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SolarPlus Optimizer: Integrated Control of Solar, Batteries, and Flexible Loads for Small Commercial Buildings

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Publication Date
2022-08-22

Peer reviewed

SolarPlus Optimizer: Integrated Control of Solar, Batteries, and Flexible Loads for Small Commercial Buildings

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ABSTRACT

Building-level microgrids may be a key strategy to unlock the combined potential of flexible loads, renewable generation, and energy storage. However, few software options exist for integrated control of building loads and other distributed energy resources at this scale. The commercial software solutions on the market can force customers to adopt one particular ecosystem of products, thus limiting consumer choice. The SolarPlus Optimizer (SPO) is an open-source building-level microgrid control platform that uses Model Predictive Control to optimize both building loads and behind-the-meter energy storage to reduce energy bills and increase demand flexibility. This paper evaluates the capabilities of SPO in a small commercial building in Northern California under multiple electricity tariffs and demand response scenarios. Comparing SPO operation with an emulated battery and baseline operation employing a commercial optimization service, SPO reduced electricity bills by an estimated 7.3% in summer, 3.2% in spring, and 3.7% in winter. In a “load shape” scenario meant to counter the “duck curve”, SPO achieved 71% fewer violations from the load signal than the baseline control method. During a three hour long load shed event, SPO reduced cooling and refrigeration load by 38%. This research shows significant potential to provide load flexibility for building-level microgrids for this type of control systems. Finally, the paper discusses the future direction of research on open-source control systems.

Introduction

Commercial buildings account for almost 35% of total electrical consumption in the United States (EIA 2021), and packaged air conditioning systems compose 60% of the cooling equipment installed in these buildings (EIA 2012). Estimates indicate that using temperature setpoint control in commercial facilities like these could save more than 30% of the electricity costs of air conditioning (Cai et al. 2019). There is a significant opportunity for cost savings, and also for enhanced demand flexibility, by effectively controlling the temperature setpoints of packaged air conditioning systems like rooftop units (RTUs). Increased availability and variety of inexpensive Internet of Things (IoT) building sensors, and the convergence of building automation systems to a common set of protocols, present new options to accomplish this goal (Minoli, Sohrabi and Occhiogrosso 2017).

Solar photovoltaic (PV) generation of electricity has been increasing rapidly over the past decade, growing an average 33% annually over 2011-2021, and the Solar Energy Industries Association expects that 29% of new solar systems will be paired with storage by 2025 (SEIA 2021). As solar plus storage systems increase in prevalence, and grid-disrupting extreme weather events like heat waves and forest fires in California and other western states increase, the operation of these systems to enhance resiliency and demand flexibility will become ever more important. Advanced control algorithms that produce optimal supervisory setpoints can provide these capabilities.

Model Predictive Control (MPC) is a control strategy that has demonstrated the ability to optimally control both behind-the-meter energy storage and RTUs in simulation and in field studies (Drgoňa et al. 2020). MPC uses a model of a particular subject, along with forecasts of external information such as prices or PV generation, to predict the effect of different control actions on that subject's behavior. These predictions are then used to choose optimal control actions based on their cumulative effect on specific objectives, such as reducing a utility bill while maintaining building thermal comfort. MPC can be used to manage several systems in concert to create control strategies that are better than what can be provided by standalone systems. In an MPC study controlling multiple packaged HVAC units for energy cost reduction, 4-9% energy cost savings was achieved (Kim et al. 2022). In (Allen et al. 2020), a supervisory MPC for solar, battery energy storage, and building loads (EVs, HVAC, and Lighting) was investigated in simulation. MPC for net energy reduction using a moving horizon estimation forecast generated 12.8% cost savings versus rule-based control. In (Kromer et al. 2020) an optimal dispatch controller used MPC to optimize the net load of a virtual power plant consisting of solar PV, battery energy storage, and flexible customer loads. With the objective of peak shaving and energy cost reduction, peak load was reduced by 16% relative to a non-storage baseline. To deploy MPC, a building needs to be outfitted with connected devices and software capable of communicating with building equipment if a building automation system (BAS) does not exist.

The SolarPlus Optimizer (SPO) is a control platform for grid responsive building microgrids with an MPC optimization engine (Prakash et al. 2020). It was designed to manage building energy system controls in tandem with on-site energy resources. SPO is a vendor-agnostic and protocol-independent control platform built using open-source software that can be installed on any site. SPO is scalable, which means that it can be adapted and modified throughout the life of the building hardware while protecting users from being tied into a particular manufacturer ecosystem. These features increase SPO’s flexibility, extend its lifetime, and reduce its installation cost. SPO’s attributes make it a perfect candidate for small- and medium-size buildings that do not typically have a BAS (Katipamula et al. 2012).

SPO uses MPC to optimize the operation of Heating, Ventilation, Air Conditioning, and Refrigeration (HVAC&R) and battery systems in response to various grid requirements as well as minimizing the building electricity bill. SPO receives energy price, demand charge, and load-based demand response signals[1]. The MPC engine, described in greater depth in (Zhang et al. 2022) calculates an optimal control scheme over a specific control interval – every five minutes in this study. It uses JModelica.org (Akesson et al. 2009), which uses CasADi (Andersson et al. 2012) to compute function derivatives and IPOPT (Wachter et al. 2006) for optimization.

At each interval MPC predicts building behavior over a 24-hour prediction horizon using a built-in building model. MPC then works to minimize a cost function subject to various demand and cost constraints to determine optimal setpoints for each building system (i.e.,

[1] Load-based demand response signals are soft constraints suggesting SPO to keep the site net load above and/or below some time-varying power value.

battery, HVAC, refrigeration), while maintaining comfortable site temperatures and food-safe refrigeration temperatures. SPO functions as a supervisory controller, sending these setpoints to the local controllers, which in turn manage systems through their internal control loops.The specific design of SPO is described in detail in (Prakash et al. 2020).

This paper examines the effectiveness of SPO to control building loads and energy storage given external conditions, building demand, and weather forecasts. SPO's performance is evaluated on its ability to reduce utility bills using battery and load control, to control building net load according to load-based demand response events, and to shift demand using HVAC&R temperature setpoint control.

Methodology

Site Specifications

The pilot site for SPO is a convenience store and gas station located in Blue Lake Rancheria, California (Figure 1). The key SPO-controlled systems at the site are two rooftop HVAC units (RTUs), a refrigerator room, a walk-in freezer, and battery energy storage. Uncontrolled loads include lighting, plug loads and slot machines in the store. These slot machines are a major source of internal heat, and are a significant constant load as they cannot be turned off.

The two RTUs serve all the HVAC needs within the store. The store is divided into east and west zones, with one thermostat and one RTU serving each. The store does not have any physical barrier between the zones, so there is significant air mixing and heat transfer from one zone to the other. The refrigerator and freezer store and display beverages and food items for customers behind glass reach-through doors. They have a timed defrost cycle that is independent of SPO. During baseline operation, HVAC and refrigeration (HVAC&R) systems are controlled with constant temperature setpoints. HVAC operates with a temperature deadband range of 66F to 70F. The refrigerator and freezer have cooling setpoints of 33F and -7F, respectively. During SPO operation, thermal comfort setpoints for the HVAC system are constrained to between 67 F and 74 F. To maintain food safety, the refrigerator setpoint was constrained between 33F and 38F, and the freezer setpoint between -30F and -2F.

The project site has a PV array of capacity 60 kW-DC/50-kW-AC. The PV panels are installed on the gas station canopy. Frequent overcast days at the pilot location made overgeneration of solar infrequent, and overgeneration was not a major issue due to net metering. The site also has a commercial battery with an energy storage capacity of 174 kWh and a peak discharge power of 109 kW. The PV capacity and the storage battery are both somewhat oversized relative to the average building load, which is approximately 33 kW. This choice was made so that this microgrid would have greater resilience and could be integrated with the greater community microgrid system in the future. Resilience has been extremely beneficial at this site, as this convenience store, with its gas station and cold storage services, served essential community needs during PG&E Public Safety Power Shutoffs due to wildfire risk (Waraich 2019, Alstone et al. 2020).

Figure 1: Image of the pilot site, convenience store/gas station at the Blue Lake Rancheria.
Credit: Blue Lake Rancheria

Testing Setup

Six Wattnode power meters were installed to measure power flows at the project site. These meters measured the instantaneous power consumption of the RTUs, the freezer and refrigerator compressors, and the freezer evaporator fan, and the building as a whole. Indoor temperatures were measured by two thermostats, one in the east and one in the west zone of the project site.

Data from the real battery on site were collected at 15 minute intervals from its internal monitoring system. Unfortunately, a delay which arose during delivery, installation and deployment of the battery did not allow sufficient time to commission the battery with SPO, and to later recommission it with commercial optimization software (for long term operations). For this reason, an emulated battery was used instead of the physical on-site battery for testing. Additionally, the emulated battery allowed us to resize the battery to test different capabilities of SPO.

Baseline Model

During testing, the performance of SPO was compared to the predicted performance of baseline operation during the test. This baseline operation is termed business as usual (BAU). To compare the performance of SPO and BAU subject to the same external conditions, a black-box model for baseline HVAC&R load was created.

The baseline HVAC&R load is calculated using a Random Forest (RF) regression model trained on real operational data from 88 days of baseline operation from throughout the testing period. The outdoor temperature, solar irradiance, uncontrolled building load, day of the week, and time of the day were the parameters. Tested using eight-fold cross validation, the model achieved an R-squared value of 0.91 and a root mean square error (RMSE) value of 1.9 kW. The model has a temporal resolution of every 15 minutes. Figure 2 shows a few comparison days of the modeled and real BAU HVAC&R load.

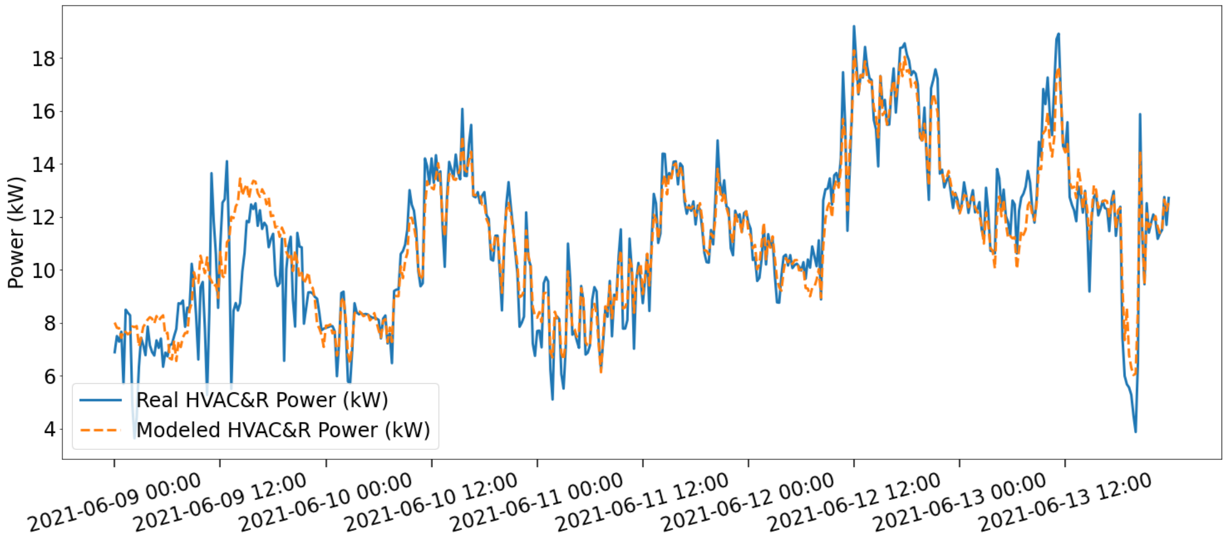

Figure 2: BAU modeled HVAC&R load compared to the real HVAC&R load

During price optimization, an emulated battery identical to the installed BAU battery was used for testing. The battery is modeled using the bucket model approach by considering the battery as a repository for energy (Reniers et al. 2018). The emulated and BAU batteries had a 174 kWh capacity and a 109 kW max discharge rate. They were configured with a 25% minimum state of charge (SOC) and a 94% maximum SOC. The 25% minimum SOC allows the battery to provide resilience during an unexpected grid disruption. The 94% maximum SOC gives the control system time to curtail PV generation if there is excess generation coinciding with an islanding event. The measured charge and discharge efficiencies of the commercial battery were applied to the emulated battery's charge and discharge values, not considering efficiency differences due to charge/discharge magnitude. SPO and the commercial optimization software for the BAU ran concurrently on the emulated and installed batteries respectively. They were thus subject to the same external factors. In demand response tests, the installed battery reduced BAU performance with respect to the different demand flexibility metrics because the commercial optimizer was not capable of demand response. This made the comparison less fair, so the battery is not included in the BAU scenario for these tests.

Case Studies

SPO uses time-varying demand charges, time-of-use (TOU) energy prices, minimum site-load and maximum site-load signals. Thus, SPO can pursue many different modes of operation or demand response events. The different objectives tested were bill optimization, load tracking, load shifting, and load shedding. In bill optimization mode, SPO ran throughout the year under the different seasonal variations of an electricity rate consisting of TOU energy price and demand charge components. In load tracking mode, the ability of SPO to continually and accurately control the site's net load was tested using relatively tight minimum and maximum load constraint signals throughout a day. In load shifting mode, SPO's ability to shift load specifically from one time to another was tested. This test was run using demand constraint signals with a flat energy price signal (the same energy cost and demand charges at all times of the day) and with a dynamic TOU energy price signal. Lastly, load shedding was tested using a maximum load constraint for a specific period during the day. All of these signals differ in complexity and motivation, and test different characteristics of SPO operation.

Bill Optimization

In this mode, SPO minimizes the electricity bill of the system. It accomplishes this by looking at the marginal TOU energy cost and demand charge increase given a specific electricity tariff. In an electricity tariff, the TOU energy price changes in periods over the day, and is the price per kWh used. The demand charge is the price per kW for the highest power use within a billing period. Demand charges are judged on a 15 minute basis, and there can be multiple demand charges for the different periods defined in a tariff.

The operating tariff of the pilot site was used for this test, PG&E B-19 (PG&E 2021b). Tests were conducted in winter (December 19-21, 2020), spring (May 1-2, 2021) and summer (July 23-25, 2021). The B-19 tariff is different in each of these seasons. The winter tariff, lasting from October to February, has a peak period during 16:00-21:00, and an off-peak period at all other times. Demand and energy prices differ little between the two periods. In spring (March to May), a super off-peak period is introduced from 9:00-12:00 that has a lower energy price. In summer (June to September), there is no super off-peak period, but part-peak periods are introduced before and after the peak period, with intermediate energy and demand charges. In summer, the energy and demand charges during the peak period increase significantly. Prices for this tariff are shown in Table 1.

Table 1: PG&E B-19 Energy and Demand Prices

Period	Energy ($/kWh)	Demand ($/kW)
Peak (16:00-21:00)	0.14 (winter, spring) 0.16 (summer)	1.79 (winter, spring) 25.58 (summer)
Part-Peak (14:00-16:00, 21:00-23:00)	0.13	5.23
Off-Peak (all other times)	0.11	0
Super Off-Peak (9:00-12:00, only in spring)	0.068	0
Max demand (from any period)	NA	21.08

SPO's cost savings for each season were estimated by conducting a short test in each season. Figure 3 below shows the estimated electricity costs for BAU and SPO operation in each season.

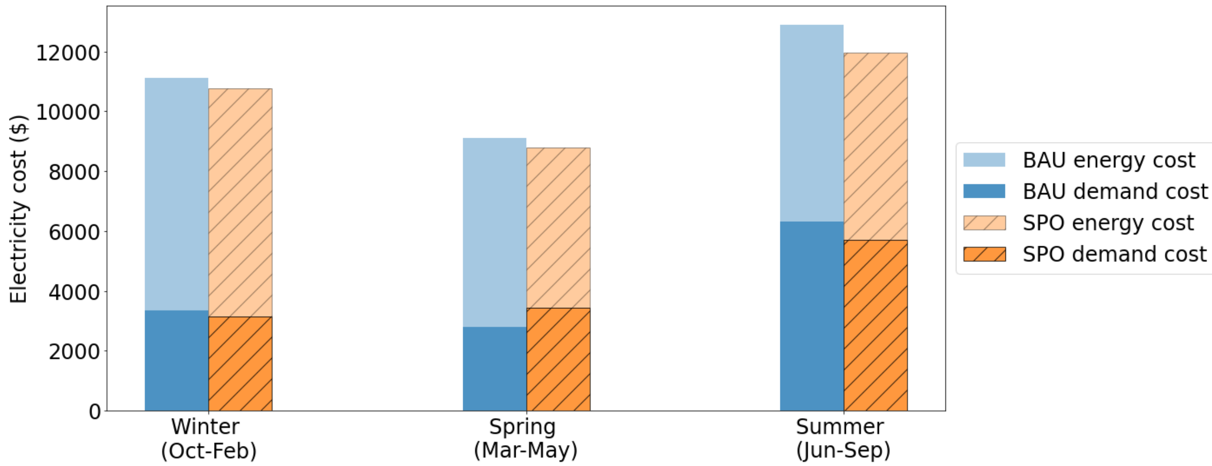

Figure 3: Estimated seasonal utility bills (left) and energy use (right) for MPC and BAU

In summer, savings was 7.3%, in spring, 3.2%, and in winter 3.7%. In all seasons, SPO was able to slightly reduce electricity bills relative to BAU operation. In summer and winter, SPO saved on costs arising from both energy and demand charges compared to BAU. Winter shows low overall savings because of the similarity between peak and off-peak prices. This means the battery has little opportunity for energy arbitrage. Additionally, since the weather is cold there is little opportunity for cooling demand response. Summer shows the highest savings because these features are reversed, and there is a greater difference between each pricing period. In addition, hot weather gives the opportunity for HVAC&R savings from SPO operation. The spring shows the least absolute cost savings. Though SPO operation reduced overall energy costs in every season, it exceeded BAU on demand charges. The difference between SPO and BAU operation during the spring shows important aspects of SPO's optimization strategy. Figure 4 compares SPO and BAU behavior during this period.

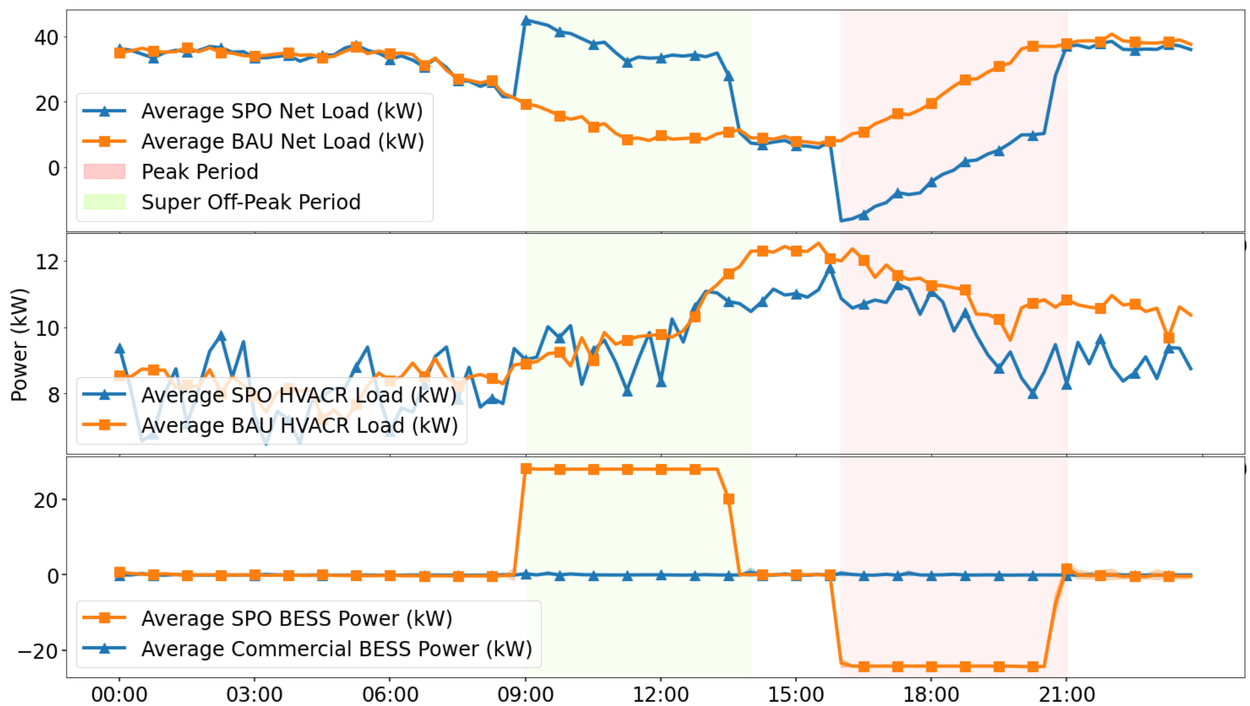

Figure 4: Spring energy bill optimization results comparing BAU and SPO net loads (top), HVAC&R loads (middle), and battery charge and discharge behavior (bottom)

SPO fully charges the battery during the super off-peak period, and discharges the battery completely during the peak period, shown in Figure 4c. This performance aligns with rule of thumb expectations for battery behavior, while BAU doesn't cycle the battery at all. Counter intuitively, the batteries generate essentially the same savings. This is due to a possible flaw in the electricity rate design. The super off-peak period has a reduced energy price, which incentivizes increased consumption, but the maximum demand charge for the day can still be set during this period. This means that shifting demand to this period (ie: charging the battery) is incentivized by the low $/kWh energy costs, but if the maximum demand for the month occurs during that period, it can significantly increase the high $/kW demand charge on the electricity bill. SPO charging the battery during the super off-peak period increases the demand charge roughly as much as it decreases the energy charge. It is possible that suboptimal demand charge reduction is caused by how SPO addresses these charges. SPO incorporates marginal demand increase into the MPC optimization cost function. This marginal demand increase is judged against a baseline site demand that was set at the approximate building demand, not including solar or HVAC&R demand reduction. Demand is not exceeding that initial level by a large amount, and thus the marginal increase in the cost function may be too small to incentivize demand charge reduction as opposed to energy cost reduction.

By not cycling the battery, BAU operation does not increase the demand charge and it reduces cycling and related battery capacity degradation. These are factors that SPO does not take into account, but that may be important in commercial battery optimization systems.

Load Tracking

The load tracking test took place on April 24, 2021. During the load tracking test, SPO attempted to manage the building's demand so that the net load would stay within a reference net load signal. The load signal was generated by flattening the noon-evening net load profile of the site from the previous day, to counter the duck curve. A ±3kW margin of error was used for the allowable power limits around this profile. This test showcased the ability of SPO to continuously adjust a building's net load, primarily through battery dispatch.

The success of load tracking is evaluated based on how long the power profile is outside the acceptable range and how many kilowatt-hours are used outside of the acceptable range. Table 2 compares how SPO performed against the BAU scenario, static HVAC&R temperature setpoints and no battery energy storage.

Table 2: Load Tracking Metrics

Metric	BAU	SPO	Percent Difference
Time in Violation	16.25 Hours	10.5 Hours	-35%
Average Power in Violation	8.9 kW	4.1 kW	-55%
Energy in Violation	145 kWh	43 kWh	-71%

Over the course of the load tracking test, the SPO exceeded the allowed limits for over 10.5 hours, approximately 40% of the day. When outside of the allowed limits, SPO was on average 4.1 kW away. This is significantly less than the BAU. The reduced time and power in violation of the load signal translated to SPO using only 43 kWh outside of the allowed limits, 71% less than without SPO control. There was overall more energy consumption by SPO, but this is because the SPO controlled battery ended the day at a higher SOC than when it started. The building load and battery operation are shown in Figure 5.

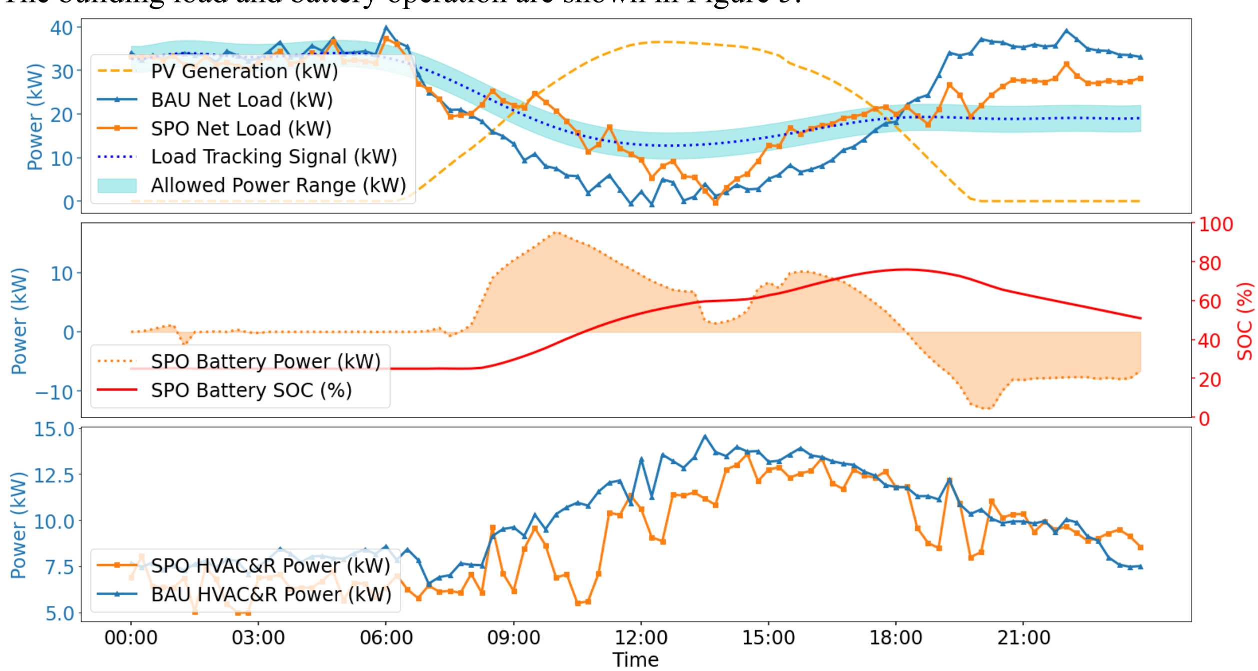

Figure 5: Load tracking test power profiles: SPO and BAU net loads with the load tracking signal (top), SPO battery state of charge and power (middle), and HVAC&R load (bottom)

Though general conclusions about the performance of SPO in load tracking mode can not be made from a single day of testing, examining this day shows interesting and promising control of the HVAC&R and battery loads. Behavior from 9:00-12:00 suggests a key benefit of having a single optimization for both HVAC&R and battery energy storage, rather than having both systems independently optimized. In this period, the battery charging peaks simultaneously with peak HVAC&R load reduction. SPO moves load shed potential from the HVAC&R system to the battery, to be used later in the day. Without this simultaneous battery charging, any HVAC&R load shedding during that period would have only driven the site net load further into violation, rather than contributing to load shaping later in the day. In the evening at 19:00, HVAC&R and battery control again work together to keep the site net load on target. However, after this time the SPO net load is in violation of the signal.

Load Shifting

The goal of load shifting is to increase the site load during a specific period during the day, and decrease the load during a period later that day by the same amount. The load constraint signals directed SPO to increase load by at least 20kW from 9:00-14:00, and decrease load by at least 20kW from 16:00-21:00. Two different shift tests were conducted using two price signals: a flat price all day, and TOU energy prices reinforcing the demand shift power signal (high prices during the load shedding period, low prices during the load taking period). For the dynamic price signal, the spring variation of PG&E B19 was used, as it aligned well with the shift event's motivation. SPO is designed to receive both load and price signals, and optimize for price while treating the load signals as soft constraints for site maximum and minimum load. Treating the load signals as soft constraints means that they are added as weighted penalties to the optimization cost function. Conducting load shifting tests with different price signals investigated the effects of conflicting price and load signals on SPO. Each shift test was judged against the BAU scenario. Both shift tests showed similar take values, 23.8 kW under the TOU price and 20 kW under the flat price. However, SPO performed markedly better load reduction with the TOU energy signal than with the flat price signal: 24.6 kW reduced with the TOU signal, and only 11.0 kW with the flat signal. Examining the battery behavior shows how conflicting price and load signals affect the SPO optimization.

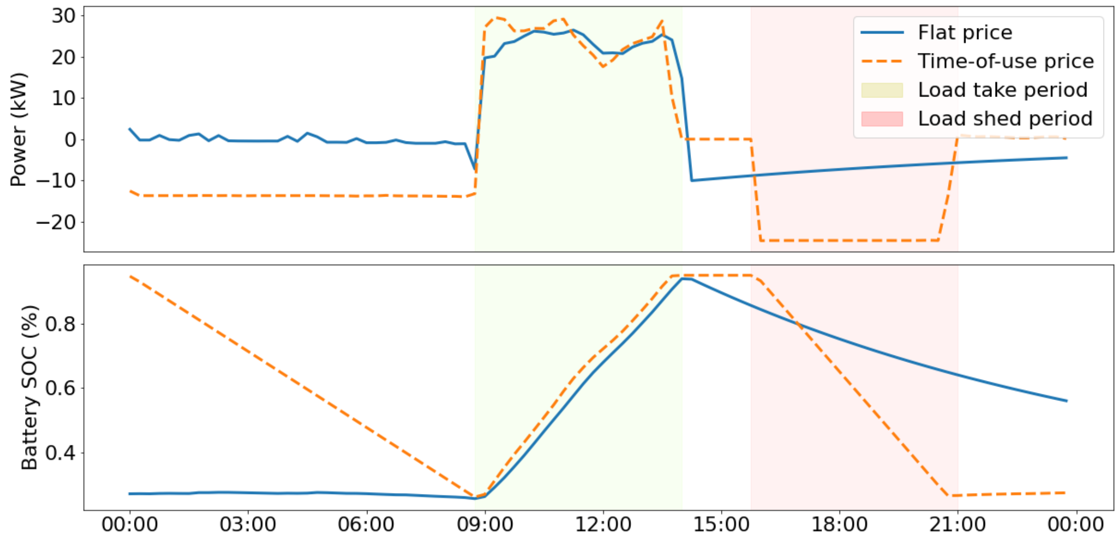

Figure 6: Load shifting battery behavior under a flat price signal and a TOU energy price signal reinforcing the load signal. Battery power (top) and battery SOC (bottom)

As Figure 6 indicates, battery behavior is the same in the take period under both signals, charging from the minimum SOC to the maximum at a nearly constant rate. Under the flat price signal, this is optimal for demand response but not bill reduction. The energy price is not decreased during this period, so no energy cost savings is generated, while the demand charge is increased by the high rate of battery charging. During the load shed period, battery behavior differs. For the flat price signal, the battery is discharged throughout the evening until it is at half capacity. This leads to reduced load reduction during the shed period, and is suboptimal for demand response. With a flat price signal, there is no low cost period to recharge the battery after the shed event, so fully discharging the battery to satisfy the load shed constraint is suboptimal for bill reduction. Bill optimization appears to completely outweigh the soft load constraint during the shed period.

During these load shifting tests, SPO fully relied on the battery rather than HVAC&R load shifting. The battery represented a readily available shiftable load that could satisfy the goals of the load shifting signal without negatively affected thermal comfort at the site. A load shedding event with a reduced capacity emulated battery was executed to measure SPO's ability to specifically shed HVAC&R load when it represented a greater proportion of the SPO controlled distributed energy resource (DER) energy capacity.

Load Shedding

The load shedding test was run on September 3, 2020. In this test, SPO attempted to reduce net power consumption by 3kW between 15:00 and 18:00, the same time period as a PG&E peak day pricing event (PG&E 2021a). This test reduced the reliable energy storage from the battery[2], and explored SPO's ability to control HVAC&R load shedding. Table 2 summarizes HVAC&R net load reduction during this test.

Table 2: Load Shedding Results

Metric	Load Shed Event
Load Reduction by HVAC&R Mean (kW)	3.8
Load Reduction by HVAC&R Mean (%)	38
Load Reduction Std. Deviation (kW)	3.7

As the metrics in Table 2 show, the average HVAC&R load reduction was greater than the 3 kW target. Figure 7 shows the load curve of SPO-controlled HVAC&R in comparison to BAU.

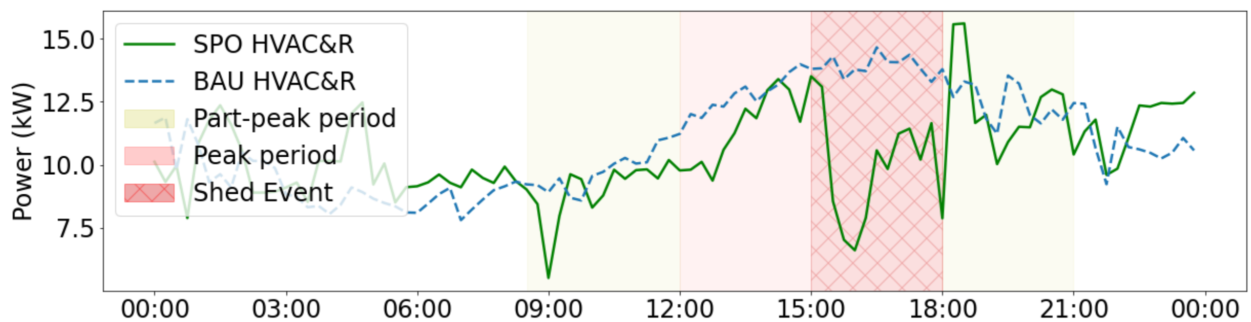

Figure 7: SPO vs BAU HVAC&R load during load shedding test

SPO was able to reduce HVAC&R load for the entire event (Figure 7). The majority of this load shedding was at the beginning of the event, with load shed dropping below 3 kW during the final third of the event, due to reaction to the progressive violation of thermal comfort. Additionally, immediately after the event ended there was a compensatory increase in HVAC&R demand above the BAU value, to bring the indoor temperature back to the original value before the event. This was expected, but it means that for this test day SPO had a higher peak load than BAU, but this peak happened outside the event window. The average HVAC&R load shedding shown during this event was greater than other tests.

Discussion

The design objective of SPO was to provide a portable and interoperable solution for optimization in building-level microgrids. The software can minimize customer bills and react to a variety of grid signals, by changing the operation of HVAC and refrigeration systems as well as batteries. SPO is publicly available as an open-source software, and does not require specific vendors or any particular communication protocols for its connected devices. The MPC used in this study was tuned to the specific building characteristics of the site, but the general MPC

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[2] Emulated battery size was reduced to 27 kWh with a peak output of 14 kW for this test. This size was chosen because the kWh capacity is more appropriate for a site of this size, and it represents a battery of the same make and model as the installed battery, simply with fewer cells.

formulation can be extended to any small-to-medium-sized building using thermostat-controlled packaged HVAC units. These systems are present in more than 60% of the small/medium buildings. Additionally, SPO can optimize building operation by considering time-varying energy price, demand charge, and load signals, so it can achieve bill and demand optimization under a very wide variety of electricity rate structures and demand response events. To achieve such a result, SPO coordinates the different end uses and storage systems, and can be easily extended to control other distributed energy resources (DERs).

The case studies presented in this paper provide preliminary performance data as well as lessons learned about the SPO design decisions. Managing bill optimization with TOU prices in tandem with load-based demand response events (i.e., reduction of load by a specific amount) was achieved by optimizing a bill reduction cost function with soft load constraints. As SPO responds to multiple signals simultaneously, it's difficult to guarantee optimal behavior from the customer standpoint. This was observed during load tracking and load shifting tests, when battery behavior detracted from SPO performance with respect to the demand response metrics. For instance, during the take period, the optimization engine delivered the desired load increase, but during the shed period SPO optimized solely for bill reduction. Though these are only preliminary results they illustrate the challenges of multi-objective optimization.

Similarly, integrating multiple DERs with a single optimization is challenging. In the load tracking scenario, SPO coordinated the operation of HVAC&R and the battery. This demonstrated SPO's ability to fulfill the load tracking signal in a way only possible with an integrated optimization. However, comparing the results of the load shedding test to results of load shifting suggests that, with a large battery relative to the amount of HVAC&R flexibility, the optimizer may rely on the battery and ignore the HVAC&R. This behavior was probably specific to the test site, since the HVAC&R system was somewhat undersized, and had a reduced margin of flexibility before occupant comfort and food safety was affected. We believe that in more typical buildings with a smaller battery and HVAC&R systems with proper sizing, the optimizer would have used both systems for shifting and shedding loads. Future research includes more extensive testing in additional sites, as well as exploration of the extensibility of this or improved approaches to different types of DERs and systems.

Conclusion

This paper evaluates the effectiveness of SPO, a control platform using MPC to reduce electricity bills and to control site net load according to demand response events. SPO was tested at a convenience store in northern California under a variety of demand flexibility scenarios.

Comparing SPO control of HVAC&R and an emulated battery versus baseline HVAC&R operation with static setpoints and battery optimization by an advanced commercial software, SPO achieved a savings of 7.3% in summer, 3.2% in spring, and 3.7% in winter. These results are promising, but we believe they could be higher in more typical buildings and scenarios. This is suggested by the load shedding test, which produced a 38% HVAC&R load reduction during the event. SPO was also able to accomplish 71% less violations of a load tracking signal than under baseline operation.

Relative sizes of the systems (e.g., battery capacity vs HVAC&R electrical consumption), as well as degree of undersizing of the HVAC&R system, play a significant role in the optimization strategy and degree of flexibility achievable. SPO's successful optimization performance is largely due to the flexibility of its design that adjusts not only to different signals, but also to changes in external parameters, such as weather, over the day.

Acknowledgements

This work was supported by the California Energy Commission Electric Program Investment Charge (EPIC) Program, Solicitation Grant Funding Opportunity Number: EPC-17-002, entitled "Scaling Solar+ for Small and Medium Commercial Buildings". This work was also supported by the Assistant Secretary for Energy Efficiency and Renewable Energy, Building Technologies Office, of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231. The authors would like to acknowledge the support and leadership by the Schatz Energy Research Center team: Peter Alstone, Marc Marshall, and Jim Zoellick and Lawrence Berkeley Lab's staff: Rich Brown and David Blum. We want to thank the Blue Lake Rancheria staff for providing cost share and their convenience store as a pilot site to deploy the SolarPlus Optimizer software.

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