU) pricing plan used in Ontario, and a real-time pricing plan used in Illinois. TOU plans divide the day into a small number of periods with different rates. The price within each period is known in advance and reset rarely, typically every month or season. For example, the Ontario Electric Board divides the day into four periods (7pm-7am, 7am-11am, 11am-5pm, and 5pm-7pm) and charges either a off-peak-, mid-peak, or on-peak rate (6.2¢/kWh, 9.2¢/kWh, or 10.8 ¢/kWh) each period.

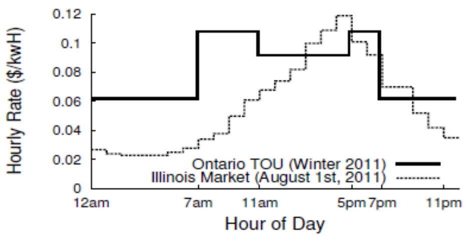

Fig.2. Example TOU and hourly market-based rate plans in Ontario and Illinois, respectively

E. Markets price fluctuations

Wholesale energy prices exhibit significant fluctuations during each day due to variations in demand and generator capacity. Home users are traditionally not exposed to these fluctuations but pay a fixed retail energy price, as shown in Figure 3 (a).

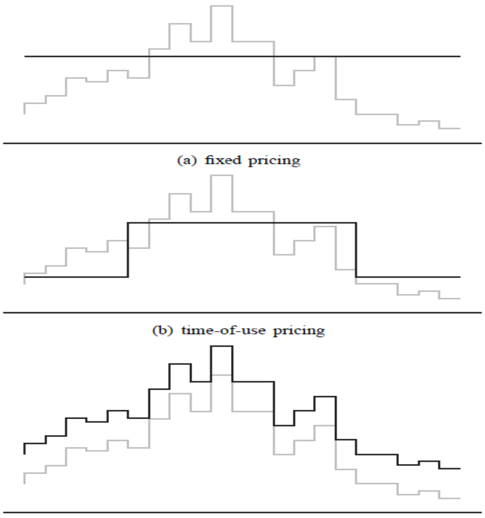

Fig .3.The wholesale energy price (gray) and various approaches to retail pricing (black).

Economists have long argued to remove the fixed retail prices in favor of prices that change during the day. Such dynamic pricing reflects the prices of the wholesale market and has been predicted to lead to lower demand peaks and lower average level and volatility of the wholesale price. Dynamic pricing has been enabled by recent smart-grid technologies such as smart meters. A first example of dynamic pricing that is being increasingly adopted is time-of-use pricing (Figure 3(b)). Such schemes typically provide two or three price levels (e.g., 'off-peak', 'mid-peak' and 'on-peak') where the level is determined by the time of day. The price levels are determined well in advance and are typically not changed more than once or twice per year. A second example of dynamic pricing is real-time pricing (Figure 3(c)) where the retail energy price changes hourly or half-hourly to reflect the price on the wholesale energy market.

Dynamic pricing creates an opportunity for users to reduce energy costs by exploiting the price fluctuations. However, in practice users show only a minor shift in their demand to match the energy prices . A possible remedy is to equip homes with a battery that can be used for home energy storage. This battery can be charged when the energy price is low and the stored energy can then be used to protect against high prices. This allows users to benefit from the varying energy price without having to adjust their usage patterns accordingly. Energy can be stored both by a dedicated battery,or by using the battery pack of an electric car. In the past such setup was not economically viable due to the high cost of batteries, but current developments have brought storage applications within reach.

III.GREENCHARGE ALGORITHM

GreenCharge cuts electricity bills by combining on-site renewable generation with energy storage that stores energy during low-cost periods for use during high-cost periods. GreenCharge extends our SmartCharge system that only uses energy storage to cut electricity bills without renewables. The total possible savings each day is a function of both the home's rate plan and its pattern of generation and consumption. we use power data from a Real home we have monitored for the past two years as a case study to illustrate GreenCharge's potential benefits. The home is an average 3 bedroom, 2 bath house in Massachusetts with 1700 square feet. To measure electricity, we instrument the home with an e Gauge energy meter , which installs in the electrical panel by wrapping two 100A current transducers around each leg of the home's split-leg incoming power. We have monitored the home's power consumption every second for the past two years. Separately, we have deployed solar panels to study variation in solar power generation. Figure 4 depicts power generation from a sunny day.

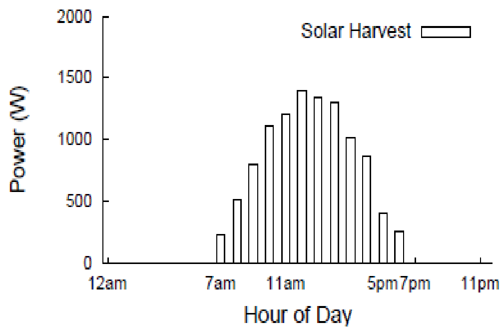

Fig. 4. Example solar harvest data from a day in August.

A. *Potential Benefits:-*

To better understand GreenCharge's potential for savings, it is useful to consider a worst-case scenario where 100% of the home's consumption occurs during the day's highest rate period. Figure5 then compares GreenCharge using renewable production from Figure 2 with a home has only energy storage but not renewables (labeled SmartCharge), and home with no energy storage or renewables. Now consider our home's hourly electricity use on January 3rd, 2012, as depicted in Figure 5 in red. On this day, the home consumed 43.7 kWh, primarily due to the occupants running multiple laundry loads after returning from a holiday trip. With Ontario's TOU plan, if the home had consumed 100% of the day's power during the 10.8¢/kWh on peak period, and all consumption was shifted to the 6.2¢/kWh off-peak period, then the maximum savings is 43%, or $2.01(from $4.72 to $2.71) for the day. Since the home did not consume 100% of its power during the on-peak period, the maximum realizable savings (if we shift all of the on-peak and mid-peak consumption to the off-peak period) is only 30%,a decrease of $1.14 for the day (from $3.85 to $2.71). In practice, battery and inverter inefficiencies, which combine dare _80% efficient, reduce the savings further, to $0.99 for the day. Finally, if we then add in the 10.5kW generated by renewable the savings increases by $0.93 to $1.92. This per day savings rate translates to a yearly savings of $702, if the system achieves it every day. Real-time pricing plans, as in Illinois, offer even more potential for savings, since the difference between the highest and lowest rate is significantly larger than a typical TOU plan. Of course,

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energy consumption and generation patterns, as well as hourly rates vary each day, which may decrease (orincrease) a building's actual yearly savings. To understand why energy consumption and generation patterns are important, consider the following scenario using the Ontario TOU pricing plan.

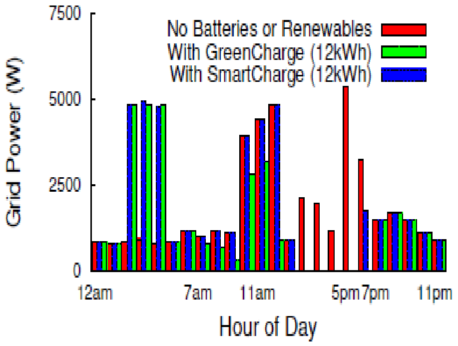

Fig.5.Example from January 3rd with and without GreenCharge.

In Ontario, while GreenCharge may fully charge its battery array during the lowest rate period (7pm-7am), it may also consume that stored energy during the day's first high rate period (7am-11am). If the home expects to consume at least the battery array's entire usable capacity, even when accounting for renewable generation, during the day's second high rate period (5pm-9pm), it is cost-effective, assuming ideal batteries, to fully charge the batteries during the mid-rate period (11am-5pm) when electricity costs are 17% less than in the high rate period. However, if the home only expects to use 20% of the battery's capacity during the subsequent high rate period, e.g., because renewables will generate some power during this time, it is only cost-effective to charge the battery 20% during the mid-rate period, since there will bean opportunity to charge the battery further (for 33% less cost) during the next low-rate period. In this case, charging the battery more than 20% wastes money. Introducing more price tiers, as in real-time markets, complicates the problem further. As a result, we frame the problem of minimizing the daily electricity bill as a linear optimization problem.

B. Problem Formulation:-

While batteries exhibit numerous limitations (e.g., charging rate, capacity), inefficiencies (e.g., energy conversion efficiency, self-discharge), and non-linear relationships (e.g., between capacity, lifetime, depth of discharge, discharge rate, ambient temperature, etc.), GreenCharge's normal operation places it at the efficient end of these relationships. We frame GreenCharge's linear optimization problem as follows. The objective is to minimize a home's electricity bill using a battery array with a usable capacity (after accounting for its DOD) of C kWh. We divide each day into T discrete intervals of length I from 1 to T. We then denote the power charged to the battery from the grid during interval i as s_i, the renewable power charged to the battery as gi, average renewable power available to the home as ri, the power discharged from the battery as di, and the power consumed from the grid as pi. We combine both the battery array and inverter inefficiency into a single inefficiency parameter e. Finally, we specify the cost per kWh over the ith interval as ci, and the amount billed as mi. Formally, our objective is to minimize$\sum_{i=1}^{T}$ mieach day, given thefollowing constraints.

$si \geq 0,\ \forall i \in [1, T]$ (1)

$di \geq 0,\ \forall i \in [1, T]$ (2)

$gi \geq 0,\ \forall i \in [1, T]$ (3)

$gi \leq ri,\ \forall i \in [1, T]$ (4)

$si \leq C/4,\ \forall i \in [1, T]$ (5)

$gi \leq C/4,\ \forall i \in [1, T]$ (6)

$X\ i\ t{=}1\ dt \leq e * X\ i\ t{=}1\ st + e * X\ i\ t{=}1\ gt,\ \forall i \in [1, T]$ (7)

$(X\ i\ t{=}1\ st + X\ i\ t{=}1\ gt - X\ i\ t{=}1\ dt/e) * I \leq C,\ \forall i \in [1, T]$ (8)

$mi = (pi + si - di) * I * ci,\ \forall i \in [1, T]$ (9)

The first second and third constraint ensures the energy charged to, or discharged from, the battery is non-negative. The fourth constraint ensures that total renewable energy charged to the battery is less than or equal to the available renewable energy. The fifth and sixth constraint limits the battery's maximum charging rate. The seventh constraint specifies that the power discharged from the battery is never greater than the total power charged to the battery multiplied by the inefficiency parameter. The eighth constraint states that the energy stored in the battery array, which is the difference between the energy charged to or discharged from the battery over the previous time intervals, cannot be greater than its capacity. Finally, the ninth constraint defines the price the home pays for energy during the ith interval. The objective and constraints define a linearly constrained optimization problem that is solvable using standard linear programming techniques. GreenCharge solves the problem at the beginning of each day to determine when to switch between grid and battery power, and when to charge the battery from grid vs renewables. SmartCharge uses a similar linear programming formulation without the constraints specific to renewable energy. Since the approach uses knowledge of next-day consumption and generation patterns, we next detail techniques for predicting next day consumption and generation, and quantify their accuracy for our case study home.

IV. PREDICTING CONSUMPTION AND GENERATION

For solving GreenCharge's linear optimization problem requires a priori knowledge of next day consumption and generation patterns. We develop a machine learning based approach to predicting demand, and use an approach developed in prior work to predict next day energy harvesting based on weather forecasts.

A. ML-based Demand Prediction:-

A simple approach to predicting consumption is to use past predicts-future models that assume an interval's consumption will closely match either that interval's consumption from the previous day or the prior interval's consumption. As we show, the approach does not work well for the multi-hour intervals in Ontario's TOU pricing

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plan. Instead, we develop statistical machine learning (ML) techniques to accurately predict consumption each interval. While our techniques have numerous applications, e.g., dispatch scheduling in microgrids, we focus solely on their application to SmartCharge in this paper. We experimented with a variety of prediction techniques, including Exponentially Weighted Moving Averages (EWMA),Linear Regression (LR), and Support Vector Machines (SVMs)with various kernel functions, including Linear, Polynomial, and Radial Basis Function (RBF) kernels. EWMA is a classic past-predicts-future model that predicts consumption in the next interval as a weighted sum of the previous interval's consumption and an average of all previous intervals' consumption.

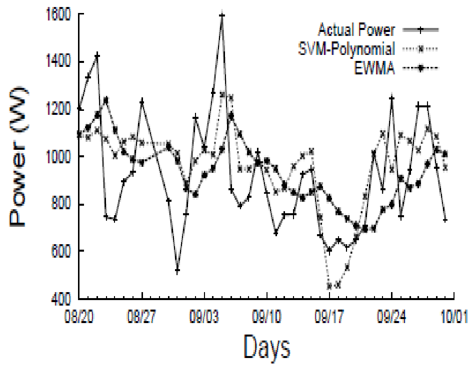

Fig.6. Predicting energy consumption using the past does not capture day to-day variations due to changing weather, weekly routines, holidays, etc.

Both LR and SVM are regression techniques that combine and correlate numerous indicators (or features) of future power consumption to predict next-day usage. We experimented with a total of nine features: outdoor temperature and humidity, month, day of week, previous day power, previous interval power, as well as whether or not it is a weekend day or a holiday. We also included the EWMA prediction as an additional feature. To predict next-day temperature and humidity, we used weather forecasts from the National Weather Service available from the National Digital Forecast Database. To evaluate our techniq use used power data collected every second from our case study home over a period of four months from June to September2011. For the LR and SVM models, we used the first 70days of the data set for model training, and the last 40 days for evaluating the model's accuracy. We use the Lib SVM library to implement our LR and SVM models. Our SVM models use the nu-SVR regression algorithm, which we found always performed better than the SVR algorithm Before training our model, we employed Correlation-based Feature Subset Selection (CFSS) to refine the number of input features. CFSS evaluates the predictive ability of each individual feature along with the degree of redundancy between features. We apply CFSS separately for each of the five intervals, since the pattern of power consumption varies each interval. CFSS reduces the number of features in prediction model from nine to: four for 12am-7am, seven for 7am-11am, seven for 11am-5pm, six for 5pm-9pm, and five for9pm-12am. In general, we find that more features are useful during periods with high, variable consumption.

B. Predicting Energy Harvesting from Weather Forecasts:

For a given solar panel deployment this model translates the forecasted sky cover, by National Weather Service (NWS), into solar energy have sting prediction. The NWS publishes weather forecast including sky condition forecast, every hour. The forecast contains predicted sky condition for next 24 hours. The model computes predicted solar harvesting power for every hour as:

$$\text{Power} = \text{MaxPower} * (1 - \text{Sky Condition})$$

Power in above expression is the predicted solar harvesting power, Max Power is the maximum possible solar power that can be harvested from the given solar panel in a given hour of day assuming perfectly sunny day, and Sky Condition is the fraction of sky that is covered with clouds.

V. EXPERIMENTAL EVALUATION

To illustrate GreenCharge's potential for savings, we use the home to evaluate the savings using Ontario's TOU rate plans . While our home is not located in Ontario, it lies at the same latitude and experiences a similar climate. Thus, the prices are not entirely mismatched to our home's consumption and generation profile. In our experiments, we vary the pricing plans and battery characteristics to see how future price trends and battery apply EWMA to each interval independently on a daily basis. As might be expected, since home consumption patterns vary largely around mealtimes, we found that predicting consumption based on the preceding interval to be highly inaccurate. To predict next-day usage, we use the SVM-Polynomial model. Finally, to quantify the optimal savings, we compare with an oracle that has perfect knowledge of next-day consumption and generation. Unless otherwise noted, our experiments use home power data from the same 40 day period in late summer as the previous section, and generation data from our own solar panel installation scaled up to generate equal to the home's average power consumption. We use CPLEX, a popular integer and linear programming solver, to encode and solve GreenCharge's(and SmartCharge's) optimization problem, given next-day prices and expected consumption levels. Note that we consider only usable storage capacity in kWh in this section, which is distinct from (and typically much less than) battery capacity. In the next section, we discuss the battery capacity necessary to attain a given storage capacity. We use an energy conversion efficiency of 80% for the battery and a C/4 charging rate for the usable storage capacity.

A. Household Savings:-

Figure7 shows the average savings per day in USD for the TOU rate plan over the 40 day period, as a function of storage capacity, while Figure 8 shows the savings as a percentage of the total electricity bill. The graphs show that a storage capacity beyond 30kWh does not significantly increase savings. Further, smaller storage capacities, such as12kWh, are also capable of reducing costs, near 10% for SmartCharge and 20% for GreenCharge. If we extrapolate the savings over an entire year, we estimate that Green Charge with 24kWh of storage is capable of saving $200, while SmartCharge is capable of saving $100.

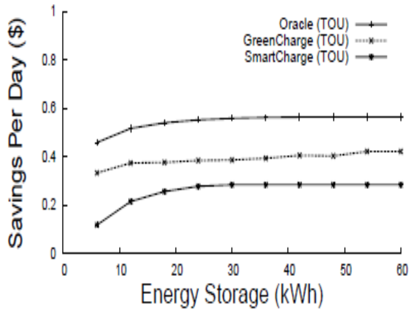

Fig.7. Average dollar savings per day for both SmartCharge and Green-Charge in our case study home.

Finally, the graphs show that GreenCharge's performance is close to that of an oracle with perfect knowledge of future consumption and generation miss predictions only cost a few dollars each year with 24kWh storage capacity, or under 10% of the total savings.

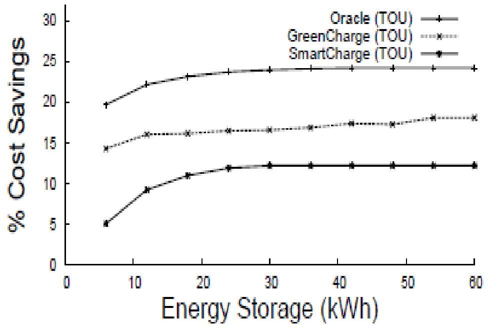

Fig.8. Average percentage savings for both SmartCharge and GreenCharge in our case study home.

The experiments above assume that we use today's battery characteristics and price levels. Of course, a more efficient battery and inverter would increase the usable storage capacity in a battery array. As the experiments above indicate, increasing storage capacity increases the savings up to a 30kWh capacity. We evaluate the effect of maximum battery charging rate on home savings using TOU pricing plan over 40 day traces in presence of 24kWh battery capacity. Figure 9 demonstrates that the maximum charging rate has a minimal effect on savings, since the TOU rate plan offers a long period of relatively low rates during the night for charging. The charging rate need only be high enough, e.g., a C/10 rate, to charge the battery over these periods. Figures 10(a) and (b) show how the savings change if we vary either the average price(while keeping price ratios constant) or the peak-to-off-peak price ratio (while keeping the average price constant) for a24kWh capacity, assuming C/4 charging rate for the usable storage capacity, for both GreenCharge and SmartCharge. The graphs demonstrate that, as expected, rising prices or ratios significantly impact the savings. In the former case, the relationship is linear, with a doubling of today's average price resulting in a doubling of the savings for both GreenCharge and SmartCharge. Thus, if average electricity prices continue to rise 5% per year, as in the past, the expected savings for both systems should also increase at 5% per year. Finally, Figure11 shows the additional savings homes are able to realize by sharing battery capacity with neighbors. Sharing is beneficial when homes exhibit peaks at different times by allowing them to share the available storage capacity. For the experiment, we use power data for a single day from apool of 353 additional homes we monitor (described below),such that each point is an average of twenty runs with a set of k randomly chosen homes. We report both the additional dollar and percentage savings per home. We include 90%confidence intervals for the dollar savings. The experiment shows that sharing a battery array between homes results in additional savings as we increase the number of homes.

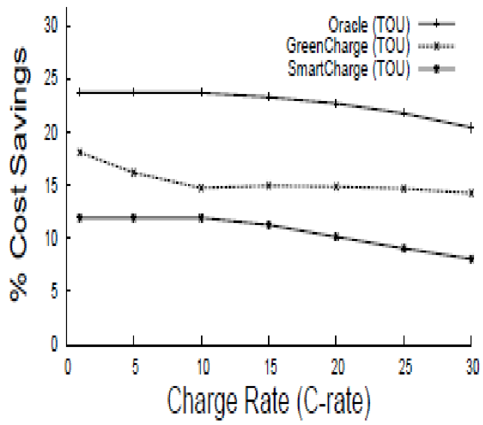

Fig.9.SmartCharge's and GreenCharge's savings as a function of the charging rate for a 24kWh storage capacity.

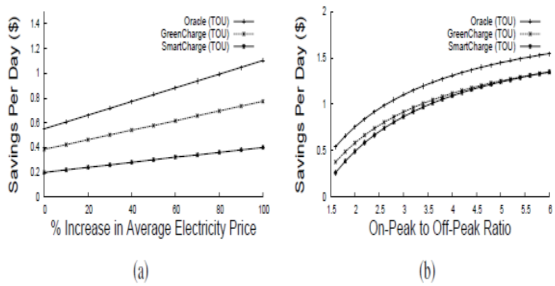

Fig.10. Varying the average electricity price (a) and the peak-to-off-peak price ratio (b) impacts savings.

As expected, more homes require more storage capacity to reap additional benefits. With 10 homes sharing 24kWh per home, the additional savings is 25%. However, with 12kWh per home the percentage savings does not increase beyond 15% when sharing with more than four homes.

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B. Grid Peak Reduction

The purpose of market-based rate plans is to lower peak electricity usage across the entire grid. We evaluate the potential grid-scale effect of GreenCharge using power data from a large sampling of homes. We gather power data at scale from thousands of in-panel energy meters that anonymously publish their data to the web. Power consumption trace for each home is at the granularity of one hour. Since we do not know if the meters are installed in commercial, industrial, or residential buildings, we filter out sources that do not have typical household power levels and profiles, i.e., peak powerless than 10kW and average power less than 3kW. We also filter out sources with large gaps in their data. After filtering, we select 435 homes from the available sources.

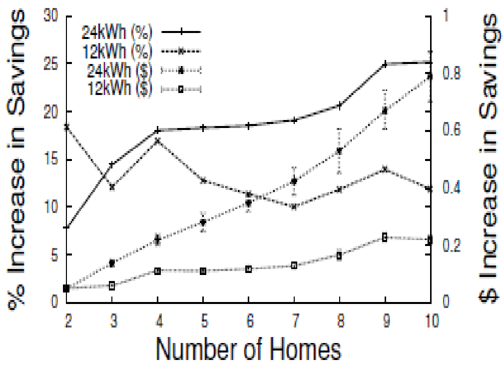
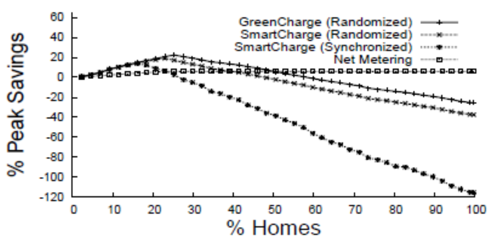
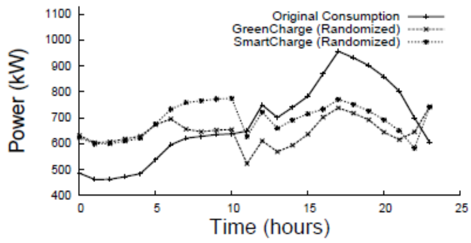


Fig.11. Additional savings (in % and $) from sharing 12kWh and 24 kWh between homes.

Figure12 plots the peak power over all the homes as a function of the fraction of homes using GreenCharge and SmartCharge with energy storage. For these experiments we assume that each home has available energy storage equal to half the home's average daily consumption. Charging rate of C/4 for the usable storage capacity is assumed. The figure shows that GreenCharge and SmartCharge are capable of reducing peak power by roughly 20% when little more than 20% of homes use the system, as long as the homes randomize when they begin overnight charging.



(a)



(b)

Fig.12. With 25% of homes using GreenCharge, the peak demand decreases by 22.5% (a) and demand flattens significantly (b).

If everyone begins charging at the same time, e.g., at 12am at night, the peak reduction decreases to a maximum of only 8%. Even using randomized charging, if more than 22% of consumers install GreenCharge or Smart Charge, then the peak reduction benefits begin to decrease, due to a nighttime "rebound peak". Once 45% of consumers use the system the evening rebound peak actually becomes larger than the original peak. The same point occurs when only 25% of homes use the system without randomized charging. 'Net Metering' represents those homes which have on-site renewable deployments, however, they don't have on-site battery installations for storing this energy. Hence, the renewable energy is consumed as soon as it is generated. In contrast to GreenCharge and Smart Charge the peak savings from 'Net Metering' increase from 0% to 5.75%and then flattens out. The reason being, net metering does not use any on-site battery storage, it simply uses the renewable energy whenever it is available else the power is drawn from the grid. Also, as can be seen from figure 6.6 net metering effectively flattens out the mid day peaks between 11am and2pm, however, it does poorly to shave the evening peak which occurs after 5pm. This is because solar energy harvest reduces significantly towards sunset.

Discussion on GreenCharge's and SmartCharge's economics at scale further . Figure12 (b) shows grid power usage over time, with 0% and 22% of the homes using GreenCharge and SmartCharge with randomized charging, and demonstrates how both approaches cause demand to "flatten" significantly. Such a peak reduction would have a profound effect on generation costs, likely lowering them by more than 20% . Finally, with 20% of homes using Green Charge or Smart Charge, the increase in total energy usage is only2%. The result demonstrates that the benefits of flattening likely outweigh the increased energy consumption due to battery/inverter inefficiencies.

VI. COST-BENEFIT ANALYSIS

A. Return-on-Investment

In many instances, homes already have the necessary infrastructure to implement GreenCharge. For example, many homes in developing countries already utilize UPSs because of instability in the power grid. In addition, homes with photovoltaic (PV) systems require on-site energy storage to balance an intermittent supply with demand without the aid of net metering. Batteries in electric vehicles (EVs) could also serve as energy storage. In each case, the homes already include the required infrastructure

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and battery capacity to implement GreenCharge. Since the homes would not need new infrastructure, the ROI is positive in these cases. Below, we discuss the ROI for homes that do not already have the necessary infrastructure. GreenCharge's largest expenses are its battery array and solar panel installation.

Sealed VRLA/AGM lead-acid batteries are the dominant battery technology for stationary home UPSs and PV installations, due to their combination of low price, high efficiency, and low self-discharge rate. By contrast, lithium ion batteries, while lighter and more appropriate for EVs, are much more expensive. We use, as an example, the Sun Xtender PVX-2580L with a 3kWh rated capacity (at a C/20 discharge rate), which costs $570 and is designed for deep-cycle use in home PV systems. The battery's manual specifies its life time as a function of its number of charge-discharge cycles and the DOD each cycle. We use the data to estimate the yearly cost of batteries—in $/kWh of usable storage capacity—as a function of the depth of discharge (Fig.13) amortized over their lifetime, assuming Green Charge's typical single charge discharge cycle per day. The usable storage capacity takes DOD into account: a battery rated for 10kWh operated at50% depth of discharge has a usable capacity of only 5kWh. Fig.13 demonstrates that cost begins to increase rapidly after a 45% DOD, with an estimated cost of $118/kWh of usable capacity.

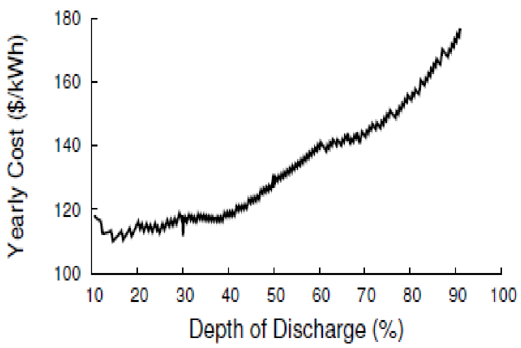

Fig.13. Amortized cost per kWh as a function of depth of discharge

B. Comparison of batteries

Recent advancements in battery technology promise to dramatically reduce battery costs in the near future. Lead-carbon batteries have an expected lifetime 10 times longer than today's sealed lead-acid batteries at roughly the same cost. Figure 14 shows the extended lifetime using data from recent tests conducted at Sandia National Labs comparing today's sealed lead-acid battery and a new lead carbon battery (the Ultra Battery). In addition, solar panel prices per installed watt are predicted to drop to $1 per watt over the next decade. Lead-carbon batteries combined with modest and expected price increases (25%) and peak-to-off-peak ratios (25%), as well as a decrease in solar panel prices, would produce a positive ROI for GreenCharge in a few years.

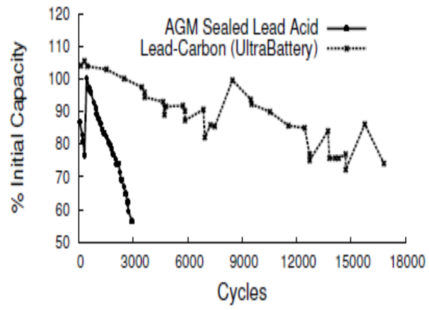

Fig.14. Comparison of sealed lead-acid and lead-carbon battery lifetime

C. Distributed vs. Centralized

Utilities have already begun to deploy large, centralized battery arrays to reduce peak usage and integrate more wind and solar farms, which require substantial energy storage to match an intermittent supply with variable demand. However, distributing battery storage and energy harvesting throughout the grid has a number of inherent advantages over a centralized approach. In particular, local energy storage and generation serves as backup power during extended blackouts, lessening the economic impact of power outages and promoting a more stable grid. A centralized system also introduces a single point of failure. Further, substantial home energy storage and generation may be a catalyst for implementing micro grids, where matching supply and demand is difficult without an energy buffer. Storing and generating energy at its point-of-use also reduces transmission losses by eliminating losses incurred from generator to battery array. Finally, perhaps the most important argument for installing many distributed battery arrays and energy harvesting deployments in homes, rather than large centralized arrays, isto encourage distributed generation without relying on net metering. While today's PV installations typically use net metering to offset costs by selling energy back to the grid,it is not a scalable long-term solution. Injecting significant quantities of power into the grid from unpredictable and intermittent renewables has the potential to destabilize the grid by making it difficult to balance supply and demand. GreenCharge provides an alternative to net metering to offset costs in home PV systems that use batteries instead of net metering.

VII. CONCLUSION

In this paper, we explore how to lower electric bills using Green Charge by storing low-cost energy for use during high cost periods. We show that typical savings today are near 20% per home with the potential for significant grid peak reduction (20% with our data). Finally, we analyze Green Charge's costs, and show that recent battery advancements combined with an expected rise in electricity prices and decrease in solar panel prices may make Green Charge's return on investment positive for the average home within the next few years.

Both, RES and micro grids are tend to be solutions for improving existing grids in a future. Smart grids are able to transform the quality of whole distribution system thanks to dispersed RES. Variable character of these sources implicates a necessity to manage the load. Local micro grids will gain a better quality of energy, a stability of supply and energy independence. That is why a development of RES should be perceived at a local, commune level. RES can enhance power quality and reliability and potentially reduce the need for traditional grid expansion. The difficult RES' management process can be improved with an implementation of smart, local micro grids and – in a next phase – popularization of electric vehicles and their storage possibilities V2G.

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