Incentivizing Advanced Load Scheduling Algorithms in Smart Homes

Abstract

In recent years, researchers have proposed numerous advanced load scheduling algorithms for smart homes with the goal of reducing the grid's peak power usage. In parallel, utilities have also introduced variable rate pricing plans to incentivize residential consumers to shift more of their power usage to low-price, off-peak periods, also with the goal of reducing the grid's peak power usage. In this paper, we show that variable rate pricing plans *do not* incentivize consumers to adopt advanced load scheduling algorithms. While beneficial to the grid, these algorithms simply do not lower a consumer's electric bill. To address the problem, we propose *flat-power pricing*, which directly incentivizes consumers to flatten their own demand profile, rather than shift as much of their power usage as possible to low-cost, off-peak periods. Since most loads have only limited scheduling freedom, load scheduling algorithms often cannot shift much, if any, power usage to low-cost, off-peak periods, which may be many hours in the future. In contrast, flat-power pricing encourages consumers to shift power usage even over short time intervals to flatten demand. We evaluate the benefits of advanced load scheduling algorithms using flat-power pricing, showing that consumers save XX% on their electric bill, compared with XX% using an existing time-of-use rate plan.

1 Introduction

Rising electricity prices over the past 20 years combined with a growing awareness of the environmental effects of burning fossil fuels, e.g., air pollution, climate disruption, water contamination, is motivating both energy producers and consumers to better optimize their electricity generation and consumption, respectively. The simplest and most direct way to optimize the electric grid is for consumers to simply use less energy. Unfortunately, despite continuing improvements in the energy-efficiency of electrical devices, society's energy demand continues to grow at a rapid pace—estimated to increase by 50% over the next 20 years—driven in large part by population growth and improving economic conditions in developing countries. Since reducing overall energy consumption presents many non-technical challenges, one promising alternative approach to grid optimization has been to focus on reducing the grid's peak usage.

The magnitude of the grid's peak usage has a disproportionate impact on electricity generation's capital and operational costs, as well as its carbon emissions. For instance, a lower peak usage directly translates to less idle, unused generation capacity and a need for fewer expensive power plants. In addition, the marginal cost to generate each additional watt of electricity increases non-linearly, since utilities usually dispatch the highest-cost "peaking" generators last. In fact, the cost to generate each watt using an oil-based peaking generator may be more than ten times the cost using a coal-fired baseload power plant. Finally, since peaking generators tend to be the least efficient generators, they also produce more carbon emissions per watt. These trends have led utilities to introduce new variable rate electricity pricing plans that incentivize residential consumers to shift their power usage to the grid's peak usage. These pricing plans vary the price of electricity throughout the day, such that electricity costs more when grid demand is high, i.e., *peak periods*, than when it is low, i.e., *off-peak periods*. Figure 1 shows how electricity prices vary over a day with time-of-use (TOU) and real-time pricing (RTP). With RTP plans, rates change every hour of every day based on the real-time price of electricity in the wholesale market, while with TOU plans, rates change only a few times each day and each day's rate profile remains constant over long periods, e.g., 3-6 months.

The goal of these new variable rate plans is to incentivize consumers to lower their electric bill by manually altering their behavior, i.e., when they perform certain energy-intensive tasks during the day. For example, if electricity prices are much lower in the evening, consumers might choose to perform energy-intensive tasks, such as doing their laundry or running their dishwasher, in the evening, rather than the middle of the day. In addition, variable rate pricing plans have also motivated researchers to develop a variety of advanced load scheduling algorithms for buildings and homes that programmatically control when electrical devices (or *loads*) operate to lower a building's electricity bill.

Instead of requiring consumers to manually alter their behavior, which many consumers may choose not to do regardless of electricity's price, these load scheduling algorithms exploit a limited degree of scheduling freedom available in a subset of loads. This freedom includes the option to transparently *shift*, *slide*, *stretch*, *store*, or *sell* some amount of power from some loads without involving end-consumers. For example, a load scheduling algorithm may partially i) *shift* a thermostatic or timer-driven load's duty cycle, ii) *slide* a batched load's start time into the future, iii) *stretch* an elastic load's operation to reduce its peak usage, iv) *store* power in a battery to alter a load's profile, or v) *sell* power produced by renewables back to the grid or other buildings, e.g., in a microgrid. Of course, each dimension of scheduling freedom has inherent scheduling limitations. For example, an algorithm may only shift a refrigerator's duty cycle so far before its interior temperature becomes too high and food spoils.

Widespread adoption of these load scheduling algorithms would result in a significant reduction in the grid's peak us-

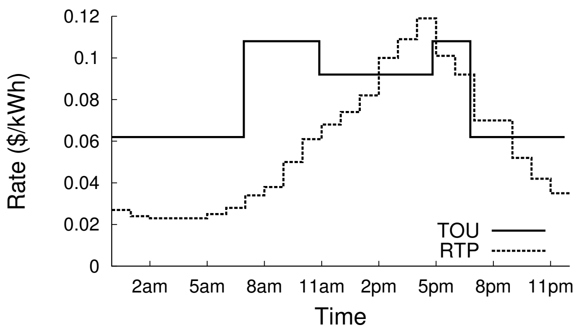

Figure 1. Examples of how electricity rates vary under time-of-use (TOU) and real-time pricing (RTP).

age, which in-turn would result in a significant decrease in the cost to generate electricity. However, in this paper, we argue that today's variable rate pricing plans do not properly incentivize consumers to adopt these algorithms. In particular, we show that optimizing each degree of scheduling freedom, either in isolation or collectively, within reasonable limits does not significantly reduce, e.g., by more than XX%, a representative consumer's electric bill. We also describe the potential adverse effects to the electric grid, including grid oscillations and higher peak load, if consumers were to adopt advanced load scheduling algorithms in large numbers under these pricing plans. Unfortunately, since the original purpose of variable rate pricing plans was to alter consumer behavior with the implicit assumption that only a small fraction of consumers would respond to the pricing incentives, these plans neither encourage nor support advanced load scheduling, especially at large scales.

To address the problem, we propose a *flat-power pricing* to directly incentivize consumers to flatten their own demand. In particular, our pricing plan charges a higher price for electricity that is above a consumer-specific target set *a priori* by the utility. As a result, a flat-power pricing plan incentivizes shifting a load's power usage over shorter intervals than variable-rate pricing plans. As a result, under flat-power pricing, consumers save more money on their electric bill by adopting advanced load scheduling algorithms. In addition, as we discuss, since flat-power pricing encourages consumers (and load scheduling algorithms) to flatten their own demand, it avoids the adverse grid effects caused by the widespread adoption of load scheduling algorithms under today's variable rate plans. Our hypothesis is that flat-power pricing better incentivizes advanced load scheduling algorithms, encouraging their adoption at large scales, than today's variable rate electricity pricing plans. In evaluating our hypothesis, we make the following contributions.

Combined Load Scheduling. We develop a linear programming (LP) formulation that combines all the degrees of scheduling freedom mentioned above to minimize electricity costs under variable rate pricing plans. The LP formulation combines similar types of formulations from prior work that focus on optimizing each degree of scheduling freedom in isolation. For a representative home, we show that combined load scheduling is only able to lower the electric bill by XX% and XX% under an existing time-of-use (TOU) and real-time pricing (RTP) plans, respectively.

Flat-power Pricing Model. We introduce flat-power pricing, and discuss its benefits relative to existing pricing models, including variable rate and peak-based pricing, with respect to incentivizing advanced load scheduling algorithms and encouraging consumers to change their behavior.

Evaluation. We alter our combined LP formulation above to schedule loads to minimize electricity costs under our flat-power pricing plan. For the same home as above, we show that with flat-power pricing, advanced load scheduling algorithms lower the electric bill by XX%—significantly more than the savings from existing pricing plans.

2 Background

We first introduce the different dimensions of scheduling freedom available in electric loads, as well as highlight prior research that focuses on optimizing each particular degree of freedom in isolation, either to reduce consumer costs or the grid's peak usage. In addition, we discuss the limitations of each metric in exploiting variable rate pricing plans to lower a consumer's electric bill. The primary degrees of freedom we identify include the ability to transparently shift, slide, stretch, store, or sell power. Note that some loads may exhibit multiple degrees of scheduling freedom.

Shifting power refers to scheduling on-off loads that operate over one or more duty cycles, such that within each duty cycle the load is on for some period of time and off for some period of time. The length of the duty cycle and the amount of time a load is on within each cycle may be either static, e.g., if driven by a timer, or dynamic, e.g., if driven by a thermostat. In either case, the load must be on for a fixed amount of time during a cycle to satisfy its objective, such as keeping the temperature of an enclosed space within a specified range or guardband. As long as the scheduler ensures the load is on for this time during the cycle, it is free to determine *when* the load is on during the cycle without violating the objective. This freedom is often referred to as *slack* [1, 12].

Prior work focuses on scheduling these shiftable on-off loads either to i) align as much load as possible with renewables [12], ii) defer loads during times of grid constraint [4], or iii) flatten a building's demand profile [1, 6]. However, prior work does not address the lack of monetary incentive for consumers to shift loads. Since the duty cycle length for common shiftable loads, such as an air conditioner or refrigerator, are at most a couple of hours, and often much less, schedulers are only able to shift these loads within narrow time periods without violating their objectives. As a result, shiftable loads cannot exploit the TOU/RTP pricing models from Figure 1, which require consumers to shift load to off-peak periods that may be 12 hours away from peak periods.

Sliding power refers to deferring the start time of a batched load, such as a dishwasher, washing machine, or dryer, that perform a, usually non-preemptible, batch task for a fixed, well-known period of time [12]. These loads are first initialized by a user, then run for a pre-determined amount of time without user intervention, and are finally emptied and reset by the user. In some cases, these loads are pipelined. For example, clothes are usually washed and then dried in sequence. In addition, some loads may also be preemptible, in which case, once started, they also act as shiftable loads that operate over a single duty cycle. As long as an user has initialized a load, e.g., filled it with clothes or dishes, a scheduler has the freedom to indefinitely delay its start time. Of course, delaying the start time also delays the end time, which may in-turn cause delays in the pipeline. The primary constraint for scheduling slide loads with respect to load scheduling is the amount of inconvenience a user is willing to tolerate. Since user's directly control when to initialize and start slide loads, incentivizing users to change when they operate slide loads is an important goal of existing variable rate pricing plans. Unfortunately, as above, users are often unwilling to delay start times many hours into the future, e.g., from daytime to nighttime, which limits scheduling freedom.

Stretching power refers to extending an elastic load's running time, while lowering its average power usage, while keeping its energy consumption constant for a particular task [11]. Typically, elastic loads utilize resistive heating elements or variable drive motors, which enable a scheduler to precisely adjust temperature or speed, respectively, as well as running time. Examples of elastic loads cited in prior work include washing machines, dryers, dishwashers, ovens, stoves, refrigerators, freezers, air conditioners, electric water heaters, and electric space heaters. Schedulers cannot arbitrarily stretch a load, since the average power usage and duration of a task affect its operation. For example, running dryers at high heat for a short duration works well for heavy fabrics, while low heat for a long duration is better for delicate fabrics. Thus, prior work [11] places a relatively low upper limit—$\sim$10%—on stretching a load's running time.

Storing large amounts of power during high price periods and then using this stored power during low price periods is the most effective way to transparently schedule loads under today's variable rate pricing plans to lower a consumer's electricity bill. Prior work explores many different aspects of scheduling energy storage, largely in the form of lead-acid batteries, to exploit this opportunity for arbitrage [2, 3, 7, 8, 13, 14]. Unfortunately, energy storage, especially at small scales, is expensive. As prior work shows, either electricity prices would need to rise, or battery prices would need to fall, by an order of magnitude before the return-on-investment would be near a break-even point [2, 8]. One issue with existing TOU/RTP pricing plans is that they require consumers to shift as much load as possible from high-price daytime periods to low-price nighttime periods, which requires a large amount of storage capacity.

Selling power, e.g., via net metering, is an option for homes that generate their own power using on-site renewables, such as solar power. In many cases, the price utilities pay consumers for power is less than the price they charge them for power. In addition, current laws often place strict cap on the amount of power a utility must buy back from a consumer. These dynamics alter the scheduling problem by incentivizing consumers, to not only transfer load to low-price, but also to align as much load as possible with renewable generation [9, 12, 15]. Aligning a home's load with renewable generation also decreases the grid's transmission losses, since it increases the amount of power consumed at the point of generation. The limitations above also affect the freedom schedulers have to align load with renewable generation.

3 Combined Load Scheduling

The prior research described in §2 focuses on optimizing different dimensions of scheduling freedom in isolation. In this paper, we compare the performance of optimizing each scheduling dimension in isolation with a combined approach that jointly optimizes scheduling for all types of loads, e.g., shiftable, stretchable, slidable, etc. As in prior work, we formulate our combined scheduling problem as a mixed integer linear program (MILP). In particular, we extend the MILP used by Parasol [5], a solar-powered micro-data center, that schedules batch jobs with well-known running times and deadlines. As with our MILP, Parasol's objective is to minimize electricity costs under TOU/RTP rate plans and maximize the use of solar power, albeit for a data center instead of a home. However, while Parasol accounts for energy storage, net metering, and slide loads (which are akin to batch jobs), we extend our MILP to schedule shiftable and stretchable loads. Of course, our work also differs from Parasol, since a home is substantially different than a data center in terms of its users, workloads, devices, and scheduling freedom.

We frame our MILP using the parameters in Table **??**. We model both $L_{slide}[\vec{power}]$ and $L_{shift}[\vec{power}]$ as vectors of tuples that specify each load's start time, running time, and power usage. We assume slide loads also have a completion deadline. We then divide each day into T discrete intervals of length l from 1 to T with the objective of minimizing $\sum_{i=0}^{T}(m_i * P_g^i rid - \alpha * m_i * N_{green}^i)$ each day, or the net bill after any net metering, given the following constraints.

$$\forall i \in T, B_{green} + B_{grid} \leq \frac{C}{4} \tag{1}$$

$$\sum_{i=0}^{T} L_{battery} - e * \sum_{i=0}^{T} (B_{green} + B_{grid}) \leq 0 \tag{2}$$

$$\sum_{i=0}^{T} B_{green}^i + \sum_{i=0}^{T} B_{grid}^i - \frac{\sum_{i=0}^{T} L_{battery}}{e} \leq C \tag{3}$$

$$\forall i \in T | L_{battery}^i > 0, N_{green} = 0 \tag{4}$$

$$\forall i \in \{T | L_{battery}^i > 0\}, B_{green}^i + B_{grid}^i = 0 \tag{5}$$

$$\forall i \in T, L_{green}^i + B_{green}^i + N_{green}^i \leq g_i \tag{6}$$

$$\forall i \in T, L_{grid}^i + B_{grid}^i = P_{grid}^i \tag{7}$$

$$\forall i \in \{T | L_{grid}^i > 0\}, N_{green}^i = 0 \tag{8}$$

$$\begin{aligned} \forall i \in T, L_{battery}^i + L_{grid}^i + L_{green} \\ = L_i - L_{slide}^i[\vec{power}] - L_{shift}^i[\vec{power}] \end{aligned} \tag{9}$$

$$\begin{aligned} \forall \vec{L_{shift}^i}, \forall i \in \frac{T}{L_{shift}^i[period]}, \sum L_{shift}^i[power] \\ = L_{shift}[power] \end{aligned} \tag{10}$$

Briefly, the constraints above ensure the following properties: (1) the battery's charging rate is not more than its capacity divided by 4; (2) the energy charged to the battery never exceeds the energy discharged from it; (3) the energy stored in the battery never exceeds its capacity; (4) net metering and battery charging do not occur at the same; (5) battery charging and discharging do not occur at the same time; (6) renewable generation can charge the battery; (7) renewable generated can be net metered; (8) cannot consume grid power and net meter at the same time; (9) every load is powered by only one energy source; (10) the amount of power shiftable loads consume per period is constant; and (11) slide loads cannot run past their deadline.

Constraints (4), (5), and (8) are non-linear mutual exclusion constraints. We convert these to linear constraints by introducing a binary variable $b \in \{0,1\}$ and replacing each non-linear mutual exclusion constraint with five linear constraints that enforce the same invariant. In this case, we replace any constraint of the form $\forall i \in \{T|x>0\}, y=0$ with $x - \inf * b \leq 0$, $-\inf * x + b \leq 0$, $y + \inf * b \leq \inf$, $x \geq 0$, and $y \geq 0$. Finally, ensuring slide loads complete within their deadline does also not map well to a linear constraint. Thus, for a given slide load each day, we simply run the MILP T/i times for each possible start time of the slide load and then use minimum cost schedule. Of course, as the number of slide loads increases, we must run the MILP for each possible combination of start times. However, the approach is tractable, since the number of slide loads is typically small, e.g., usually three or less, and they often do not run everyday.

XXX Need to say something about stretchable loads

We use our MILP above to quantify the cost savings from each dimension of scheduling freedom, both in isolation and in combination over a 60-day period for a representative home for both the TOU and RTP pricing plans depicted in Figure 1. In our experiments, we run our MILP at the beginning of each day with $T = 24$, assuming that we know home's power demand p_i, renewable generation g_i, and the electricity cost each interval. In practice, our system requires predictions for these parameters [10, 8]. Thus, our results represent an upper-bound on the cost savings due to scheduling.

Figure 2 shows the percentage cost savings from scheduling only shiftable loads (a), slidable loads (b), and stretchable loads (c) in isolation. In each case, the x-axis represents the degree of scheduling freedom for each load. The result demonstrates that as scheduling freedom increases, so do the savings. Unfortunately, practical values for the x-axis in each case are generally low. For example, as the length of the duty cycle for a shiftable load increases, the scheduler has more freedom to shift power usage long periods of time without violating the constraint that energy usage within a duty cycle must be constant. In practice, common shiftable loads, such as refrigerators, freezers, heaters, and air conditioners, have duty cycles of only a few hours or less, which results in savings of less than 10%. Similarly, slide loads only reduce costs, if a scheduler is able to

4 Evaluation

5 Conclusion

6 References

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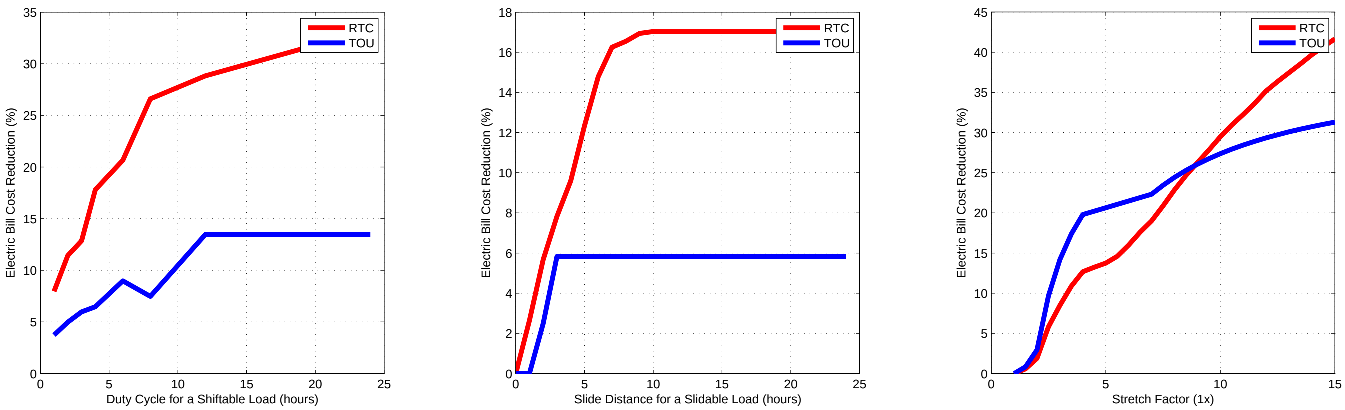
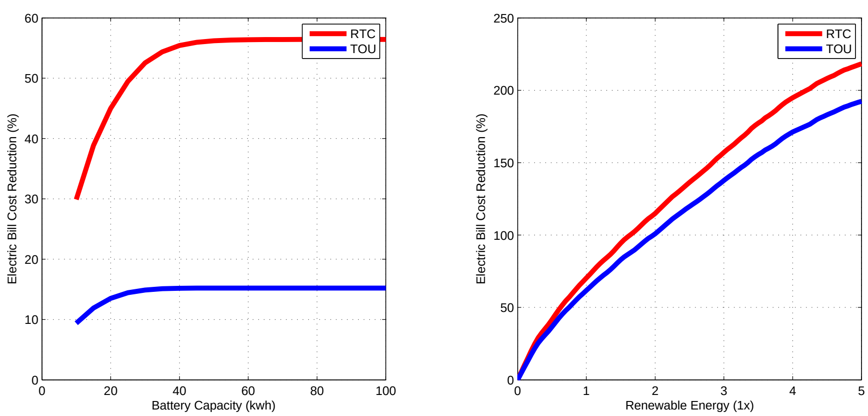


(a) Shift (b) Slide (c) Stretch

Figure 2. Cost savings from scheduling shiftable, slidable, and stretchable loads as scheduling freedom increases.



(a) Store (b) Sell

Figure 3. Cost savings from using energy storage and net metering, as capacity and renewable generation increases.