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Applications of Optimal Building Energy System Selection and Operation

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Environmental Energy Technologies Division

paper presented at Microgen'II: Second International Conference of Microgeneration and Related Technologies, University of Strathclyde, Glasgow, Scotland, 4-6 Apr 2011

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APPLICATIONS OF OPTIMAL BUILDING ENERGY SYSTEM SELECTION AND OPERATION

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ABSTRACT

Berkeley Lab has been developing the Distributed Energy Resources Customer Adoption Model (DER-CAM) for several years. Given load curves for energy services requirements in a building microgrid (µ·grid), fuel costs and other economic inputs, and a menu of available technologies, DER-CAM finds the optimum equipment fleet and its optimum operating schedule using a mixed integer linear programming approach. This capability is being applied using a software as a service (SaaS) model. Optimisation problems are set up on a Berkeley Lab server and clients can execute their jobs as needed, typically daily. The evolution of this approach is demonstrated by description of three ongoing projects. The first is a public access web site focused on solar photovoltaic generation and battery viability at large commercial and industrial customer sites. The second is a building CO2 emissions reduction operations problem for a University of California, Davis student dining hall for which potential investments are also considered. And the third, is both a battery selection problem and a rolling operating schedule problem for a large County Jail. Together these examples show that optimization of building µ·grid design and operation can be effectively achieved using SaaS.

INTRODUCTION

Background

The commercial building sector offers many promising applications for efficiency measures, combined heat and power (CHP), solar photovoltaic (PV) and other renewable generation, as well as demand response capability and possibly ancillary service provision. Furthermore, on-site load management measures can reduce the costs of operating a facility, especially when complex tariffs or costly operating constraints apply.

To obtain best results, fuel cells, internal combustion engines, absorption cooling, PV, solar thermal, electrical and heat storage, grid export of energy and ancillary service as well as passive efficiency measures should be part of a systemic energy management strategy covering both equipment selection and operation. By contrast, current building design and operation approaches tend to consider each technology sequentially and in isolation. Since the viability of various technology alternatives are evaluated one-by-one, it is highly unlikely an outcome close a global optimum for the facility will be found and implemented. The goals of RETScreen and HOMER are similar, although these models are more focused on remote systems. Also, they do not use analytic optimization methods and so do not find pure optimums, nor execute at comparable speed. The most significant differences would be experienced with complex optimization, such as battery scheduling under a variable tariff.

The importance of the building sector in post-industrial economies is widely recognized, e.g. about 70% of total U.S. electricity use is consumed in buildings. Two key sources of potential electricity consumption growth, plug-in electric vehicle charging and ground source heat pump space heating will likely further extend the sector's dominance. Building systems are more complex than many believe. Choosing and operating multiple technologies on both supply and demand sides under complex tariff regimes, possibly involving feed-in rates and rewards for ancillary service provision, with highly variable building loads dependent on weather, occupancy, building repurposing, etc. poses a daunting technical and economic problem, and one that is unlikely to be solved by simple search algorithms and engineering rules of thumb.

This paper reports on efforts at the Lawrence Berkeley National Laboratory (LBNL or Berkeley Lab) to develop capabilities to attack these formidable challenges. Particularly, methods and software under ongoing development aim to aid optimum building equipment selection and operation under the conditions described above. Three examples of this work are described. 1. An open access optimization tool, the Storage Viability and Optimization Web Service (SVOW) is under development that can provide energy managers at large commercial and industrial facilities with optimal investment decisions for PV and batteries (Stadler, et al., 2010). 2. A direct data exchange has been established between Berkeley Lab and a building on the University of California, Davis (UCD) campus. Based on monitored conditions and other data sources a week-ahead operating schedule is developed. And 3., Berkeley Lab is assisting with making a large stationary battery selection for a local county jail, and will be finding ongoing optimal operating schedules for it when it has been installed.

Micrograms

While the methods described in this paper are applicable to various types of buildings under many administrative structures, a strong motivator for this research programme is the belief that our familiar centralised power system (*macrogrid*, *megagrid* or *M·grid*) is undergoing radical change that will fundamentally change the nature of local electricity systems. This vision suggests that in addition to the highly centralised supply network and control paradigm with which we are so familiar, dispersed control will emerge at multiple levels of the power system and with multiple objectives.

One of these levels, namely control of a single buildings or a local grouping of buildings behind a single point of common coupling (PCC) is often referred to as a *microgrid* or *μ·grid*. A formal definition of a microgrid emerging from a *Conseil International des Grandes Réseaux Electriques* (CIGRÉ) working group on the topic reads as follows:

Microgrids are electricity distribution systems containing loads and DER, (such as distributed generators, storage devices, or controllable loads) that can be operated in a controlled, coordinated way either while connected to the main power network or while islanded.

The notion that this new entity will be a feature of the future smart grid is achieving growing currency and offers appealing opportunities. This argument holds that appropriate incentive schemes together with the selection and operation of equipment, the purchase of fuels and endue devices, as well as the control of loads all under localised control, will result in more rational tradeoffs between alternatives. In other words, the market failures that have bedevilled building energy use, such as under-investment in efficiency measures, will be mitigated.

Outline

The Distributed Energy Resources Customer Adoption Model (DER-CAM) has been developed to solve the μ·grid equipment selection and operation problem analytically (Marnay, et al. 2008). This paper will report on three applications of this approach. The principles underlying DER-CAM are set out in the METHODS section, and the RESULTS section contains descriptions of the three projects together with results.

METHOD

Distributed Energy Resources Customer Adoption Model

All three examples described in this paper depend on the common DER-CAM optimization engine, which has been under development at Berkeley Lab for a number of years.

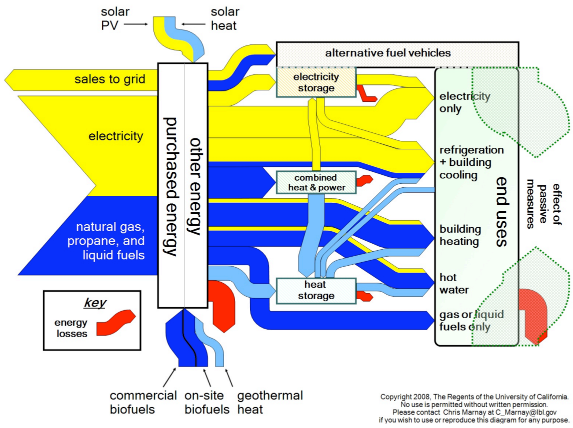

Figure 1 Energy Flows in a Building Microgrid

DER-CAM solves a μ·grid's investment optimization problem given its end-use energy loads, energy tariff structures and fuel prices, and an arbitrary list of equipment investment options. The Sankey diagram in Figure 1 shows energy flows in a building-scale μ·grid.

DER-CAM analysis begins with the services requirements shown on the right, which are typically subdivided into electricity only, e.g. lighting, computing, etc. Farther to the right passive measures are shown, i.e. many services can be provided by improving the building envelope, by daylighting, etc., which tend to lower the requirements on active systems shown to the left.

DER-CAM solves the Sankey systemically, taking the interactions between end-uses and simultaneity of solutions into account. An example of interactions might be that a window retrofit might change the active heating, cooling, and even lighting loads. Cooling is the classic example of the latter, simultaneity, effect. For example, partially cooling a building using waste heat fired absorption technology lowers the residual electrical load and permits downsizing of all electrical systems, including on-site generating capacity.

Figure 2 shows the data flow and results in DER-CAM, which is implemented as a mixed-integer linear program on the General Algebraic Modeling System (GAMS®) platform using the CPLEX® solver. An example high-level description of the model logic is shown in Figure 3. This case has minimization of annual energy costs as its objective, but carbon emissions (or a combination) or other objectives could be similarly applied.

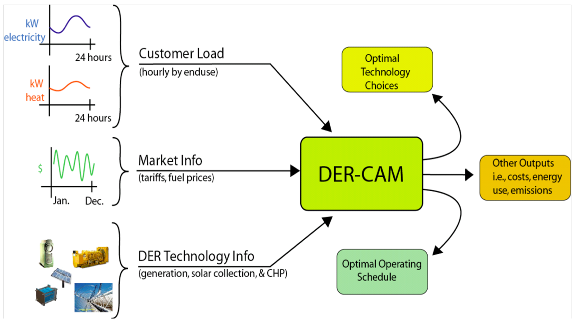

Figure 2 DER-CAM Inputs and Outputs

This approach is fully technology-neutral and can include energy purchases, on-site conversion, both electrical and thermal on-site renewable harvesting and/or storage, and end-use efficiency investments. Regulatory, engineering, and investment constraints are all considered. Energy costs are calculated using a detailed representation of utility tariff structures and fuel prices as well as amortized DER investment costs and operating and maintenance (O&M) expenditures.

```
MINIMIZE
   Annual energy cost:
     energy purchase cost
     + amortized DER technology capital cost
     + annual O&M cost
SUBJECT TO
   Energy balance:
     - Energy purchased + energy generated exceeds demand
   Operational constraints:
     - Generators, chillers, etc. must operate within
       installed limits
     - Heat recovered is limited by generated waste heat
   Regulatory constraints:
     - Minimum efficiency requirements
     - Maximum emission limits
   Investment constraints:
     - Payback period is constrained
   Storage constraints:
     - Electricity stored is limited by battery size
     - Heat storage is limited by reservoir size
```

Figure 3 DER-CAM Optimization Problem

For a specific site, the source of end-use energy load estimates is rarely actual data, although monitored data is increasingly available as data acquisition and archiving systems such as OSIsoft's PI Server described below become more widespread. More commonly building energy simulation estimates from a model based on the DOE-2 engine, such as eQUEST, or a simulation using a more modern model, such as EnergyPlus, must be used. Note that in the SVOW case described below, the user can rely on default electricity load shapes or overwrite with hir own.

APPLICATION 1: SVOW

Project Description

California's non-residential sectors offer many promising applications for electrical storage. The state's time-of-use (TOU) tariffs, which usually include a stiff demand (monthly peak power use) charge, present an incentive for storage of off-peak electricity for use on the subsequent on-peak period (usually hours 12:00-18:00). Further, the ongoing introduction of Peak Day Pricing (PDP), which imposes extreme prices on about 12 afternoons a year when the grid is stretched, tends to further enhance the load shifting incentive.

Nonetheless, choosing and operating storage under complex tariff regimes poses a daunting technical and economic problem that is likely to discourage potential customers, potentially resulting in lost carbon and economic savings. Vendors offering limited equipment lines are unlikely to provide adequate environmental analysis or unbiased economic results to potential clients, and are even less likely to completely describe the robustness of choices in the face of changing fuel prices and tariffs.

Given these considerations, site managers need a place to start their quest for independent technical and economic guidance on whether storage is even worth the considerable analytic effort. The SVOW open access, web-based electrical storage and PV analysis calculator has been designed and developed to provide economically sound and technology-neutral guidance. SVOW resides on an open access Berkeley Lab server, and is powered by an analytic engine essentially consisting of a simplified DER-CAM model that considers only electricity use and focuses on just the technologies of interest. Nonetheless, storage optimization under complex tariffs is an analytic challenge and SVOW provides a powerful tool for large electricity customers.

Status

SVOW aims to provide basic guidance on whether available storage technologies, PV or combinations of these technologies merit deeper analysis. The battery alternatives include both standard and flow batteries. The latter are more complex to optimize because multiple energy-power combinations are possible. Since the non-residential sectors encompass a broad range of facilities with fundamentally different characteristics, the tool first asks the user to select a load profile from a limited cohort group of example facilities. These examples may be modified by the user to better fit a site's unique circumstances. After the load profile selection, the user will be prompted to select a tariff, the cost option, and so on, until all of the parameters are specified. Based on the user selections, the solution set will be adjusted to provide ballpark results to the user.

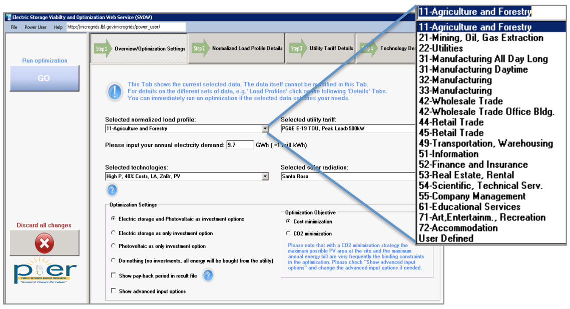

Figure 4 SVOW Start Up Page

Figure 4 shows the start-up page where the user sees an overview of options and settings, including 20 available default load profiles that can be selected from a pull-down menu. These profiles represent a cross-section of large California customers in a range of industries and businesses. The major tariffs for large customers in service territories of the three major utilities are included. These three, Sempra Utilities (San Diego area), Southern California Edison, and Pacific Gas and Electric (PG&E, northern California) together account for about 80% of large customer electricity consumption.

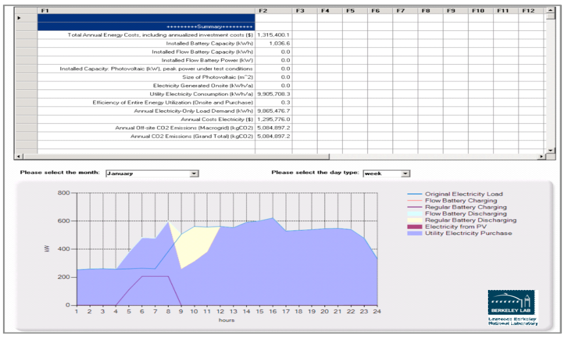

Figure 5 SVOW Results Page

A typical results page is shown in Figure 5. In this example, batteries are selected but without any PV. The user is shown estimated annual bill savings and details on selected technology. A result of particular note is an estimate of the effect of adoption on the site's greenhouse gas footprint. Hourly marginal emissions estimates are based on the Greenhouse Gas Calculator from E3. E3 derived the emissions by simulating the generation capacity and mix within the Western Electricity Coordinating Council, and the emissions represent the CO2 contribution from energy consumed in California regardless of whether the energy was generated in-state or out-of-state (Mahone, et al., 2008). Graphics also show operations on typical days. The example shows battery charging during the night-time and morning hours, with discharging during the afternoon peak period, which would be a typical schedule.

Results

SVOW has been available since mid-2010. Approximately one hundred users had established accounts by the end of January 2011. Plans are underway to dramatically extend SVOW's capabilities by addition of more technologies.

APPLICATION 2: U.C. DAVIS

Project Description

Together with OSIsoft LLC as its private sector partner and matching sponsor, the Berkeley Lab won a U.S. Department of Energy (U.S.DOE) Technology Commercialization Fund grant from the U.S. Department of Energy. The goal of the project is to commercialize DER-CAM on a web-based software as a service (SaaS) model.

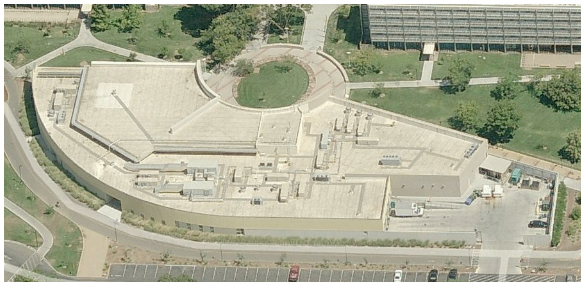

Figure 7 Aerial View of Segundo Commons

A pilot demonstration is being conducted with the large (4650 m^2) Segundo Dining Commons building on the UCD campus. This building is about 75 km from the Berkeley Lab and is pictured in Figures 7 and 8. The Commons is the dining hall for students living in nearby dormitories, and also the main central kitchen providing food to other campus buildings.

Figure 7 Interior View of the Commons

Because UCD utilizes OSIsoft's PI system for gathering and storing sub-metering data, Berkeley Lab has been able to access the historical and real-time electricity, natural gas, steam, and chilled water usage information for Segundo using OSIsoft's PI to PI protocol.

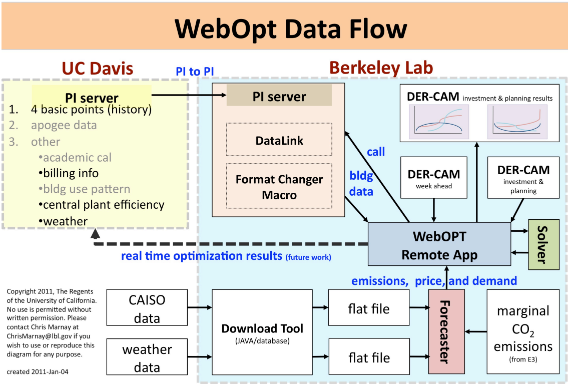

Figure 9 WebOpt Schematic

Figure 9 shows the implementation for the Commons demonstration. In the top left the PI Server data base at UCD is shown. A parallel installation at Berkeley Lab permits direct data access. At the bottom of Figure 9, the data collection from other sources is shown. Historical weather data for the Davis area are downloaded from the California's Irrigation Management Information Systems website. Temperature forecasts are taken from National Oceanic and Atmospheric Administration website. Historical daily high/low temperatures are stored in Berkeley Lab's time-series database and used as input into a demand forecaster regression model of the week-ahead. Hourly high/low 7-day ahead forecasts are also downloaded from the above link and used as input into the demand forecaster. The temperature forecast is automatically updated every day. Marginal GHG emissions are taken from the same E3 model described above.

The campus currently buys electricity through the Western Area Power Administration at an essentially flat, favorable tariff of $0.085/kWh. Berkeley Lab set out to investigate a hypothetical scenario wherein UCD has to purchase electricity on a PG&E standard TOU tariff, and to derive an optimal carbon minimizing schedule for the building.

Status

WebOpt has been largely implemented as shown in Figure 9. Whenever any user executes WebOpt, s/he does it through a secure Remote Desktop Connection (Terminal Services Client 6.0) and does not need to have any specialized software installed or run any other program. WebOpt collects data from Berkeley Lalb's PI server using DataLink, a standard OSIsoft product, and also calls the format changer macro, which converts the raw PI data so that DER-CAM can use it. As seen in the upper right of Figure 9, WebOpt can execute both investment planning and operational week-ahead versions of DER-CAM.

Since OSIsoft's PI system does not currently support data feed-back, the optimization results cannot be sent back to the building directly, and therefore, are shown in WebOpt. The week-ahead optimization capabilities have been developed in principle, but are not implemented in WebOpt. The week-ahead optimization runs without any user interface on Excel and individual Java applications. In the week-ahead optimization the building load profiles are forecasted depending on collected weather data. These forecasted loads will be sent to the week-ahead optimization and DER-CAM is executed.

Results

While not fully complete and operational, the WebOpt arrangement has demonstrated the viability of providing building µ·grid optimisation using a SaaS model.

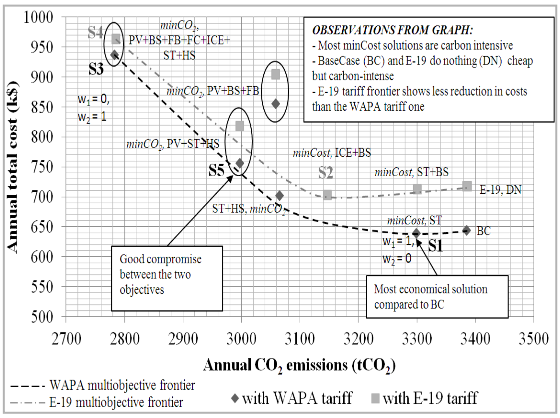

Figure 10 Cost-CO_2 Trade-Off Frontier

Figure 10 shows an example for the Commons building of one of the more interesting outputs of a DER-CAM multi-objective optimization, the cost-CO_2 trade-off curve. The current combination of carbon emissions and costs appears at the bottom right. Increasing the weight of carbon in the objective function produces results further to the left, i.e. with higher costs but lower carbon footprint. As mentioned above, this result was off particular interest to UCD, which is keen to have an impact on climate threats.

Being a large cooking facility, the Commons has a significant heat load which is normally met by a campus heat loop. In this optimisation other options to this arrangement are sought. Note that DER-CAM can jointly optimise the electricity and heat supply to a µ·grid, making it particularly powerful for selecting CHP systems.

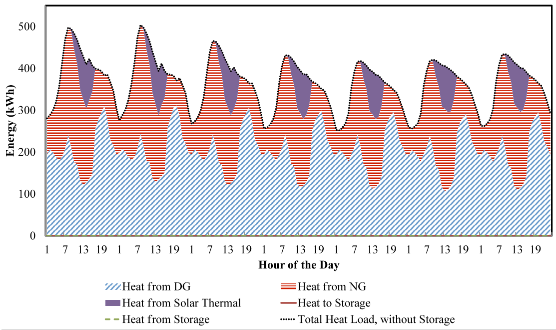

Figure 11 Heat Balance for a January Week

Figure 11 shows the heat balance from a particularly complex Commons case, in which both reciprocating engine and fuel cell CHP was selected, and the system also includes solar thermal collectors. CHP provides significant heat in all hours, while the solar thermal system augments it during the afternoons. Natural gas is used make up the shortfall. Note that with only input describing the technologies and hourly service requirements, WebOpt is finding both the optimal equipment configuration and this complex operating schedule for it.

APPLICATION 3: SANTA RITA JAIL

Project Description

The Alameda County correctional facility, the Santa Rita Jail, was opened in 1989. It currently holds about 4,500 inmates on a 9 ha property and is considered one of the most energy efficient prisons in the U.S. The County has a long history of using innovative approaches to increase energy efficiency and reduce public costs. The Jail has a fairly flat load with an electricity peak demand of about 3.0 MW, and County wants to save on its utility bills.

Figure 11 Aerial View of Santa Rita Jail

Clearly visible in Figure 11 is a 1.2 MW PV system that covers most of the cellblocks. When installed in spring 2002, it was the biggest in the U.S. In May 2006, the County added a 1 MW molten carbonate fuel cell with heat recovery providing hot water pre-heating for domestic hot water requirements.

For various reasons, the County has decided to install a large (1-2 MW and 4-6 MWh) battery at the Jail. The project is partially funded by U.S.DOE under its Smart Grids program. The battery will be equipped with Consortium for Electric Reliability Technology Solutions (CERTS) Microgrid capability, which will allow the Jail to disconnect from the grid and run islanded for extended periods (Lasseter, et al. 2002). A static switch at the Jail's substation will permit rapid disconnect and reconnect. Note that in this µ·grid, the battery will be the only controllable resource, so it must maintain energy balance alone.

Figure 12 Existing Fuel Cell and Battery Site

Under the terms of the U.S.DOE grant, the Jail must contract with PG&E to reduce the peak load on the local feeder by 15%. Reliability is also a major concern, particularly having enough energy to maintain full service during the break between a blackout beginning and the back-up diesel generators reaching full power, typically a few minutes.

Berkeley Lab will use DER-CAM to assist with the selection of a battery vendor. When the battery is in installed, WebOpt will be used to send a daily charge-discharge schedule to the Jail that minimizes its bill and meets its other objectives. Note that the optimization is very complex in this case because of the multiple objectives and the introduction of uncertainty in some variables, e.g. neighbouring feeder loads and outages.

Status

Figure 13 shows the hourly energy balance of the Jail in 2008. The blue series is the PV energy. This is a good solar site so PV output is fairly reliable. The red line shows fuel cell output, and the purple series is the total electricity use. Purchases from PG&E under a standard tariff are shown in green. In general, neither has the PV system performed well and nor has the fuel cell been reliable. Grid purchases have therefore far exceeded expected levels, with serious cost conesquences for the County. Note that a high average power draw of only 15 min triggers the demand charge.

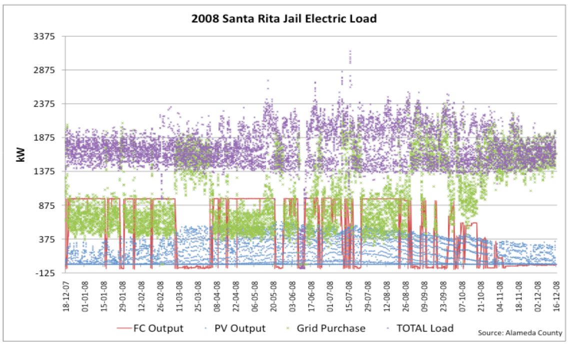

Figure 13 Jail Electricity Balance

Figure 14 shows the effective tariff at the Jail. Note the cost and complexity of the demand charge, which has three components: 1. a charge of $12.67/kW for the on-peak maximum power, 2. a charge of $2.81/kW for parital peak maximum power, and 3. a further $8.56/kW charge for maximum power at the time of the site's own peak, irrespective of timing. The upshot of these charges is that in the summer months, peak charges account for a third of the Jail's bill. Finally, together with most large customers in California, the Jail will soon be exposed to PDP. This means that on 9-15, with an average of 12, afternoons per year with a day's warning, PG&E will levy an extra $1.20/kWh. The base rates will lower slightly. This will make the summer on-peak price roughly $0.14/kWh normally, but the peak days will effectively raise the average to $0.24/kWh.

E-20 Rate Summer Tariff Parameters	Value
Peak Hours	12:00 - 18:00
Partial Peak Hours	8:30 - 12:00 18:00 - 21:30
Off Peak Hours	21:30 – 8:30
Peak Energy ($/kWh)	0.14606
Part Peak Energy ($/kWh)	0.10168
Off Peak Energy ($/kWh)	0.08339
Max Peak Demand ($/kW)	12.67
Max Part Peak Demand ($/kW)	2.81
Monthly Max Demand ($/kW)	8.56

Figure 14 Effective Jail Tariff

Results

Selection of the battery vendor is still in progress. A version of DER-CAM similar to the SVOW engine is being used to evaluate vendor proposals for the battery installation, but no decision has been made at time of writing. Proposals cover 6 vendors and 5 chemistries.

Figure 15 shows what the 7-day rolling charging schedule might look like for an October week. These results come from a weekly operations optimization version of DER-CAM similar to the one employed by WebOpt at UCD. A 2 MW and 6 MWh sodium-sulphur (NaS) battery is assumed.

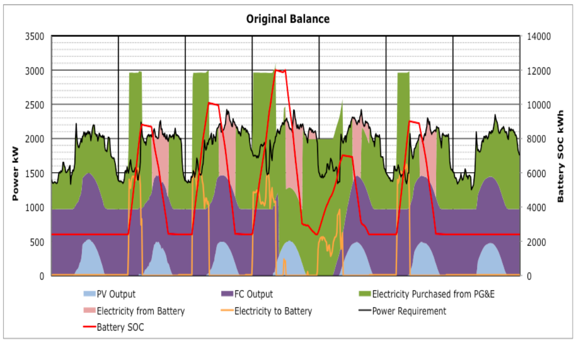

Figure 15 Example Charging Schedule

The black line is the Jail's total load. As is quite apparent, loads are fairly easily forecast. The PV output is shown at the bottom in blue, and the fuel cell output above it in purple. Note there was a fuel cell outage during this week. The green area is energy purchased from PG&E. When the green exceeds the total load the battery is being charged. The red line shows the state of charge of the battery.

The state of charge is generally determined by the expected requirements of the following day, shown by the pink discharged energy. Note that the battery is left discharged on the two weekend days, which are the first and last days shown in the graphic. The round-trip efficiency of NaS batteries is fairly low, and about 70% is assumed in this optimization, so there is a high cost to storing and retrieving energy that limits use of the battery to times when its benefits are significant. Surprisingly, the battery is not charged as much during the fuel cell outage as on neighbouring days. Note that on Thursday afternoon the pink discharge is smaller, incurring significant on-peak costs, which is a counter intuitive result. Analysis of this example revealed that this schedule is optimal. The reason for the low charge on Thursday is that the partial peak demand charge bill increase was worse than the on-peak cost burden of the low state of charge.

The orange line is the key Berkeley Lab deliverable in this case. It's the charging instruction to the Jail for its battery operation. Such a rolling 7-day schedule will be delivered to the Jail every day, following planned installation in July 2011.

CONCLUSION

Multi-technology building µ·grid design and operation under highly variable conditions poses a significant challenge that must be overcome to drive down carbon emissions and costs.

Berkeley Lab is developing optimisation methods for solving these problems. The basis of DER-CAM methods has been described and three applications presented. In general, a web-based SaaS model is being pursued to free building designers and operators from the burden of hefty optimisation problems. This overall approach has been highlighted by three examples. All three are ongoing projects and will still yield considerable additional results.

ACKNOWLEDGMENT

The work described in this paper was funded by the Office of Electricity Delivery and Energy Reliability's, Smart Grids Program, and also by the Energy Efficiency and Renewable Energy's Technology Commercialization Fund, both of the U.S.DOE under Contract No. DE-AC02-05CH11231. It was supported also by funding provided by the California Energy Commission, Public Interest Energy Research Program, under Work for Others Contract No. 500-02-024.

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Marnay, C., G. Venkataramanan, M. Stadler, A. Siddiqui, R. Firestone, and B. Chandran 2008. "Optimal Technology Selection and Operation of Microgrids in Commercial Buildings," IEEE Transactions on Power Systems, 10.1109/TPWRS.2008.922654, vol. 23(3), Aug.

RETScreen: http://www.retscreen.net/

Stadler M., et al. 2010. Storage Optimization and Viability Web Service, Public Interest Research Program, California Energy Commission 500-02-04, Sacramento CA, October. (This report as well as Information on SVOW can be found as follows: http://der.lbl.gov/microgrids-lbnl/current-project-storage-viability-website)

For more background on microgrids, please see the presentations from the six Symposiums on Microgrids held at Berkeley, CA, near Montréal, Canada, in Nagoya, Japan, on Kythnos Island, Greece, at U.C. San Diego, CA, and in Vancouver B.C., Canada. (all presentations available at http://der.lbl.gov).

GLOSSARY

µ·grid: a true microgrid that is within one site and usually behind one meter that is able to island from the surrounding grid

CERTS: Consortium for Electric Reliability Technology Solutions

CIGRÉ: Conseil International des Grandes Réseaux Electriques

DER-CAM: Distributed Energy Resources Customer Adoption Model

NaS: sodium sulphur battery

PDP: Peak Day Pricing

PV: solar photovoltaic systems

SaaS: Software as a Service

SVOW: Storage Viability Web Service

UCD: University of California, Davis campus, near Sacramento

U.S.DOE: the U.S. Department of Energy