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Green Building: Load Management Scheme for Flattening Household Electricity Usage or Demand

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Abstract-- Flattening household electricity demand reduces generation costs, since costs are disproportionately affected by peak demands. Buildings today consume more energy than either of society's other broad sectors of energy consumption industry and transportation. 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. 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. In this paper, 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 called Green Building. 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 Building, to efficiently manage the renewable energy and storage to reduce a building's electric bill.

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

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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 Green building, 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 Green building 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 Green building'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 building 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 building, 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.

B. Layout and Schematic

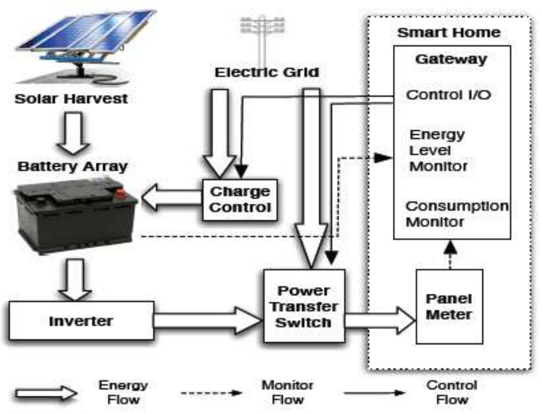

Fig.1. Green building's architecture

Green building'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 Green building's architecture is transmitting sensor data about energy consumption, energy generation, and battery status to Green building'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 building'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, Green building relies on residential market based pricing that varies the price of electricity within each day 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.

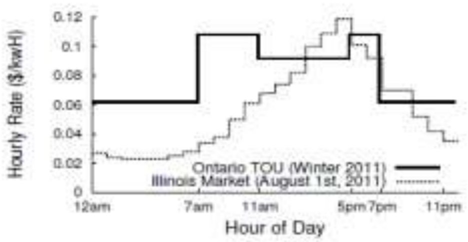

Fig.2. Example TOU and hourly market-based rate plans in Ontario and Illinois, respectively

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).

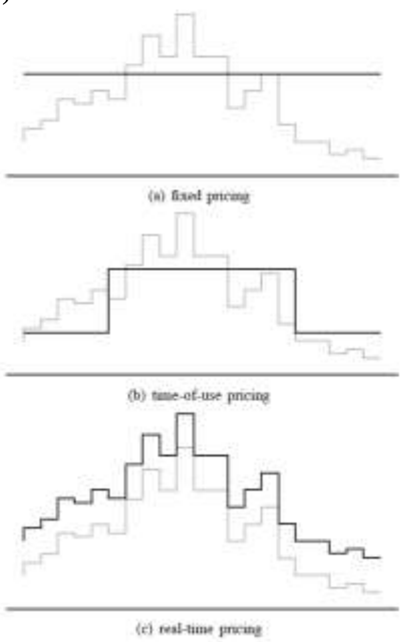

Fig .3.The wholesale energy price (gray) and various approaches to retail pricing (black).

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. LOAD ANALYSIS AND OBSERVATIONS

To study the extent to which scheduling background loads is able to flatten demand, we collect fine-grained power data from a real home that houses three occupants. We have collected the home’s aggregate power for the last 12 months and power at each outlet and switch for the past 82 days. Since our monitoring did not affect the occupants’ daily routine, our data reveals realistic home power usage patterns over the monitoring period. Our home deployment continuously gathers power usage data for the entire home every second and 30 individual outlet loads every few minutes; our prototype maintains a record of the on-off state of 30 of the home’s wall switches at every instant in time. Green Building’s gateway is also able to remotely (and programmatically) control the home’s outlets and wall switches. More details about our home deployment are available in prior work.

A. Interactive vs. Background Loads

To quantify the potential benefits of scheduling background loads, we separate the power consumption of background loads from that of interactive loads. In our prototype home, we monitor seven background loads at outlets: a refrigerator, a freezer, a dehumidifier, three window air conditioning units (A/Cs), and a heat recovery ventilation (HRV) system. By contrast, we estimate that the home used 85 distinct interactive loads over the past year[3]. Thus, Green Buildings does not attempt to schedule the vast majority of household loads, since it would affect the home's occupants. Interactive loads that we do not schedule include lights, entertainment appliances (e.g., TV, cable box, gaming console), computing equipment (e.g., routers, laptops, desktops), kitchen appliances (e.g., microwave, toaster oven, espresso maker, garbage disposal), and miscellaneous devices (e.g., clocks, vacuums, hair dryers). In most cases, disconnecting any of these loads from power when in use is readily apparent to occupants. We also group clothes dryers, washing machines, and dishwashers with interactive loads. While we could schedule the start time of these appliances, we do not include them because adjusting the start time affects occupants. To see why, consider that a scheduler may be able to decide when an appliance executes, but occupants must ultimately initialize the appliance, e.g., fill it with clothes or dishes, before its scheduled start time. Changing the start time may force occupants to initialize the appliance at an inopportune time. Further, for clothes dryers and washing machines, their operation is often pipelined, with households washing multiple laundry loads back-to-back. Observation : While background loads comprise 7.5% of the total loads over our monitoring period, they account for 59% of the average energy consumption. Table I shows the peak and average power consumption for each background load we monitor during a representative week in the summer, as well as the peak and average power consumption for all background and interactive loads. During this week, background loads consume 209 kWh, while interactive load consume 146 kWh. The three window A/C units significantly increase the fraction of energy consumed by background loads, since each A/C draws between 400W and 1kW when the compressor is on. On hot days, the compressor may run as much as half the day, depending on the comfort level the occupants desire. Note that during the winter the A/Cs do not run, since the home uses a gas furnace for heat. As a result, background load is lower in the winter. In this case, the duct heater for the HRV system, which heats incoming air from the outside, dominates background energy consumption, accounting for 70% of the total, while the refrigerator, freezer, and dehumidifier account for the remaining 30%.

Below, we highlight other observations from our home's data that influences our approach to scheduling.

Load	Peak	Average	Quantity
Refrigerator	456W	74W	1
Frezeer	437W	82W	1
HRV	1129W	24W	1
Dehumidifier	505W	371W	1
Main A/C	1046W	305W	1
Bedroom1A/C 1	571W	280W	1
Bedroom A/C 2	571W	141W	1

Background	4715W	1277W	7
Interactive	9963W	887W	85

Table I :In the summer, background loads in our home account for 59% of the total energy consumption.

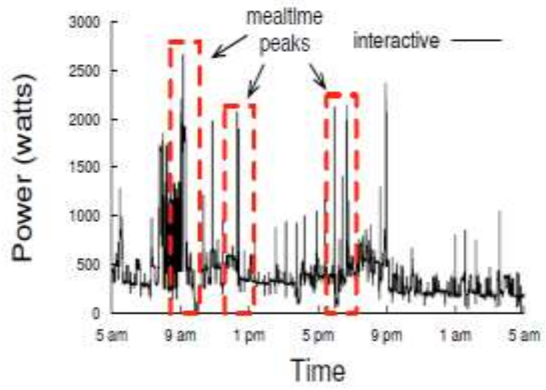

Figure 4. The power consumption of interactive loads is highly variable throughout the day. As expected, peak power consumption occurs around mealtimes in the morning, early afternoon, and early evening.

B. Interactive Variability

The power consumption of interactive loads varies due to the actions of occupants throughout the day, and is not readily predictable. Figure 4 highlights this point by showing the power consumption of the interactive loads in isolation on a typical day. Additionally, Figure 5 shows consumption patterns for four interactive loads. Notice that the power draws of these loads vary considerably throughout the day, with the peak periods occurring during the morning between 6am and 10am and in the early evening between 5pm and 9pm. These periods coincide with food preparation and are partially the result of using high-power kitchen appliances, such as a coffee pot, garbage disposal, microwave, dishwasher, or toaster oven. During the night, the minimum steady state power consumption is

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roughly200W, while during the morning and evening it frequently rises above 2kW for frequent short periods. The kitchen appliances tend to induce peaks by using large amounts of power for relatively short time periods, such as the coffee pot in Figure 5. Our observation also holds for meal preparation at breakfast, lunch, and dinner. Accurately predicting the power consumption of interactive loads at fine time scales is difficult. While the home's occupants typically eat dinner between 4pm and 8pm, if and when they use a microwave, toaster oven, dishwasher, or garbage disposal is highly variable during this four hour time window each day. Additionally, the occupants have flexible work schedules, and often work from home during the day—on this day one of the occupants ate lunch at home, which accounts for the spike in power around noon. Since interactive loads are not readily predictable, our scheduler must be able to react to drastic and sudden changes in their power consumption.

C. Background Variability

The operating period of background loads varies due to both environmental conditions and external events, and is also not readily predictable. Figure6 highlights the point by graphing the power consumption of four of the background loads we monitor. Each background load is clearly periodic: it alternates between distinct 'on' and 'off' states. While it is possible to design these loads with variable drive controllers, all the background loads in our home use simple on-off controllers that toggle between an on and off state . In this case, the on-off periodicity is a result of each background load maintaining an environmental set point: in this example, the refrigerator and freezer maintain their internal temperature within a fixed guard band, the dehumidifier maintains a humidity level within a fixed guard band, and the HRV heats outside air to a pre-specified temperature. The guard band defines the acceptable maximum and minimum levels for the load's target environmental metric. Common household loads use simple control loops to stay within the guard band. For example, when the load's metric reaches a maximum allowable value, the load turns on until the metric reaches a minimum value, at which point the load turns off. Since environmental conditions vary, neither the length nor the magnitude of a load's on-off period is entirely regular. To illustrate, the figure shows that the refrigerator (upper right) and freezer (upper-left) exhibit longer on periods in the early evening between 5pm and 9pm, along with some transient usage spikes. In both cases, the longer on periods are the result of the occupants opening the refrigerator and freezer doors, which increases the internal temperature and causes them to turn on their compressors to lower the temperature. Tasks other than maintaining temperature also contribute to the transient spikes in power consumption. For example, both the refrigerator and freezer power multiple 60W incandescent light bulbs when the door is open and also periodically make ice; the refrigerator also cools a separate freezer compartment. The refrigerator exhibits a much more irregular consumption pattern, since it resides in the kitchen and the occupants open its door more frequently than the basement freezer. The HRV and dehumidifier exhibit irregular periods for similar reasons. The dehumidifier's operating cycle dictates that it runs until it reaches a set point humidity—in our case 50%—or until it has run for two consecutive hours, at which point it remains off for 2 hours to cool down. Thus, on hot and humid summer days, the dehumidifier will run for 2 hours every 4 hours if it cannot reach its set point humidity, and consume a significant fraction of power (1.8 kWh). On moderately humid days, the dehumidifier will come on and off according to its setpoint humidity, causing an irregular on-off period. On this day, the environmental humidity was high, so the dehumidifier ran regularly. Similar to the refrigerator/freezer, the window unit A/Cs exhibit irregular periods based on changing outdoor temperatures and the frequency with which exterior doors open and close. While some environmental factors may be partially predictable, such as temperature or humidity, interactive events such as doors opening and closing also affect the period and power consumption of background loads. Thus, scheduling background loads must take into account these difficult to predict changes in their periodicity.

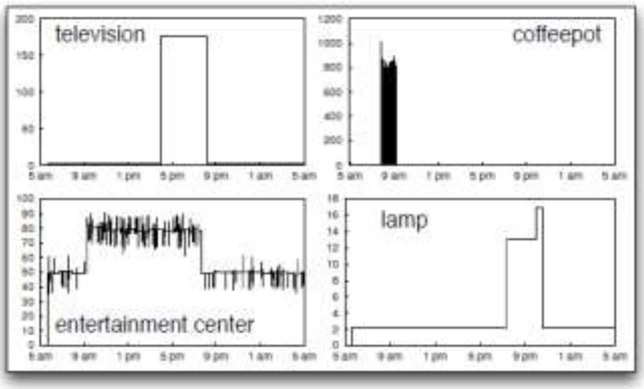

Figure 5.Power data for example interactive loads. Occupant behavior,which is not readily predictable, determines when these loads draw power.

IV. LOAD SCHEDULER

Green Building's background load scheduler leverages the well known concept of slack, which quantifies the extent to which a scheduler is able to advance, defer, raise, or lower a load's power consumption without affecting its operational goal. Before detailing the LSF algorithm, we first discuss different types of load controllers to understand the available dimensions of scheduling freedom.

A. Load Controllers

Simple on-off controllers encompass the vast majorityof controllers found in residential loads, since they arecheap and reliable. As discussed earlier, on-off controllersoften maintain an environmental metric, e.g., temperature or humidity, within a specified guardband. For these loads, slack arises from the fact that the load is able to remain off until its metric reaches the guard band's maximum (or minimum) value, at which point the load must turn on. In effect, these loads indirectly store power in their contained environment by increasing (or decreasing) a target metric, which then slowly decreases (or increases) due to leakage with the outside environment. On-off controllers are also commonly driven by timers, which dictate fixed-length on off periods. While a scheduler is able to advance or defer when these loads turn on or off, as long as they do not violate their guard band or fixed-length on-off period, it is not able to raise or lower power consumption when the loads are on. Battery chargers are another example of a load with slack, since they are capable of raising or lowering their power consumption by adjusting the charging rate. While most household batteries are small, e.g., phones, laptops, and tablets, the emergence of plug-in electric vehicles (EVs) is poised to introduce a large load with substantial slack to homes. EVs that plug into standard 120V/15A outlets are able to charge at a rate of up to 1.8kW, while a dual-pole 240V/30A circuit that uses both legs of a home's split-phase input power is able to charge at a rate of up to 7.2kW. In either case, advanced chargers are capable of varying the rate of charge up to these maximums. For battery chargers, the primary scheduling constraint is fully charging the battery over some duration, or charging to an acceptable capacity, While not present in our prototype, variable drive controllers are capable of raising and lowering their power consumption when on. These controllers offer clear benefits over on-off controllers, but they are typically not found in household appliances due to cost and reliability issues. As a result, our experiments do not study their impact.

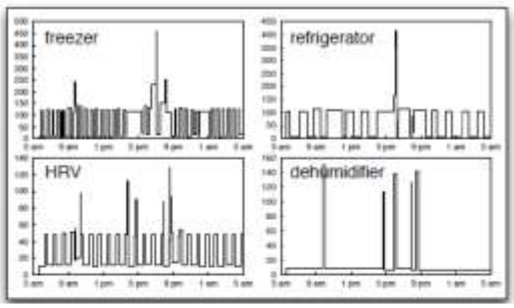

Figure 6. Power signatures for four background loads in our home. Theon-off period varies with environmental conditions, and is not regular.

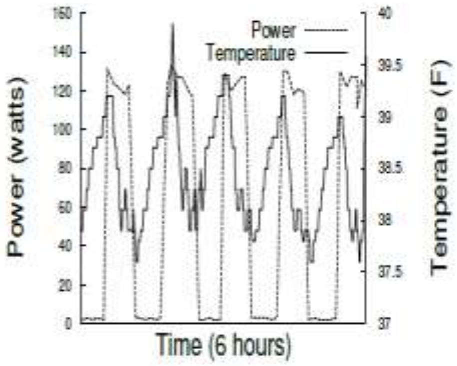

Figure 7. A depiction of slack in our refrigerator's simple on-off controlloop. The compressor turns on once the internal temperature reaches an upper threshold, and turns off once it reaches a lower threshold.

B. Scheduler

We define a load's slack at any time t as the remaining length of time the load can be off, i.e., disconnected from power, without assuring that it will violate its objective[3]. For a load that maintains an environmental condition with an on-off controller, it must turn on when its environmental metric reaches a guard band boundary. For a battery charger, it must turn on when only the maximum charging rate over the remaining plug-in duration is sufficient to fully charge the battery, or to charge it to an acceptable capacity. We define slack in units of time, rather than energy as in, only for ease of exposition—slack time is proportional to slack energy for stable load and environmental conditions. We assume each load is able to maintain an estimate of its remaining slack time based on its current power state and by monitoring the state of its internal and external environment. As shown in Figure 7, slack estimates may change over time based on both the load's power state—when the load is off slack increases—and environmental conditions, such as a refrigerator door opening or the humidity increasing. Since these changes in slack may be unpredictable, our scheduler is reactive and online, continually adjusting which loads receive power based on their available slack. Finally, we assume that our gateway is able to query the slack of each load at any time using simple models as in. Before describing our scheduler, we first illustrate a simple example using ideal background loads with well-defined on and off periods in isolation, and without uncontrollable interactive loads. The illustration demonstrates how shifting power usage is able to flatten demand. Figure 8(a) depicts an extreme example, where the slack for three window A/C units that draw 1kW when on dictates that they must turn on for 15 minutes anytime within each hour to maintain their respective setpoint temperatures. In the worst case, without any scheduling, these units may be nearly synchronized and cause power usage to reach 3kW for close to 15 minutes

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over the hour, while drawing 0W for the remaining 45 minutes. In the best case, with appropriate scheduling, it is possible to shift the on periods such that only a single A/C is on at any given time, resulting in a peak usage of only 1kW (Figure 8(b)); since the on periods of the A/Cs interleave with room to spare, we are able to perfectly flatten demand. To quantify flattening over an interval, we use the average absolute deviation from the mean power, which is an average of the absolute difference between power at every time t and the average power. We use this metric instead of the standard deviation simply because it is more intuitive; standard deviation exhibits the same trends but is greater than or equal to our metric. The magnitude of the deviation quantifies how much demand varies; a lower deviation indicates flatter demand and a better schedule. In our example, the worst case no scheduling scenario has a deviation of 1125W from the mean power, while the best-case scenario has a deviation of 375W due to 15 minutes of no power consumption at the end of the period. In this scenario, interleaving the A/Cs results in a 3x reduction in the deviation and, thus, a significantly flatter demand profile. The scheduling problem for ideal background loads with regular known on-off periods distills to a simple offline optimization problem in the absence of interactive loads. Figure 8(c) demonstrates how interactive loads alter scheduling by inserting into our previous example four 5 to 15 minute peaks of 1000W during the hour-long period, as could be expected from heating up food in a microwave. Even though A/Cs have enough slack within the hour to defer their power consumption whenever the microwave turns on (Figure 8(d)), an algorithm that determines the schedule in advance will not know about these microwave events. While this is a simple idealized example, it illustrates that load scheduling in the presence of unpredictable interactive loads is an online, and hence heuristic, process. Sudden and unpredictable changes to a load's slack, such as from opening doors or changes in weather, introduce similar issues that warrant an online approach. As we discuss in Section VI, and in contrast to Figure 8(a) and (b), we find that scheduling background loads is most advantageous during "peaky" periods with many short, but high power, interactive loads. SmartCap's scheduler executes every interval T to de-termine which background loads receive power (and howmuch for the battery charger). In our simulator and testbed, we choose T's length to be significantly less (one minute) than the typical on-off periods of our background loads; the setting also ensures that background loads are not quickly turned on and off, which may degrade their reliability. We assume that once a load's slack reaches zero, the scheduler must provide it the necessary power regardless of the increase in peak usage. We call our basic load scheduling policy Least Slack First (LSF), since it supplies power to loads in ascending order of their current slack value. Thus, loads with a lower slack have a higher priority. LSF is a direct adaption of the Earliest Deadline First (EDF) scheduling policy common in real-time operating systems. We combine LSF with a target capacity threshold to determine how many loads to power, and how much power to supply to battery chargers. Once the sum of the background loads' power usage reaches the capacity threshold, the scheduler stops powering additional background loads. Figure7 depicts how LSF scheduling flattens demand for a real power signal, assuming three A/Cs turn on near each other as in Figure 6. As in our example, LSF flattens the demand profile by interleaving the on periods. Our experiments use an adaptive threshold based on an exponentially weighted moving average of the home's power consumption over the previous hour. Setting the capacity threshold presents a trade-off. A threshold too low causes the scheduler to defer too many loads, resulting in their slack values approaching zero in tandem. This induces large peaks by ultimately forcing the scheduler into simultaneously powering many loads with zero slack. A threshold too high causes the scheduler to power too many background load sat a time, resulting in a peak that is higher than necessary.

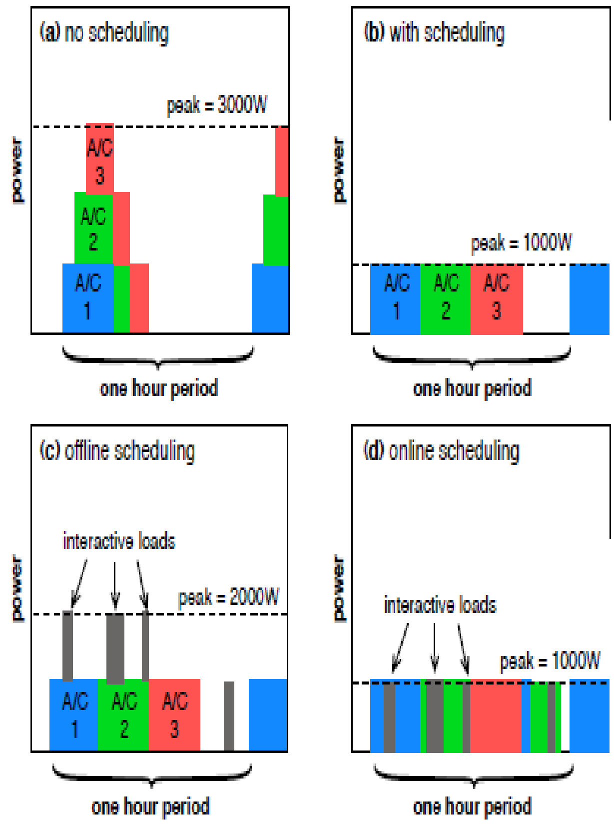

Figure 8. A background load scheduler is capable of flattening demand, but must account unpredictable interactive and background loads.

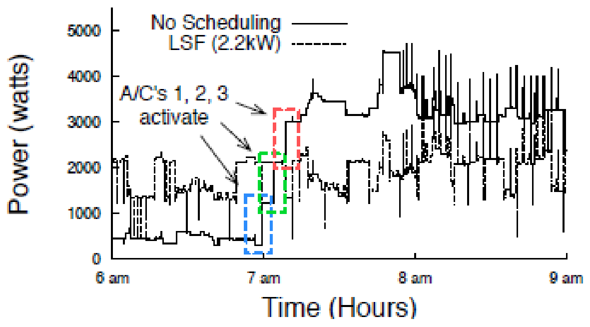

Figure 9. Example of how LSF flattens demand.

V. Experimental evaluation

To illustrate Green building'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 Green building'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:-

Figure10 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[6] and 20% for Green building. 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.

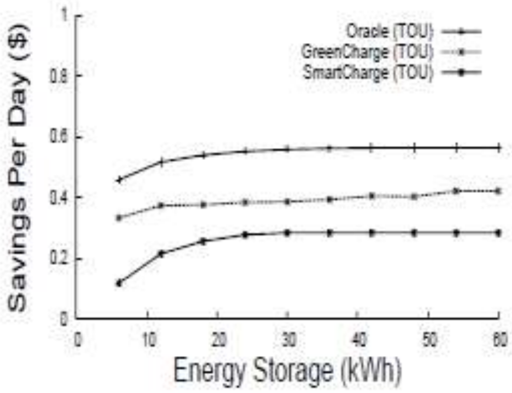

Figure10. Average dollar savings per day for both SmartCharge and Green- building in our case study home.

Finally, the graphs show that Green building'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.

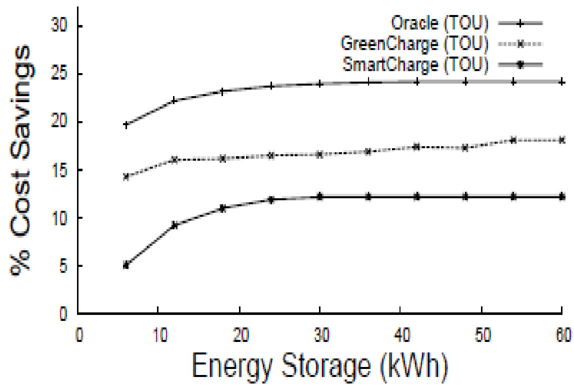

Fig.11. Average percentage savings for both SmartCharge and Green building in our case study home.

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[4]. 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 12 demonstrates that the maximum

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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 13(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 Green building and SmartCharge[6]. 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 Green building and SmartCharge[6]. 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, Figure14 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 a pool 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.

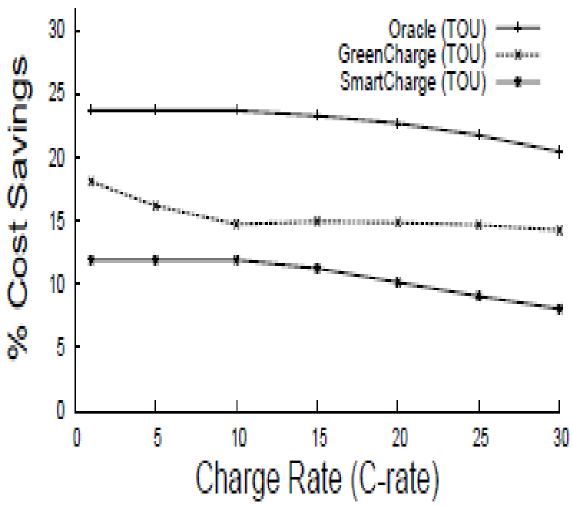

Figure12.SmartCharge's and Green building's savings as a function of the charging rate for a 24kWh storage capacity.

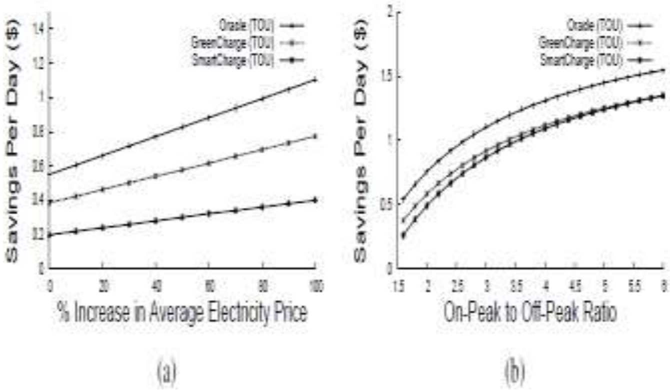

Figure.13. Varying the average electricity price (a) and the peak-to-off-peak price ratio (b) impacts savings.

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.

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 Green building using power data from a large sampling of homes[6]. 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.

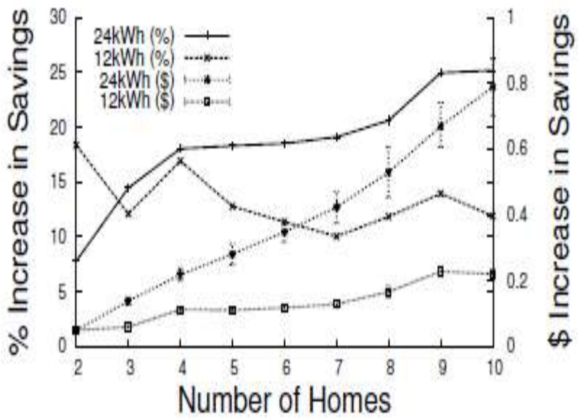

Figure.14. Additional savings (in % and $) from sharing 12kWh and 24 kWh between homes.

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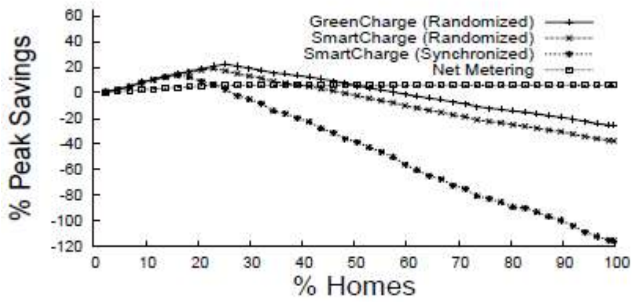
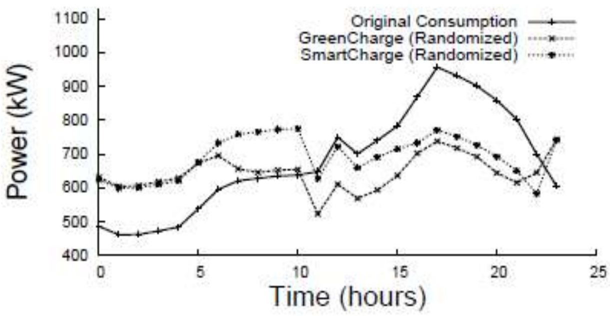
Figure14 plots the peak power over all the homes as a function of the fraction of homes using Green building and SmartCharge with energy storage. For these experiments we assume that each home has available energy storage equal to half the home's average daily consumption. Charging rate of C/4 for the usable storage capacity is assumed. The figure shows that Green building and SmartCharge[6]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)

Figure15. With 25% of homes using Green building, 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 Green building 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 Green building 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 figure12 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 Green building's and SmartCharge's economics at scale further . Figure15 (b) shows grid power usage over time, with 0% and 22% of the homes using Green building 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 building 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 Green building. 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 and battery capacity to implement Green building. 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. Green building'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 building'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.16 demonstrates that cost begins to increase rapidly after a 45% DOD, with an estimated cost of $118/kWh of usable capacity.

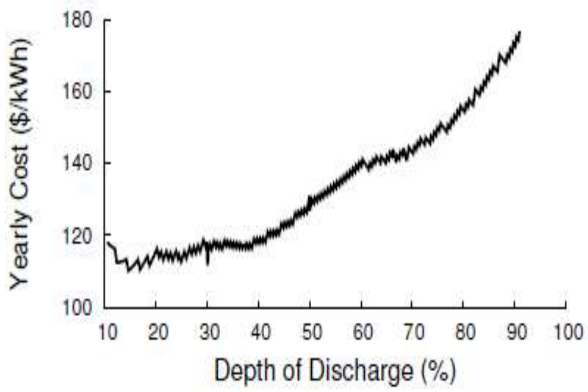


Figure.16. Amortized cost per kWh as a function of depth of discharge

B. Comparison of batteries

Recent advancements in battery technology promise to dramatically reduce battery costs in the near future[11]. Lead-carbon batteries have an expected lifetime 10 times longer than today's sealed lead-acid batteries at roughly the same cost. Figure 17 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 Green building in a few years.

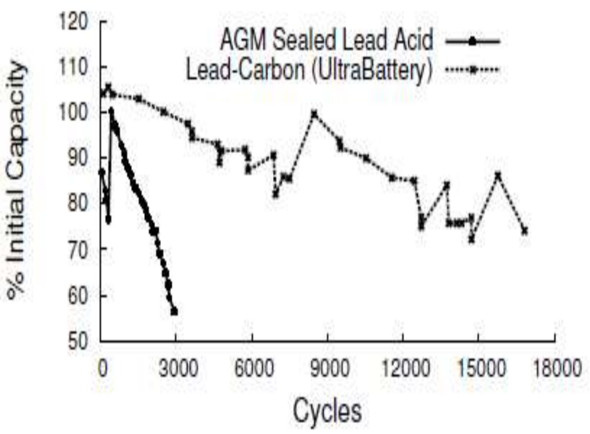


Figure.17. Comparison of sealed lead-acid and lead-carbon battery lifetime

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[12]. 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, is to 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. Green building 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 building 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 building'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 building'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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