LBNL-1334E

ERNEST ORLANDO LAWRENCE
BERKELEY NATIONAL LABORATORY

Effect of Heat and Electricity Storage and Reliability on Microgrid Viability: A Study of Commercial Buildings in California and New York States

Michael Stadler, Chris Marnay, Afzal Siddiqui, Judy Lai, Brian Coffey, and Hirohisa Aki

Environmental Energy
Technologies Division

December 2008

http://eetd.lbl.gov/EA/EMP/emp-pubs.html

The work described in this paper was funded by the Office of Electricity Delivery and Energy Reliability, Renewable and Distributed Systems Integration Program in the U.S. Department of Energy under Contract No. DE-AC02-05CH11231.

LBNL-1334E

Effect of Heat and Electricity Storage and Reliability on Microgrid Viability: A Study of Commercial Buildings in California and New York States

Prepared for the Office of Electricity Delivery and Energy Reliability, Distributed Energy Program of the U.S. Department of Energy

Principal Authors

Michael Stadler, Chris Marnay, Afzal Siddiqui, Judy Lai, Brian Coffey, and Hirohisa Aki

Ernest Orlando Lawrence Berkeley National Laboratory
1 Cyclotron Road, MS 90R4000
Berkeley CA 94720-8136

December 2008

Acknowledgments

The work described in this paper, as well as prior DER-CAM development, was funded by the Office of Electricity Delivery and Energy Reliability's Renewable and Distributed Systems Integration Program at the U.S. Department of Energy under Contract No. DE-AC02-05CH11231. This analysis relies on the contributions of numerous previous and current research colleagues including Owen Bailey, Bala Chandran, Ryan Firestone, Kristina Hamachi LaCommare, Karl Maribu, and Nan Zhou, as well as upon prior work funded by the California Energy Commission. The authors are also grateful for useful input from Profs. Robert Lasseter and Giri Venkataramanan of the University of Wisconsin at Madison, Robert Panora of Tecogen, Keith Davidson of DE Solutions, and Joe Eto of Berkeley Lab.

Disclaimer

Table of Contents

List of Executive Summary Figures and Tables

List of Figures and Tables

Acronyms and Abbreviations

AC	alternating current
CA	California
CCHP	combined cooling, heating, and power
CEC	California Energy Commission
CERTS	Consortium for Electric Reliability Technology Solutions
CEUS	California Commercial End-Use Survey
CHP	combined heat and power
ConEd	Consolidated Edison Company of New York
COP	coefficient of performance
DER	distributed energy resources
DER-CAM	Distributed Energy Resources-Customer Adoption Model
DG	distributed generation
DOE	US Department of Energy
DSP	digital signal processor
EIA	Energy Information Administration
GAMS	General Algebraic Modeling System
GWh	gigawatt hour
HHV	higher heating value
ICE	internal combustion engine
IEA	International Energy Agency
IEEE	Institute of Electrical and Electronics Engineers
IGBT	integrated gate bipolar transistor
IGCT	integrated gate commutated thyristor
kW	kilowatt
kWh	kilowatt hour
LBNL	Ernest Orlando Lawrence Berkeley National Laboratory (or *Berkeley Lab*)
Li-ion	lithium ion
MCFC	molten carbonate fuel cell
MILP	mixed integer linear program
MW	megawatt
NaS	sodium sulfur
NG	natural gas
Ni-MH	nickel metal hydride
NPS	Northern Power Systems
NREL	National Renewable Energy Laboratory
NYC	New York City
O&M	operating and maintenance
PAFC	phosphoric acid fuel cell
PEMFC	proton exchange membrane fuel cell
PG&E	Pacific Gas and Electric
PQ	power quality
PQR	power quality and reliability
PSB	polysulfide bromide batteries

PVPS	Photovoltaic Power Systems Programme
R&D	research and development
RT	refrigeration ton (= 3.516 kW)
SCE	Southern California Edison
SoCal	Southern California Gas Company
SOFC	solid oxide fuel cell
tC	metric tons of elemental carbon
TOU	time-of-use
UL	Underwriters Laboratories Inc.
UPS	uninterruptable power supply
VRB	vanadium redox batteries
WAC	alternating current Watts, AC power output PV systems
Wh	watthour
ZBB	zinc bromine batteries

Executive Summary

Research Objectives

Berkeley Lab has for several years been developing methods for selection of optimal microgrid systems, especially for commercial building applications, and applying these methods in the Distributed Energy Resources Customer Adoption Model (DER-CAM). This project began with 3 major goals:

1. to conduct detailed analysis to find the optimal equipment combination for microgrids at a few promising commercial building hosts in the two favorable markets of California and New York,
2. to extend the analysis capability of DER-CAM to include both heat and electricity storage, and
3. to make an initial effort towards adding consideration of power quality and reliability (PQR) to the capabilities of DER-CAM.

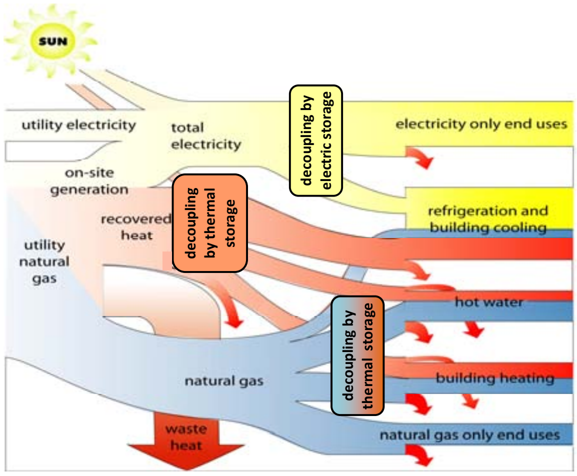
All of these objectives have been pursued via analysis of the attractiveness of a Consortium for Electric Reliability Technology Solutions (CERTS) Microgrid consisting of multiple nameplate 100 kW Tecogen Premium Power Modules (CM-100). This unit consists of an asynchronous inverter-based variable speed internal combustion engine genset with combined heat and power (CHP) and power surge capability. The essence of CERTS Microgrid technology is that smarts added to the on-board power electronics of any microgrid device enables stable and safe islanded operation without the need for complex fast supervisory controls. This approach allows plug and play development of a microgrid that can potentially provide high PQR with a minimum of specialized site-specific engineering. A notable feature of the CM-100 is its time-limited surge rating of 125 kW, and DER-CAM capability to model this feature was also a necessary model enhancement.

DER-CAM

Figure ES 1 demonstrates the fundamental philosophy of the DER-CAM approach. For the purposes of this study, the graphic can be thought of as showing the energy system of a commercial building or group of buildings. On the right are the energy services that need to be provided to building occupants, and on the left are the purchases of commercial fuels entering the facility. In between are various devices for energy use, conversion, and storage. A building may often have other fuel opportunities available, and solar is shown in the figure. The goal of DER-CAM development is to build a model that can solve the entire system shown such that the entire cost, carbon footprint, other metric, or combination of metrics is minimized. The approach is fully technology-neutral and can include energy purchases, on-site conversion, both electrical and thermal local renewable harvesting, and end-use efficiency investments. In this study, DER-CAM minimizes only the annual costs for providing energy services to the modeled site, including utility electricity and natural gas purchases plus amortized capital and annual maintenance costs for distributed generation (DG) investments. In addition to the CM-100 engines, the DER available include solar thermal, photovoltaics (PV) and fuel cells.

Furthermore, system choice considers the simultaneity of solutions, especially regarding the building cooling problem; that is, multiple technologies can be used for cooling and results reflect the benefit of electricity demand displacement by heat-activated or direct-fire cooling that lowers building peak load, and therefore, the generation requirement. Similarly, operation of storage is optimized over all time periods of the simulation. Achieving these optimums requires above all else sophisticated representation of tariffs.

Figure ES 1. Schematic of the energy flow model used in DER-CAM



Technically, DER-CAM is a mixed-integer linear program (MILP) written and executed in the General Algebraic Modeling System (GAMS) using the CPLEX solver.

Test Sites

The key site-specific inputs to DER-CAM are hourly energy service requirements aggregated into the categories shown in Figure ES 1, plus electricity and natural gas tariff structure and rates. The hourly data requirement is typically the most difficult to meet. Few monitored building results are available, so almost always the end-use detail must be developed using some form of building energy use simulation. An earlier market assessment showed that nursing homes and assisted living facilities, K-12 schools, and data centers are three promising markets, so end-use data sets were collected for representative example buildings of each of these three types in both California and New York. The details are shown in Table ES 1.

Table ES 1. Key characteristics of test buildings and sites

		floorspace (m^2)	electricity peak load (kW)	annual electricity consumption (kWh)	annual NG consumption (therms)	vicinity	elec. utility	gas utility	$F_{s,Base}$	$F_{s,Peak}$
CA	nursing home	31 587	958	5 761 690	194 522	northern CA	PG&E	PG&E	0.5	0.1
	school	17 652	885	1 508 883	24 868	southern CA	SCE	SoCal Gas	0.25	0
	datacenter	617	1 788	11 420 823	0	northern CA	PG&E	PG&E	1	1
NY	nursing home	31 587	1 067	6 016 309	243 563	NYC	ConEd	ConEd	0.5	0.1
	school	17 652	746	1 120 653	32 193	NYC	ConEd	ConEd	0.25	0
	datacenter	617	1 591	12 070 888	0	NYC	ConEd	ConEd	1	1

Data sets for these example buildings were obtained in diverse ways. The nursing homes are based on an Oakland example taken from the California Commercial End-Use Survey (CEUS). It is used as-is for California, but end-use requirements were weather adjusted for New York conditions. The two schools are standard building models taken from a database of commercial prototype EnergyPlus models. The data center is based on billing information for a real Silicon Valley facility, with a climate adjusted version used for New York.

The structure and level of utility rates frequently proves to be a critical determining input, and these examples are typical in this regard.

Table ES 2. Comparison of the average fuel costs for each case

Average Fuel Costs		**NG ($/therm)**	**NG ($/kWh)**	**Electricity ($/kWh)**
CA	Nursing Home	1.055	0.036	0.131
	School	0.996	0.034	0.172
	Data Center	1.055	0.036	0.129
NY	Nursing Home	1.436	0.049	0.140
	School	1.436	0.049	0.188
	Data Center	1.436	0.049	0.137

Fuel price levels and spark spread are not too different between California and New York, as can be seen in Table ES 2, but the tariff structures are different. Both Pacific Gas & Electric (PG&E) and Southern California Edison (SCE) have time-of-use tariffs with stiff demand charges, while Consolidated Edision (ConEd) has flat energy charges along with a severe demand charge. The ConEd tariffs, with flat electrical energy charges, and somewhat higher natural gas costs create an environment less amenable to microgrid development. The $F_{s,base}$ and $F_{s,peak}$ variables in Table ES 1 refer to assumptions about the extent to which site loads are considered critical. These two variables are fractions of base and peak loads respectively that must be met during loss of grid power, i.e. the available on-site generation and storage capacity must exceed these ratings. It is a goal of this work to add consideration of the reliability benefits of microgrids to DER-CAM analysis capabilities. The load fractions considered critical by assumption have been shown, but within the DER-CAM framework an economic value of the added reliability is sought. While it may sound as if the cost of an alternative, such as backup generation, is a reasonable indicator of the site's willingness to pay for the higher reliability, in practice this faces three problems. First, some critical loads either require backup by code or are of such high value that cost is no object. Having on-site generation offers limited advantage to such customers. Second, the advantage of a CERTS microgrid is coverage of relatively short disturbances, e.g. ones for which on-site fuel storage would not be required. Third, short outages are difficult to include in DER-CAM's hourly time resolution. The approach taken in this study is a two-step one. In the first, the true optimum system is found, and in the second, a system is forced into existence that meets the critical load requirement. Then a value of reliability is incrementally added to the objective function until the equivalent cost of the optimum system is achieved. The value necessary for this equivalency represents the value the site must put on the added reliability for this capability to be cost effective.

Equipment Available

One of the key barriers to detailed optimization of building energy systems is the potentially high computational requirement. This burden arises in part because the number of technology options is large and the number of possible combinations huge. Also, note that these are difficult optimization problems because energy purchase from the grid is always a possibility and the conditions for those purchases are complex because tariffs are complex. Further, with storage involved, decisions made in any timestep can potentially affect all other timesteps. The upshot of these conditions is a quite flat surface of alternative choice combinations that have similar objective function values. In other words, there are a large number of alternative combinations of equipment that produce similar results and choosing between them is not easy.

An effective shortcut is to include only technologies that experience has shown to be competitive. Alternatively, computation may be reduced by representing lumpy technologies with strong diseconomies of small scale as integer alternatives, while representing the others as continuous functions. The upshot of these two simplifications is the short menu of equipment shown in Table ES 3 and Table ES 5. Note that representing a technology as continuous does not mean it cannot exhibit economies of scale, only that such economies are linear and that it can be sized to exactly match the most desirable capacity and partial units are allowed. For many types of equipment, this approximation is quite reasonable, e.g. lead acid batteries are available in a wide range of sizes. Conversely, the scale economies of equipment such as gensets are considerable and they should be represented as integer technologies.

Table ES 3. Menu of available equipment options, *discrete investments*

	Tecogen CM-100	fuel cell
capacity (kW)	100	200
sprint capacity (kW)	125	
installed costs ($/kW)	2400	5005
installed costs with heat recovery ($/kW)	3000	5200
variable maintenance ($/kWh)	0.02	0.03
Efficiency (%), (HHV)	26	35
lifetime (a)	20	10

Table ES 4. Menu of available equipment options, *continuous investments*

	lead-acid batteries	thermal storage[1]	flow battery	absorption chiller	solar thermal	photovoltaics
intercept costs ($)	295	10000	0	20000	1000	1000
variable costs ($/kW or $/kWh)	193	100	220$/kWh and 2125$/kW	127	500	6675
lifetime (a)	5	17	10	15	15	20

[1] Please note that cold thermal storage is not among the set of available technologies, but could be added.

Table ES 5. Energy storage parameters

	Description	lead-acid batteries	flow battery	thermal
charging efficiency (1)	portion of energy input to storage that is useful	0.9	0.84	0.9
discharging efficiency (1)	portion of energy output from storage that is useful	1	0.84	1
decay (1)	portion of state of charge lost per hour	0.001	0.01	0.01
maximum charge rate (1)	maximum portion of rated capacity that can be added to storage in an hour	0.1	n/a	0.25
maximum discharge rate (1)	maximum portion of rated capacity that can be withdrawn from storage in an hour	0.25	n/a	0.25
minimum state of charge (1)	minimum state of charge as apportion of rated capacity	0.3	0.25	0

Results

Detailed Microgrid Results

Table ES 6. Nursing homes results

CA nursing home	do-nothing	invest in all technologies	low storage cost & 60% PV incentive
Units of CM-100 (units)		3	3
absorption chiller (kW)		48	40
Solar thermal (kW)		134	43
PV (kW)		0	517
lead-acid batteries (kWh)		0	2082
thermal storage (kWh)		0	47
electricity bill (k$)	758.02	429.42	261.83
NG bill (k$)	205.88	359.14	362.88
microgrid equipment (k$)		137.81	285.45
total bill (k$)	963.90	926.37	910.16
Bill effect (%)		-3.89	-5.58
electricity use (GWh)	5.76	3.23	2.40
electricity effect (%)		-43.92	-58.33
NG use (GWh)	5.70	9.99	10.10
NG effect (%)		75.36	77.19
carbon emissions (tC)	1087.74	945.05	833.96
carbon effect (%)		-13.12	-23.33
NYC nursing home	**do-nothing**	**invest in all technologies**	**low storage cost & 60% PV incentive**
Units of CM-100 (units)		0	0
absorption chiller (kW)		100	112
solar thermal (kW)		1438	2350
PV (kW)		0	0
lead-acid batteries (kWh)		0	294
thermal storage (kWh)		0	4862
electricity bill (k$)	845.66	825.89	823.68
NG bill (k$)	349.84	256.97	171.46
microgrid equipment (k$)		78	153
total bill (k$)	1195.50	1161.27	1148.60
Bill effect (%)		-2.86	-3.92
electricity use (GWh)	6.02	5.90	5.95
electricity effect (%)		-1.99	-1.16
NG use (GWh)	7.14	5.24	3.50
NG effect (%)		-26.61	-50.98
carbon emissions (tC)	1555.23	1439.26	1361.49
carbon effect (%)		-7.46	-12.46

Table ES 7. Schools results

CA school	do-nothing	invest in all technologies	low storage cost & 60% PV incentive
Units of CM-100 (units)		0	0
absorption chiller (kW)		139	101
solar thermal (kW)		65	72
PV (kW)		0	181
Lead-acid batteries (kWh)		0	1518
thermal storage (kWh)		0	41
electricity bill (k$)	263.93	245.90	153.24
NG bill (k$)	24.19	26.51	23.96
microgrid equipment (k$)		7	72
Total bill (k$)	288.12	279.85	249.18
bill effect (%)		-2.87	-13.51
electricity use (GWh)	1.51	1.48	1.19
electricity effect (%)		-1.99	-21.19
NG use (GWh)	0.73	0.80	0.72
NG effect (%)		9.59	-1.37
carbon emissions (tC)	360.35	358.26	291.34
carbon effect (%)		-0.58	-19.15

NYC school	do-nothing	invest in all technologies	low storage cost & 60% PV incentive
Units of CM-100 (units)		0	0
absorption chiller (kW)		96	72
solar thermal (kW)		103	187
PV (kW)		0	166
Lead-acid batteries (kWh)		0	569
thermal storage (kWh)		0	440
electricity bill (k$)	211.83	204.63	147.45
NG bill (k$)	46.37	40.37	33.76
microgrid equipment (k$)		9	62
Total bill (k$)	258.20	253.83	243.56
bill effect (%)		-1.69	-5.67
electricity use (GWh)	1.12	1.12	0.87
electricity effect (%)		0	-22,32
NG use (GWh)	0.94	0.82	0.69
NG effect (%)		-12.77	-26.60
carbon emissions (tC)	270.65	263.70	208.67
carbon effect (%)		-2.57	-22.90

Table ES 8. Data center results

CA data center	do-nothing	invest in all technologies	low storage cost & 60% PV incentive
Units of CM-100 (units)		0	0
absorption chiller (kW)		141	116
solar thermal (kW)		0	0
PV (kW)		0	1577
lead-acid batteries (kWh)		0	6434
thermal storage (kWh)		0	0
electricity bill (k$)	1478.36	1459.46	949.11
NG bill (k$)	1.78	9.73	6.01
microgrid equipment (k$)		4	467
total bill (k$)	1480.15	1473.18	1422.24
bill effect (%)		-0.47	-3.91
electricity use (GWh)	11.42	11.39	8.91
electricity effect (%)		-0.26	-21.98
NG use (GWh)	0.00	0.23	0.12
NG effect (%)			
carbon emissions (tC)	1598.92	1606.13	1253.97
carbon effect (%)		0.45	-21.57

NYC data center	do-nothing	invest in all technologies	low storage cost & 60% PV incentive
Units of CM-100 (units)		0	0
absorption chiller (kW)		0	0
solar thermal (kW)		0	0
PV (kW)		0	4
lead-acid batteries (kWh)		0	94
thermal storage (kWh)		0	0
electricity bill (k$)	1654.66	1654.66	1651.50
NG bill (k$)	0.15	0.15	0.15
microgrid equipment (k$)		0	2
total bill (k$)	1654.81	1654.81	1654.01
bill effect (%)		0	0.05
electricity use (GWh)	12.07	12.07	12.07
electricity effect (%)		0	0
NG use (GWh)	0.00	0.00	0.00
NG effect (%)		0	0
carbon emissions (tC)	2414.18	2414.18	2413.52
carbon effect (%)		0.00	-0.03

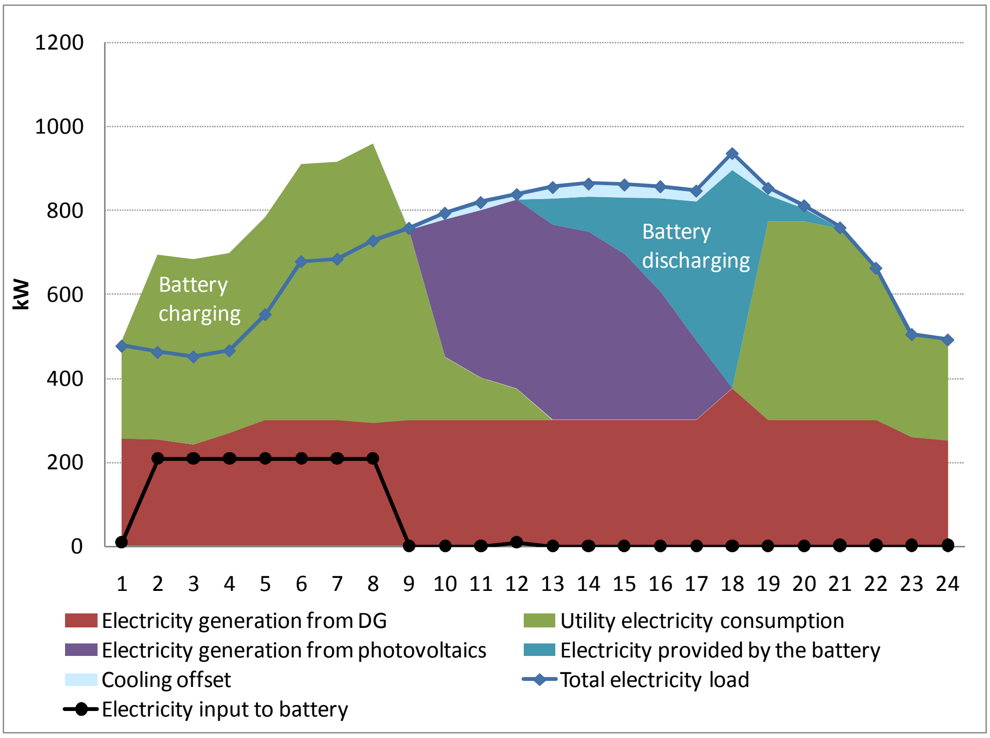
Table ES 6 through Table ES 8 show the results for the nursing homes, schools, and data centers, respectively. The tables show three cases. The *no-invest* case shows results if the sites buy all their energy from their local utilities at published tariffs. The *invest in all technologies* case is the pure optimum result from DER-CAM. This represents the lowest possible energy cost case and is the benchmark against which all others can be compared. The first two cases represent the key microgrid results. In the case of the nursing homes, the CA and NY results are noticeably different. In CA conditions, three of the Tecogen CM-100 units are selected together with an absorption chiller that is also fed by solar thermal heat. This proves the only case in which the CM-100 is chosen based on simple cost effectiveness. NG use increases by a dramatic 75% to fuel the engines, but the overall energy bill is down by 4% and the carbon footprint by 13%. In NY by contrast, the Tecogen units are not chosen but absorption chillers using solar thermal heat are, and the carbon abatement effects are smaller. The CA school also does not pick the Tecogen units, but solar thermal and absorption cooling are attractive, and in this case, the NY school results are similar. The cost and carbon reduction benefits are similarly small in both cases. The data center cases are similarly disappointing with only absorption chilling adopted in the CA case and nothing in the NY case.

Storage results

A considerable achievement of this project has been the addition of electricity and heat storage capabilities to DER-CAM. Storage poses a difficult problem because any decision made in any one time period must consider the effects on all other time periods. There are also some longer time period problems, for example how might storage on weekends for use on weekdays be handled, or potentially even storage in winter for use in summer, etc. In general, these issues have not been addressed and only storage over a day is currently considered. Both traditional batteries, such as the familiar lead-acid ones, and flow batteries are considered. The key distinction of the latter technology is that storage capacity and charge-discharge capacity are quasi-independent because the electrolyte flows through the battery and can be stored in either its charged or discharged states. All batteries are amenable to optimization using DER-CAM because finding a good charge-discharge schedule by simple search would be ineffective. Flow batteries are additionally challenging because of the dual optimization needed to pick both the storage and charge-discharge capabilities separately.

Unfortunately, as has already been reported above, when available at approximately their estimated current full cost, no storage technologies are chosen for any of the test sites, and the same is true for PV. To demonstrate the capabilities for storage and PV adoption and scheduling, and because these two technologies are connected and are strong candidates for government support, several cases with various levels of subsidy were conducted. The third case shown in Table ES 6 through Table ES 8 above, *low storage and PV costs*, is one in which storage and PV have been heavily subsidized. In this case, electricity storage costs are reduced from 193 $/kWh to 60, heat storage is halved from 100 $/kWh to 50, and 60% of PV costs are written down. With these costs, both electricity storage and heat storage become attractive to the CA nursing home, as does PV. The PV array is substantial (517 kW) and the battery bank huge (2082 kWh), while the heat storage is modest. Note that despite these significant subsidies, the net bill savings are modest, although the carbon footprint is reduced by almost a quarter. Interestingly, the NY results are almost reversed, with a huge amount of heat storage (4862 kWh) installed, but only 294 kWh of batteries and no PV. Again, given the value of the subsidy, the net effect on costs is minimal. At the CA school, all technologies except the CM-100 and flow batteries are selected. The PV array is sizeable (181 kW), as is the battery bank (1518 kWh). In this case the effect on costs is more promising (13.5%) and the emissions reduction is 19%. The NY school adopts the same fleet of technologies with almost as much PV (166 kW), but less electricity and more heat storage. The lower attraction of batteries in NY (569 kWh) is probably driven by the absence of a time of use tariff for electrical energy. The CA data center installs both a huge 1577 kW PV array and a huge battery bank (6434 kWh). Note that this PV array could supply 88% of the building peak load. Also, the battery bank could meet the peak load of the building for fully 3.6 h. The NY data center results are starkly different with only 4 kW of PV and 94 kWh of electricity storage adopted. Again, the absence of a significant diurnal electricity price differential clearly makes a dramatic difference to the outcome. Finally, consider the CA nursing home schedule for the *low storage and PV costs* run shown in Figure ES 2.

Figure ES 2. CA nursing home electricity pattern: July weekday low storage & 60% PV incentive



The graphic shows a July weekday from the DER-CAM results. The three engines run at close to full power all day and the surge capability is actually used briefly at 18:00. The heavy blue line shows the actual electricity consumed in each hour without DER. This can be thought of as the electricity service requirement. When the electricity supply exceeds this line, the battery bank is charging. This occurs from 1:00 to 9:00, as shown by the black line. The PV system produces from 9:00 to 18:00, and the battery is discharged between 12:00 and 21:00, with a strong peak discharge at 18:00. The tiny slice of light blue represents the electricity requirement that is displaced by the absorption chiller. One key result to note is that the nursing home makes considerable grid electricity purchases over the course of the day, but buys virtually nothing during the peak period, 12:00-18:00, and this shows the power of the time-of-use tariff. The engines, the PV, and the batteries are all used to avoid afternoon grid purchase. In other words, the batteries are used to save cheap off-peak electricity for consumption during the expensive on-peak hours; therefore, the PV and the batteries are in competition to provide this service.

PQR results

To model the PQR benefit of the microgrid, a certain amount of site load was assumed to be *critical*. During a macrogrid failure:

- the nursing home must meet 50% of its base load and 10% of its peak load (defined as any hourly load above the base);
- the school must meet 25% of its base load, and
- the data center must cover its entire load.

For the PQR runs, availability of the different technologies such as ICEs, batteries or PVs is important. For example, PV cannot be used as backup during the night and batteries might not be fully charged when a grid failure occurs. Additionally, lead-acid batteries can only be discharged to 30% of total battery capacity to avoid battery damaging. These boundaries limit the potential of the different technologies to contribute to sensitive loads during a grid failure.

However, DER-CAM calculates the availability of storage technologies as well as PV depending on the charge / discharge cycle and solar radiation. The reliability / availability of ICEs and fuel cells were assumed to be 90%, and there is an 18% to 22% chance that photovoltaics can contribute to sensitive loads during a grid failure (see also Table ES 9).

To satisfy the sensitive load, the product of the installed technology's availability factor and its installed capacity must be greater than the sensitive load. Or, in cases with multiple technologies, the sum of the products must be greater than the sensitive load. The detailed mathematical formulations for calculating the average availability can be found in the appendix equations A58 to A62.

Table ES 9. Electric sensitive load supply

technology	can it contribute to electric sensitive loads?	average possible contribution of max. installed capacity, availability factor (= chance that it can contribute to sensitive loads)
CM-100	yes	0.90
fuel cell	yes	0.90
electric storage	yes	0.15 to 0.21 (southern CA school)
heat storage	no	n/a
flow battery	yes	1
abs. chiller	no	n/a
photovoltaic	yes	0.18 (NY examples) to 0.22 (southern CA School)
solar thermal	no	n/a

It is further assumed that the necessary PQR features add $25/kW to the capital cost of CM-100 engines plus $100/kW for a fast DER switch, which seamlessly separates the site from the macrogrid during a grid disturbance. However, the possibility of supporting sensitive loads during a grid failure also adds benefits to the microgrid. In DER-CAM, these benefits are currently expressed only as monetary benefits. And since estimates of such benefits are difficult to find empirically, a set of PQR runs with variable benefits and fixed PQR costs were performed. Finding an optimal solution which delivers the same total bill costs as run *invest all technologies* from Table ES 6 through Table ES 8 provides an estimate of the monetary PQR benefits necessary to make the microgrid attractive. In other words, the value of PQR derived in this way is a hurdle that the site must clear to find the microgrid cost effective.

For the CA nursing home, the same equipment as in run *invest all technologies* from Table ES 6 meets the critical load. Further, the breakeven monetary benefit from PQR features is quite little, less than $25/kW (or less than 6.5 k$/a added to an annual energy bill of approaching one M$), with no additional adoption of DER generation necessary. The added reliability benefit certainly seems promising in this case. For the NY nursing home, the results are more interesting and show an adoption of two CM-100 units to satisfy the critical load condition. The monetary benefit from the PQR features is again quite little, less than $25/kW resulting in a similar cost consequence as its CA equivalent. In the NY nursing home case then, the consideration of PQR has a small effect on costs but makes a considerable difference to the attractiveness of a microgrid. Both of these examples support the notion that the nursing home/assisted living sector might be a promising market for microgrids.

In both of the school examples, DER adoption changes only slightly due to the small critical load assumed. No additional CM-100 units are installed; the only changes occur in lead-acid battery adoption; and the benefit from PQR features is low (less than $25/kW). Therefore, for the schools, a low value of the added reliability is necessary for the adoption of basic microgrid capability but it comes in the rather traditional form of battery back-up.

The data center critical load requirement is the most demanding, and the microgrid needs to satisfy 100% of the data center load during a grid failure. This requirement results in massive CM-100 adoption. The CA data center adopts 16 units and the NY data center 14; however, the found PQR benefit requirements are higher than for the other examples, $125/kW for CA and $200/kW for NY. For example, for the CA data center, this cost represents an addition of about 223 k$ to its 1.4 M$ annual energy bill. While these costs are considerable, given the extreme priority placed on reliability by data centers, they are certainly feasible.

Overall, the results of the reliability analyses are promising, while none of the results are surprising in and of themselves. For sites at which a microgrid is already or close to being viable, the added value of reliability can easily enhance the economics. The two nursing homes substantiate the claim that a large potential market exists at sites where CHP is possible and reliability has some additional modest value when a significant share of load needs to be supported. The schools tend to argue that if a microgrid is not attractive absent a reliability benefit and the sensitive load is small, alternatives to a microgrid are likely to be more appealing, e.g. traditional back-up. Finally, the data center results show that if sites with significant sensitive loads value the reliability benefit high enough — and many such sites are likely to — then the effect on the attractiveness of a microgrid could be dramatic.

Sensitivity results

Two types of sensitivity cases were completed. One imposed carbon taxes ranging from $150-1000/tC, and the other applied the prevailing standby tariff to an otherwise favorable microgird site, i.e. CA nursing home.

The imposition of carbon taxes tended to encourage the adoption of CM-100 gensets, although the effect was only dramatic in the NYC nursing home case, which installs four units at a carbon tax rate of $450/tC. The carbon taxes tend to encourage adoption of solar thermal collectors, which together with heat recovery from the gensets, feed sizable absorption chillers. Additional storage occurs in a few isolated cases, but PV adoption at its full unsubsidized price never appears. In fact, at $1000/tC, fuel cells are adopted by the NYC nursing home, while PV still does not appear.

Application of the PG&E standby tariff to the CA nursing home does not preclude adoption of gensets, but does result in higher costs because of the high fixed charge in the tariff.

1. Introduction

1.1 Background

In past work, Berkeley Lab has developed the Distributed Energy Resources Customer Adoption Model (DER-CAM). Given end-use energy details for a facility, a description of its economic environment and a menu of available equipment, DER-CAM finds the optimal investment portfolio and its operating schedule which together minimize the cost of meeting site service, e.g., cooling, heating, requirements. Past studies have considered combined heat and power (CHP) technologies. Methods and software have been developed to solve this problem, finding optimal solutions which take simultaneity into account. This project aims to extend on those prior capabilities in two key dimensions. In this research storage technologies have been added as well as power quality and reliability (PQR) features that provide the ability to value the additional indirect reliability benefit derived from Consortium for Electricity Reliability Technology Solutions (CERTS) Microgrid capability.

1.2 Purpose of research

This project is intended to determine how attractive on-site generation becomes to a medium-sized commercial site if economical storage (both electrical and thermal), CHP opportunities, and PQR benefits are provided in addition to avoiding electricity purchases. On-site electrical storage, generators, and the ability to seamlessly connect and disconnect from utility service would provide the facility with ride-through capability for minor grid disturbances. Three building types in both California and New York are assumed to have a share of their sensitive electrical load separable. Providing enhanced service to this load fraction has an unknown value to the facility, which is estimated analytically.

In summary, this project began with 3 major goals:

1. to conduct detailed analysis to find the optimal equipment combination for microgrids at a few promising commercial building hosts in the two favorable markets of California and New York,
2. to extend the analysis capability of DER-CAM to include both heat and electricity storage, and
3. to make an initial effort towards adding consideration of PQR into the capabilities of DER-CAM.

2. The Distributed Energy Resources Customer Adoption Model (DER-CAM)

DER-CAM (Siddiqui et al. 2003) is a mixed-integer linear program (MILP) written and executed in the General Algebraic Modeling System (GAMS). Its objective is to minimize the annual costs for providing energy services to the modeled site, including utility electricity and natural gas purchases, amortized capital and annual maintenance costs for distributed generation (DG) investments. The approach is fully technology-neutral and can include energy purchases, on-site conversion, both electrical and thermal on-site renewable harvesting, and end-use efficiency investments. Furthermore, the system choice considers the simultaneity of solutions, especially regarding the building cooling problem; that is, results reflect the benefit of electricity demand displacement by heat-activated cooling that lowers building peak load and, therefore, the generation requirement.

Site-specific inputs to the model are end-use energy loads,[2] electricity and natural gas tariff structures and rates, and DG technology investment options. While any equipment could be incorporated in DER-CAM, the following technologies are considered in this study:[3]

- natural gas-fired reciprocating engines, gas turbines, microturbines, and fuel cells;
- photovoltaics (PV) and solar thermal collectors;
- traditional batteries, flow batteries, and heat storage;
- heat exchangers for application of solar thermal and recovered heat to end-use loads;
- direct-fired natural gas chillers; and
- heat-driven absorption chillers.

Figure 1 shows a high-level schematic of the energy flow modeled by DER-CAM. Available energy inputs to the site are solar insolation, utility electricity, and utility natural gas. For a given site, DER-CAM selects the economically[4] optimal combination of utility electricity purchase, on-site generation, and storage as well as cooling equipment required at each time step to meet the following end-use loads:

- electricity-only loads, e.g. lighting and office equipment;
- cooling loads that can be met either by electricity powered compression or by heat activated absorption cooling, direct-fired natural gas chillers, waste heat or solar heat;
- hot water and space heating loads that can be met by recovered heat or by natural gas; and
- natural gas-only loads, e.g. mostly cooking that can only be met by natural gas.

The simulation is typically executed for a test year represented by 36 days: a weekday, weekend, and peak day for each month.

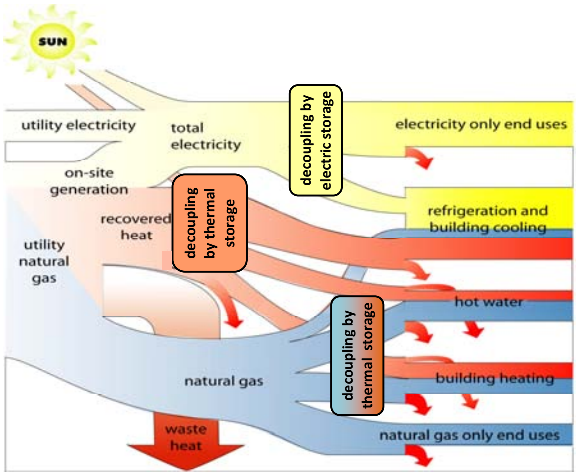
---

[2] Three different diurnal profiles are used to represent the set of daily profiles for each month: weekday, peak day, and weekend day. DER-CAM assumes that three weekdays of each month are peak days.

[3] Despite the wide variety of technologies that can be considered in DER-CAM, only a small subset of technologies are used in this work to allow focus on premium power products. See also section “DER Equipment Including Storage Technologies”.

[4] DER-CAM’s objective function is to minimize the total energy bill, but this can easily be changed to a carbon minimizing strategy or some other combination.

Figure 1. Schematic of the energy flow model used in DER-CAM[5]



The outputs of DER-CAM include the optimal DG and storage adoption and an hourly operating schedule, as well as the resulting costs, fuel consumption, and carbon emissions (Figure 2). Optimal combinations of equipment involving PV, thermal generation with heat recovery, thermal heat collection, and heat-activated cooling can be identified in a way that would be intractable by trial-and-error enumeration of possible combinations. The economics of storage are particularly complex, both because they require optimization across multiple time steps and also because of the influence of tariff structures (on-peak, off-peak, and demand charges). Note that facilities with on-site generation will incur electricity bills more biased toward demand (peak power) charges and less toward energy charges, thereby making the timing and control of chargeable peaks of particular operational importance.
The MILP solved by DER-CAM is shown in pseudocode in Figure 3. In minimizing the site's annualized energy bill, DER-CAM also has to take into account various constraints. Among these, the most fundamental ones are the energy-balance and operational constraints which require that every end-use load has to be met, and that the thermodynamics of energy production, conversion, and transfer are obeyed.

The recently added storage constraints are essentially inventory balance constraints. The amount of energy in a storage device at the beginning of a time period is equal to the amount available at the beginning of the previous time period plus energy charges and minus energy discharges/losses. Finally, investment and regulatory constraints may be included as needed. A limit on the acceptable simple payback period is imposed to mimic typical investment decisions made in practice. Only investment options with a payback period of less than 12 years are considered for this paper. For a complete mathematical formulation of the MILP with energy storage solved by DER-CAM, please refer to Appendix A or Siddiqui et al. 2007.

[5] Please note that thermal storage contains also heat for absorption chillers, and therefore, Figure 1 considers cold thermal storage indirectly. However, direct cold storage is not considered in DER-CAM at this stage, but can be added in future versions.

Figure 2. High-Level schematic of information flow in DER-CAM

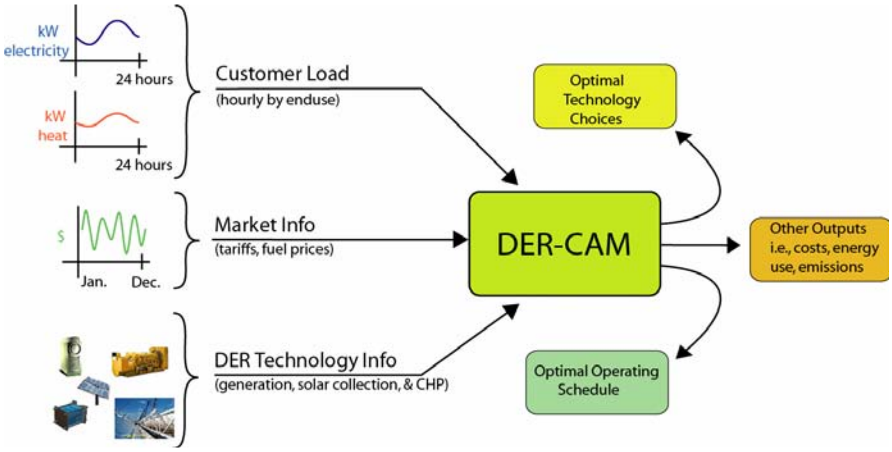


Figure 3. MILP solved by DER-CAM[6]

```
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
```

A complete mathematical formulation of DER-CAM can be found in Appendix A.

3. The sites

3.1 Key characteristics of the test buildings and sites

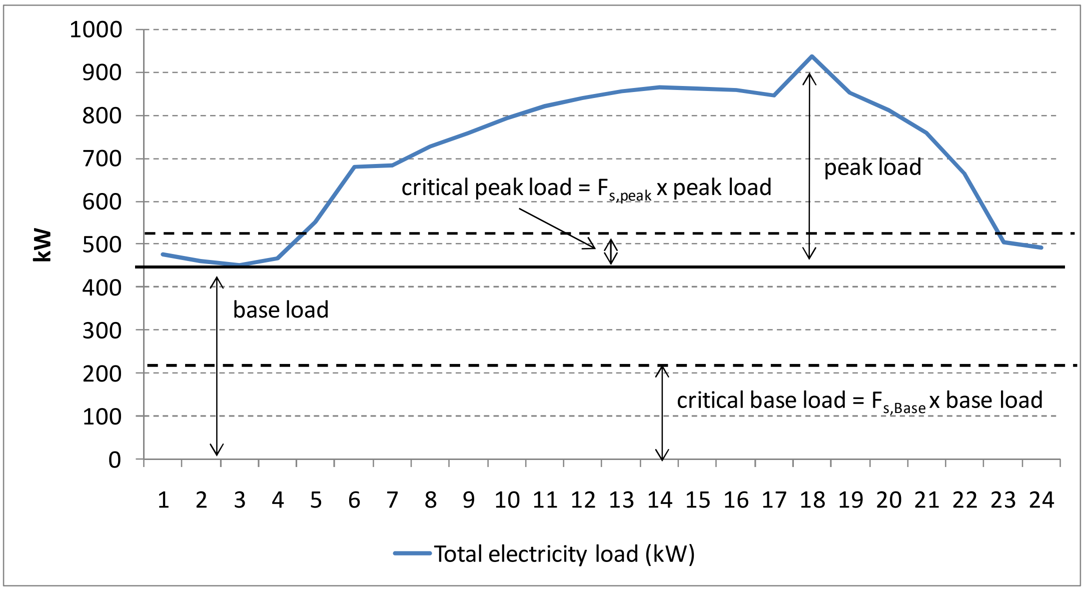
To estimate the impact of electrical and thermal storage on the installation of DG with and without CHP, PV, solar thermal systems as well as absorption chillers, the following three types of buildings in both California and New York, have been analyzed:

[6] Not all constraints are shown, e.g. flow batteries have more constraints than electrical storage.

- nursing home: Nursing homes generally have high capacity factors and high electricity and heat loads which favor distributed generation with heat recovery.
- school: Schools make up a sizable portion of the building stock and frequently have heated pools which might favor the use of waste heat from DG units or from solar thermal systems. To assess the impact of heated pools, a school in southern California (Riverside) is modeled. The corresponding New York City school does not have a pool, but has a significant space heating requirement.
- data center: Data centers have high critical loads.

Henceforth, the critical load factor (F_s) is defined as the portion of the maximum electrical load that must be supplied during a macrogrid disturbance. To be able to consider base[7] and peak loads separately DER-CAM uses $F_{s,Base}$ and $F_{s,Peak}$ (see also Figure 4).

Figure 4. Critical base and peak load for the CA nursing home example



For example, half of nursing home base load and 10% of the peak load, i.e. above base load, is considered critical. The school has few sensitive loads while the data center is considered all sensitive.

[7] The "base load" is the minimum electricity requirement experienced during any hour in the year.

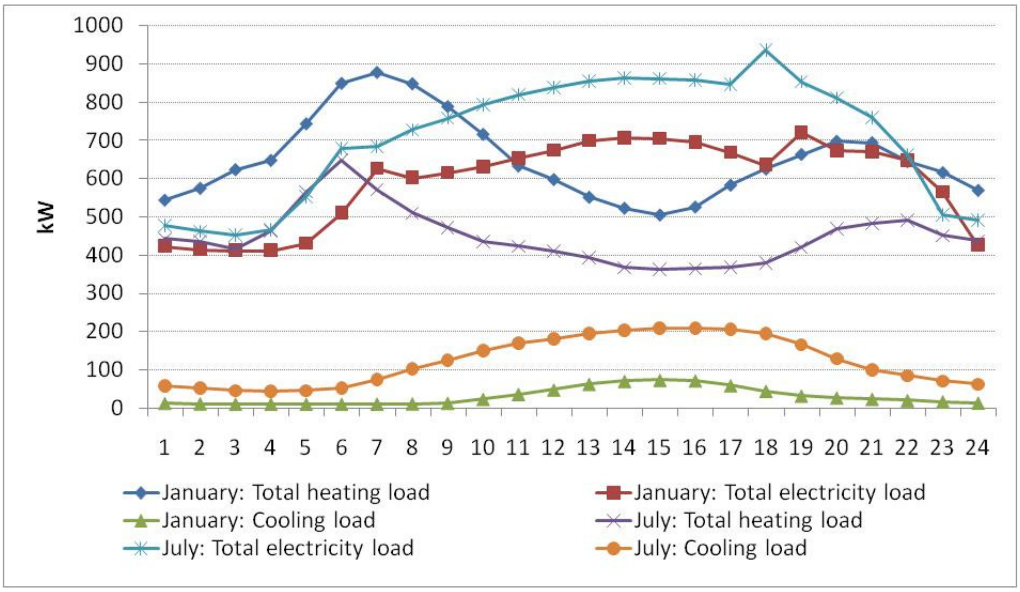
Table 1. Key characteristics of test buildings and sites

		size (m^2)	electricity peak load (kW)	annual electricity consumption (kWh)	annual NG consumption (therms)	vicinity	elec. utility	gas utility	$F_{s,Base}$	$F_{s,Peak}$
CA	nursing home	31 587	958	5 761 690	194 522	northern CA	PG&E	PG&E	0.5	0.1
	School	17 652	885	1 508 883	24 868	southern CA	SCE	SoCal Gas	0.25	0.0
	datacenter	617	1 788	11 420 823	0	northern CA	PG&E	PG&E	1.0	1.0
NY	nursing home	31 587	1 067	6 016 309	243 563	NYC	ConEd	ConEd	0.5	0.1
	School	17 652	746	1 120 653	32 193	NYC	ConEd	ConEd	0.25	0.0
	datacenter	617	1 591	12 070 888	0	NYC	ConEd	ConEd	1.0	1.0

3.2 CA nursing home

The California nursing home, which is located in northern California, is characterized by relatively stable seasonal demand, and therefore, only July and January profiles are shown in Figure 5. The complete data set for a representative full care 24 hour nursing facility with five floors and a total area of 31 587 m^2 (340 000 sq. ft) was obtained from the California Energy Commission (CEC). This is a site from the California Commercial End-Use Survey (CEUS).

Figure 5. CA nursing home January and July weekday electricity[8] and total heat (space + water heating)[9] demand



[8] Please note that cooling demand is expressed in electricity consumption of the electric chiller with an assumed COP of 4.5.
[9] 1 kW = 3 412.14 BTU/h

As can be seen in Figure 5, the off-peak heat demand is roughly 60% of the peak demand. Additionally, during the daytime hours, heat can be used to lower the electrical peak. When cooling demand increases, this can constitute a stable heat sink if waste heat for absorption chillers is considered. Finally, the electricity demand coincides with the total heat demand and this favors the installation of DG units with CHP.

The simultaneous use of heating and cooling is caused by a) the complexity of nursing facilities where heating and cooling can appear in different zones at the same time and b) hot water loads.

3.3 CA school

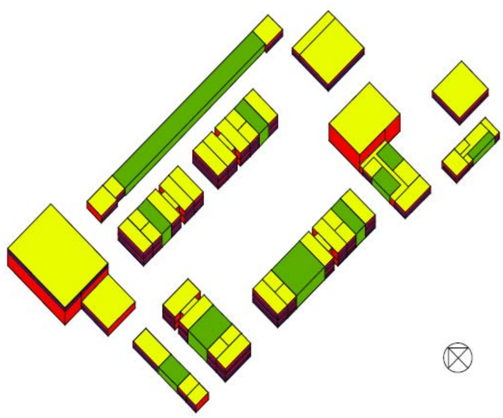
Load profiles for a 17 652 m^2 (190 000 sq. ft) multi-building school with a heated pool have been obtained from EnergyPlus simulations and used as inputs for DER-CAM. Climate data from southern California (Riverside) have been used within the EnergyPlus simulations. A complete description of the EnergPlus building module can be found at DOE Commercial Building Integration Benchmark Input Table 2007.

The following end-use loads are considered within DER-CAM and are obtained from EnergyPlus:

- electricity-only loads, e.g. lighting and office equipment;
- cooling loads that can be met by electricity powered compression, heat activated absorption cooling (using waste or solar heat), direct-fired natural gas absorption, or mechanical chillers;
- hot water and space heating loads that can be met by direct natural gas combustion, waste heat recovery, or solar thermal heat; and,
- natural gas-only loads, e.g. mostly cooking that can be met only by natural gas.

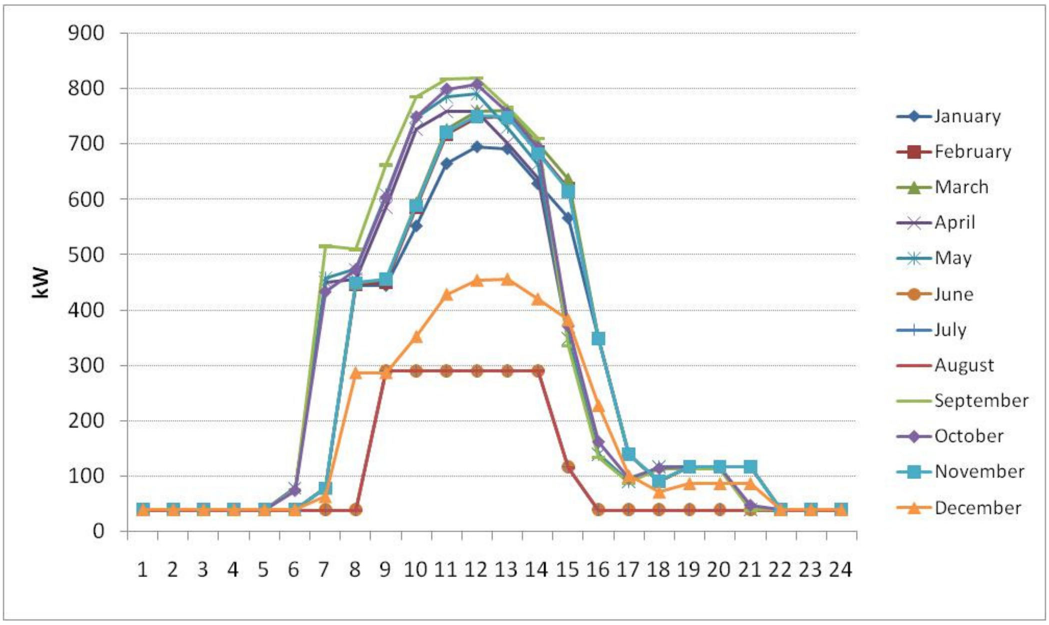
Please note that three different diurnal profiles are used to represent the set of daily end-use profiles for each month within DER-CAM: weekday, peak day, and weekend day. DER-CAM assumes that three weekdays of each month are peak days and the representative weekday profile is used for all weekdays except the three peak days.

Figure 6. Layout of bi-level multi-building secondary school in Southern California



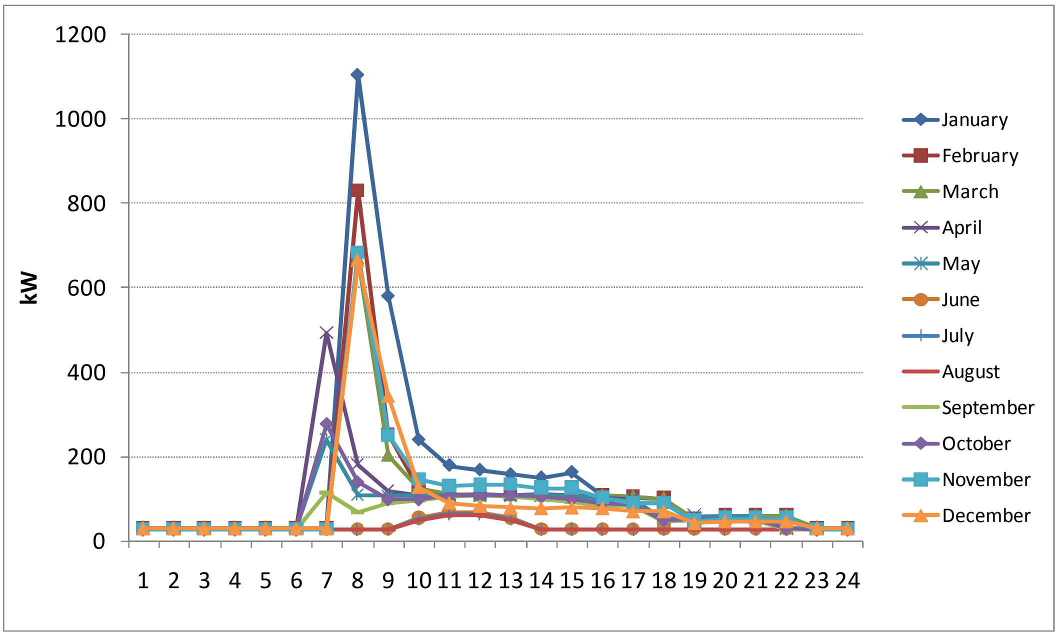
source: Huang 1991

Figure 7. CA school weekday total electricity (inclusive of cooling)[10] demand



June, July, and August are school holidays so no cooling demand occurs in those months.

Figure 8. CA school weekday total heat (space + water heating) demand[11]



[10] Please note that cooling demand is expressed in electricity consumption of the electric chiller with an assumed COP of 4.5.

[11] 1 kW = 3 412.14 BTU/h

3.4 CA data center

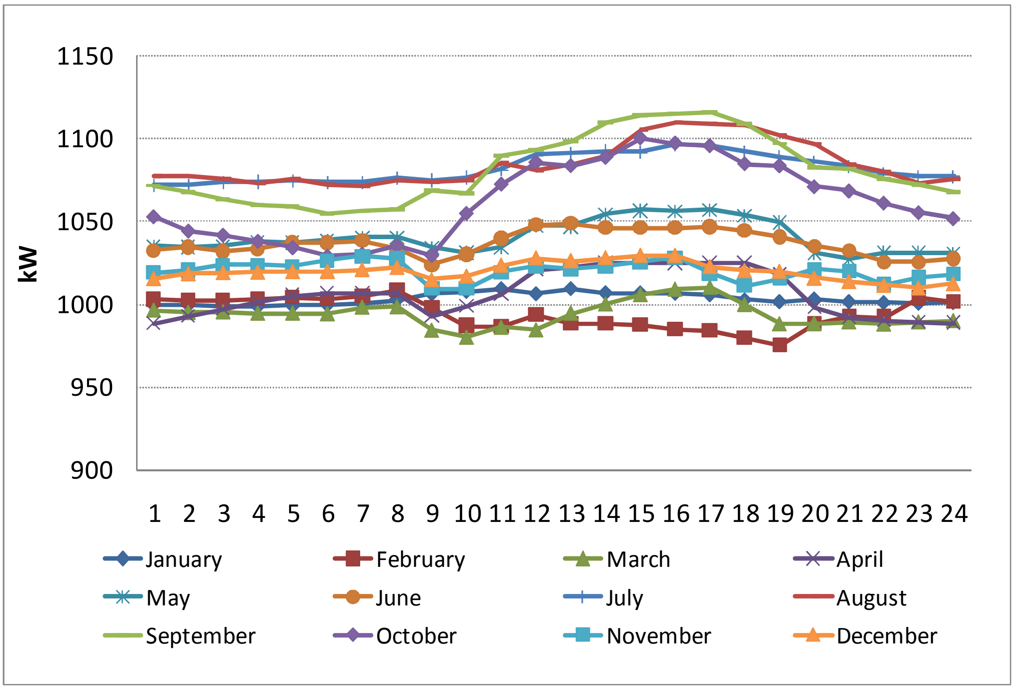
The data center is located in northern California (Sunnyvale) and has 617 m^2 (6 638 sq. ft.) of server space dedicated to the data center's internal data management needs. A Hess combined cooling heat and power (CCHP) system was installed approximately two years ago. However, the increasing natural gas price makes operation uneconomical, as shown by the results in section 6.3.

The peak electrical load is 1 788 kW. Designed so that the electrical base load demand could be entirely met by the Hess Microgen reciprocating engine CHP units, the system is now mainly operated in "peak shaving" mode. Base load operation is no longer economical with the recent increased cost of natural gas, although using less electricity during peak times still enables the company to buy power at a lower rate. Additionally, for this study, 100% of the load is assumed critical and this can favor the installation of distributed generation (see also section 6.3).

In Sunnyvale's low humidity climate where summer daytime heat is often paired with coolness in the evening, intelligent design of the cooling system can significantly reduce electrical demand. If the temperature outside is below 18°C (65°F), an economizer brings in outside air, which is enough to cool the facility for a third of the year. For the remaining two-thirds of the year, the facility needs supplemental cooling. The impact of the economizer is considered in Figure 10 and in the corresponding DER-CAM runs.

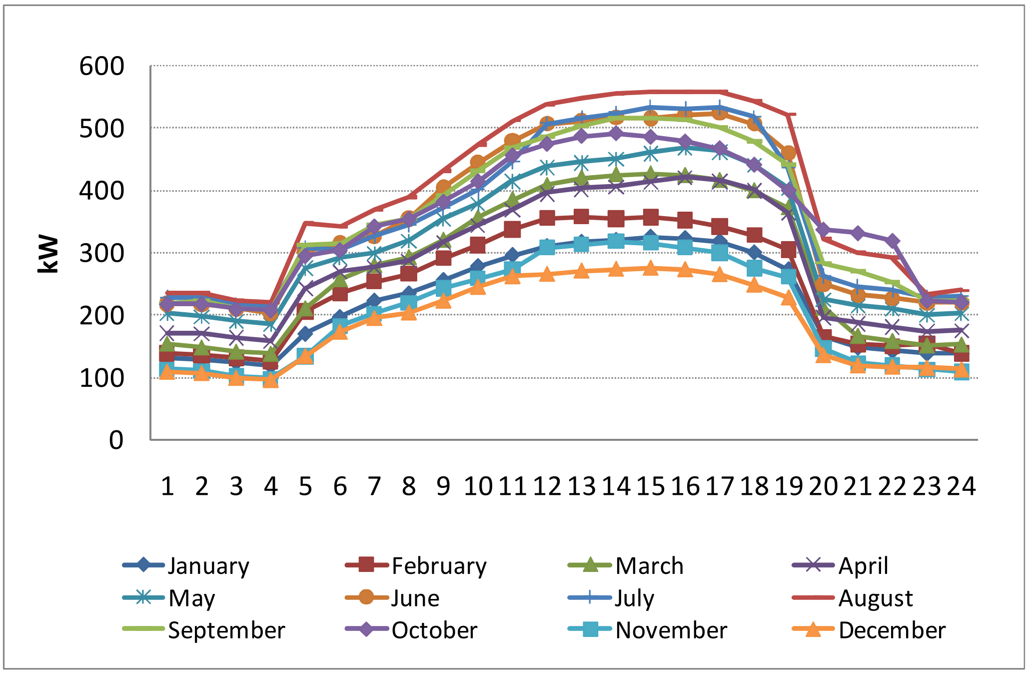
For this research, the de minimus heat demand and corresponding natural gas consumption is ignored. This aspect of data centers as "non-traditional" CHP candidates makes them of special research interest.

Figure 9. CA data center weekday electricity demand



The electricity demand from Figure 9 also contains cooling related auxiliary demand, e.g. fans, and therefore, the electricity demand goes up with the cooling demand.

Figure 10. CA data center weekday cooling demand[12]



3.5 NYC nursing home

The NYC nursing home is based on the CA nursing home data. Regression analyses between the hourly Oakland temperature data and hourly cooling and heating demand were performed for the CA nursing home. This procedure delivers two equations that describe the cooling and heating dependency on the temperature[13].

$$Demand_{Cooling} = 20 \cdot Temperature - 200 \quad \textbf{(1)}$$

$$Demand_{Heating} = 3866.7 - 166.67 \cdot Temperature \quad \textbf{(2)}$$

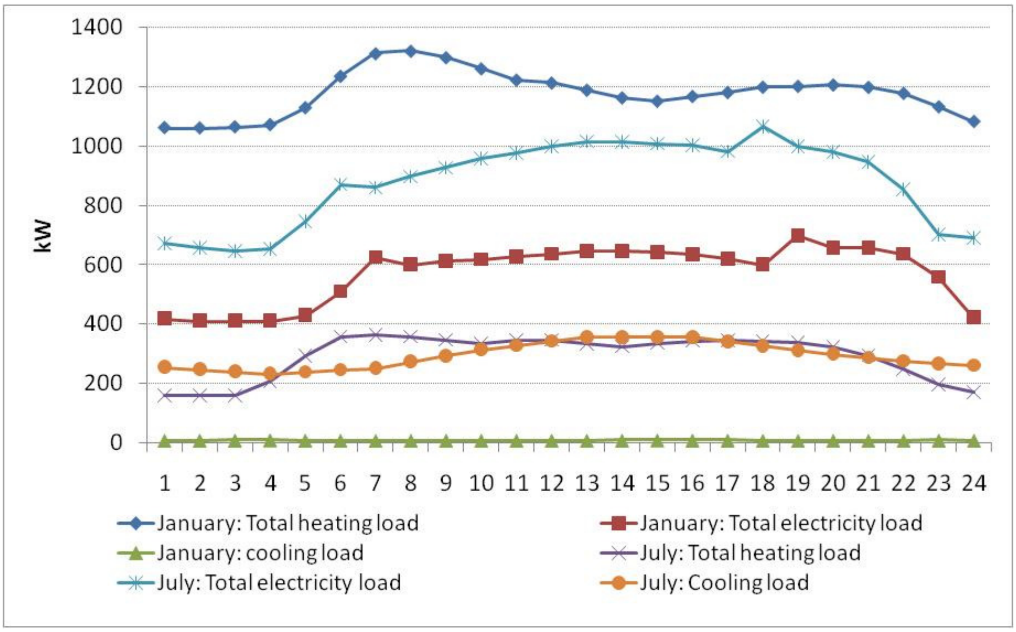
$Demand_{Cooling}$	kW
$Demand_{Heating}$	kW
$Temperature$	°C

Insertion of NYC hourly temperature data allows estimation of the heating and cooling demand for the NYC nursing home (see Figure 11). Please note that this procedure assumes that the NYC nursing home is exactly the same size, zoning, and design as the California nursing home.

---

[12] Expressed in terms of electricity (kW) of an electric chiller with an effective COP of 4.5.
[13] This calculation neglects the impact of humidity.

Figure 11. NYC nursing home January and July weekday electricity[14] and total heat (space + water heating)[15] demand



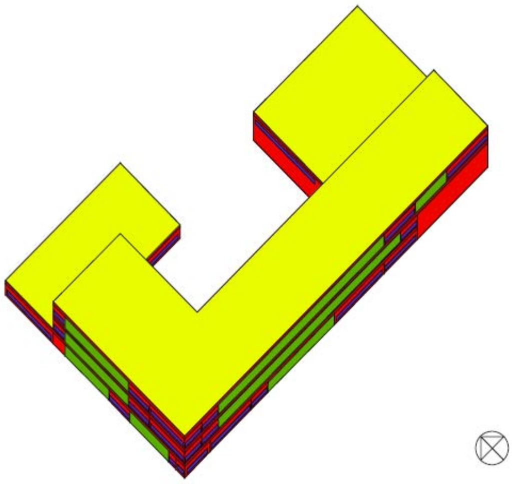
One major difference between the NYC and the CA nursing homes is the constant total NYC heating load. The off-peak heat demand is roughly 80% of the peak heat demand on a typical January weekday. Another major difference is the higher cooling load in NYC due to higher summer temperatures; however, in contrast to the CA facility, the NYC winter cooling load is almost zero.

3.6 NYC school

To simulate the energy demand of the single building school with 17 652 m^2 (190 000 sq. ft) *without* a heated pool, climate data from New York City (La Guardia) were used for the EnergyPlus runs. A complete description of the EnergPlus building module can be found at DOE Commercial Building Integration Benchmark Input Table 2007.

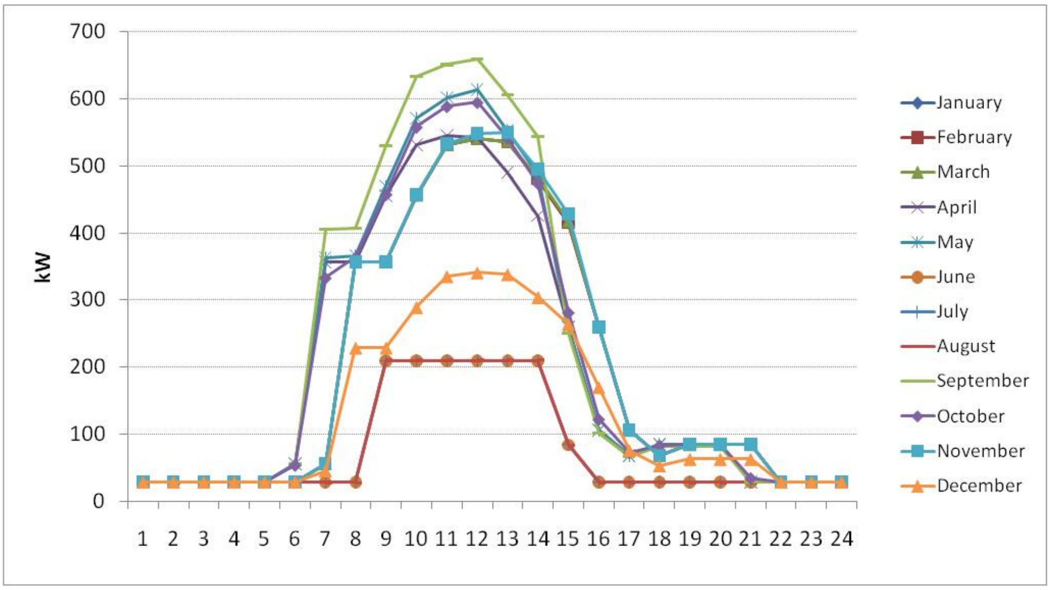
[14] Please note that cooling demand is expressed in electricity consumption of the electric chiller with an assumed COP of 4.5.
[15] 1 kW = 3 412.14 BTU/h

Figure 12. Layout of three storey secondary school building in New York City



Source: Huang 1991

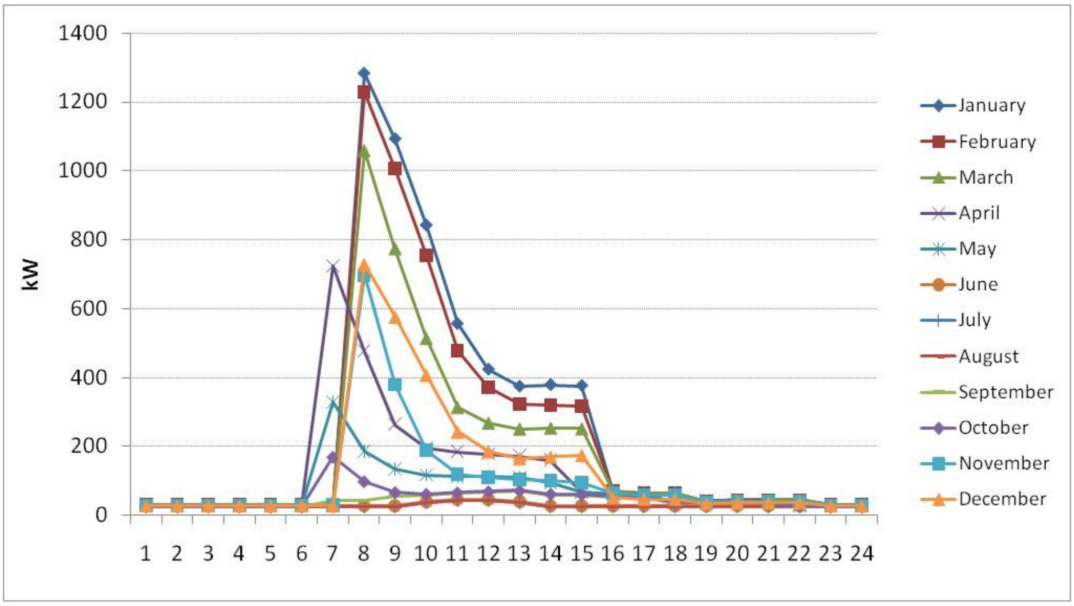
Figure 13. NYC school weekday total electricity (inclusive of cooling)[16] demand



Again as for the CA school, there is no cooling during the summer months of June, July, and August, which results in the highest observed electricity demand occurring in September.

[16] Please note that cooling demand is expressed in electricity consumption of the electric chiller with an assumed COP of 4.5.

Figure 14. NYC school weekday total heat (space + water heating) demand[17]



3.7 NYC data center

The NYC data center is based on the CA data center but uses a different cooling load due to the absence of economizers and the NYC temperatures. The relation between cooling demand and temperature for the CA data center was found based on a regression analysis (see Equation 3). This relationship, together with average hourly NYC temperatures from Figure 15, was used to determine the cooling load at the NYC data center.

$$Demand_{Cooling} = 9.507 \cdot Temperature - 225 \quad \textbf{(3)}$$

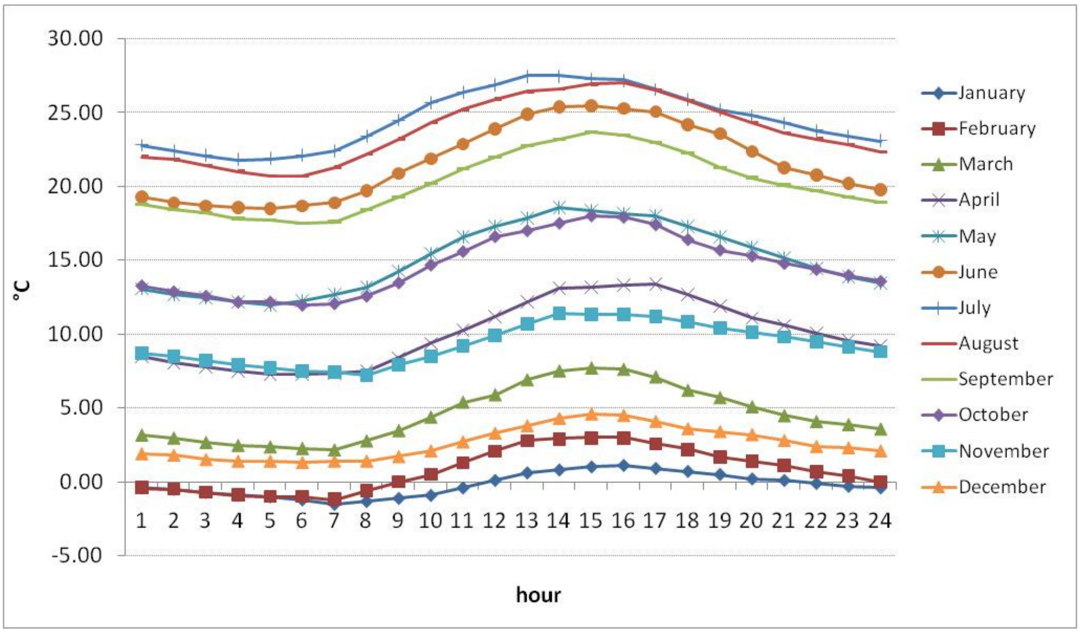
$Demand_{Cooling}$	kW
$Temperature$	°C

Without economizers, which would have been operating during night hours, the cooling load of the NYC data center increases, especially during night hours (see also Figure 10 and Figure 17).

The electricity demand from Figure 16 also contains cooling fan demand, and therefore, electricity demand goes up with the cooling demand.

[17] 1 kW = 3 412.14 BTU/h

Figure 15. Average NYC temperatures used for the NYC data center



source: DOE, EnergyPlus

Figure 16. NYC data center weekday electricity demand

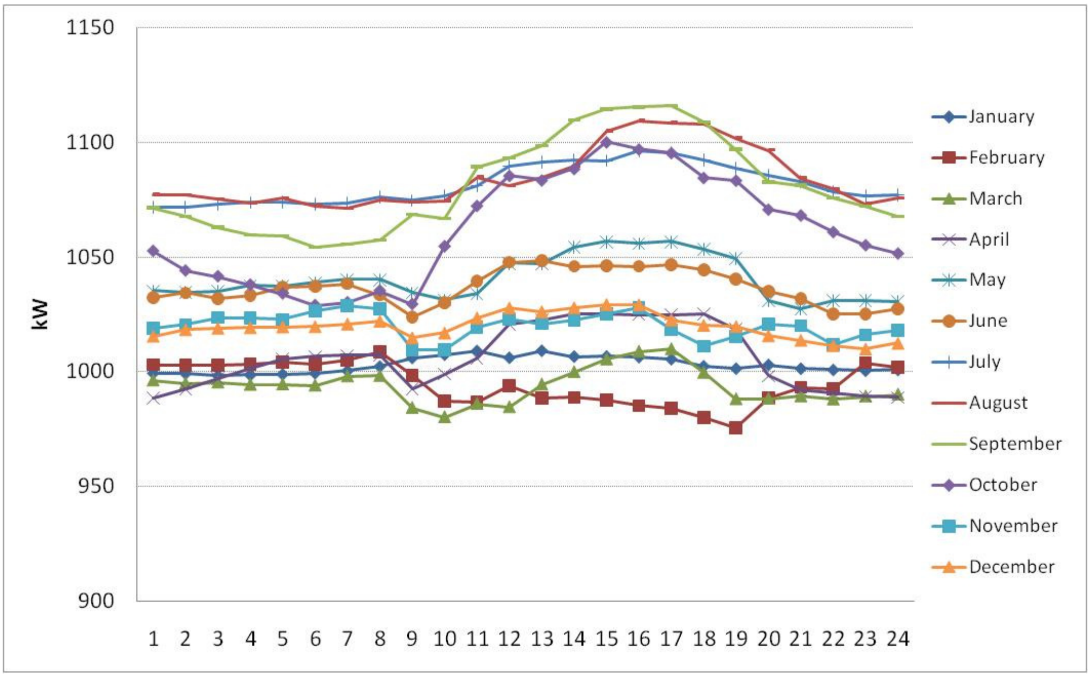
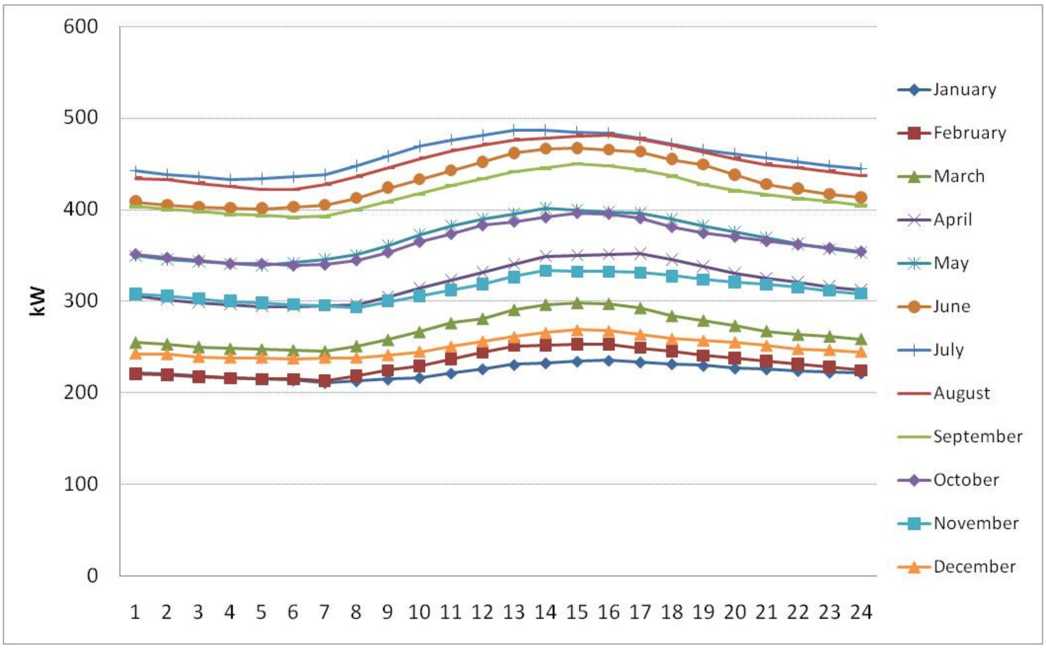


Figure 17. NYC data center weekday cooling demand[18]



4. Brief description of technologies

This chapter briefly describes some of the technologies considered in DER-CAM and for this study and does not constitute a comprehensive description of currently available technologies. For example, further information can be found at Schoenung et al. 1996, 2003, EPRI-DOE Handbook 2003, Goldstein, L. et al. 2003, DOE Electricity Delivery and Energy Reliability as well as the Pacific Region CHP Application Center.

4.1 Electrical storage

There are various electrical storage systems, depending on the applications, such as power quality enhancement, uninterruptable power supply (UPS), energy management, and large scale storage for electric utilities. In terms of daily energy management for microgrids or single buildings only lead-acid batteries, lithium ion (Li-ion) batteries, flow batteries, and sodium sulfur batteries (NaS) are considered in this work. Further information on batteries can be also found at Schoenung et al. 2003, EPRI-DOE Handbook 2003 and at the Electricity Storage Association.

4.1.1 Lead-acid batteries

Lead-acid batteries are widely used in the electric storage devices found in everything from vehicles to building UPS's. Many conventional building electrical storage systems are based on lead acid batteries, which are frequently the least expensive option. Lead-acid batteries are often considered the first candidate for electrical energy storage or load management. Although their energy mass density is among the lowest, around 30-40 Wh/kg, lead acid batteries are reliable at high surge currents, which are needed for vehicles, data centers, and telecommunication

[18] Expressed in terms of electricity usage (kW) of an electric chiller with a COP of 4.5.

facilities. Lead acid batteries typically cost about $100 per kWh for "wet" types and between $125 and $200 per kWh for more advanced "valve regulated" types (Schoenung et al. 1996). Their roundtrip electrical efficiency typically ranges between 70% to 85% and they usually last up to 1000 charge/discharge cycles. Despite their ubiquity and low cost, alternatives are being developed due to the low storage capacity, the toxic materials used in manufacturing, and the impacts of their disposal on the environment.

4.1.2 Lithium ion (Li-ion) batteries

Li-ion batteries are widely used for mobile equipment, e.g., cell phones and laptops, because of their high energy storage mass densities, typically between 150–200 Wh/kg. Li-ion is promising as an alternative storage medium for replacing lead-acid or nickel metal hydride (Ni-MH) for hybrid vehicles. Larger sized Li-ion batteries can also be used for energy management and as building UPS. However, a major drawback is their high capital cost of $500/kWh–$1500/kWh. In contrast, their advantage is lifespan, which ranges from 1200 to 3000 charge/discharge cycles. Compared to conventional lead and nickel based batteries, this technology takes up less space and recharges faster. Typical charge/discharge efficiencies can reach 85%. At lower costs, Li-ion batteries could significantly enable large scale deployment of plug-in vehicles that would contribute significantly to DG and PQ for the grid.

4.1.3 Sodium sulfur (NaS) batteries

Sodium sulfur (NaS) batteries have high power capacity, up to MW scale. Their energy/mass density is approximately 120 Wh/kg, which is three times that of lead-acid batteries. Their charge/discharge efficiency approaches 90%, life cycle time is up to 2500 cycles, and cost roughly $600/kWh. NaS batteries can be used for peak shaving, compensation of variable PV output, and energy management. One big disadvantage of NaS batteries is that they have to always be on and consume electricity in order to maintain high operational temperature (320-340^{o}C).

4.1.4 Flow batteries

Although a relatively new technology, flow battery systems show many advantages over conventional batteries. Not only can flow battery cells be safely discharged completely, they can exceed over 10 000 charge/discharge cycles with almost no loss in performance. Flow batteries use liquid electrolytes. They are stored in tanks and pumped to cell stacks for charge or discharge purposes. One major advantage is that energy and power capacities are completely independent of each other; energy capacity (kWh) is determined by the electrolyte tank size and power capacity (kW) depends on the size of pumps and on the cell stack. The electrolyte materials depend on the manufacturers and vanadium redox batteries (VRB) or zinc bromine batteries (ZBB) are in general use.

VRB systems are designed to store and release energy over extended periods, but they can also be used for full UPS. Conventional UPS devices are not designed for energy storage. The cells run in the range of a few hundred kW to MW in size and cost $500 to $800 per kWh. As the overall capacity of the system increases in size, the cost per kWh decreases significantly. For larger systems, the incremental cost of the cells is expected to be approximately $220 per kWh (EPRI). The power related costs are typically in the range of $2000/kW, which do not consider the costs for grid connection or engineering planning (EPRI). The biggest disadvantage seems to be the high cost. One reason is that flow batteries need stable environmental conditions, often requiring buildings around the batteries, which creates high cost uncertainty.

Table 2. Key Characteristics of selected electric storage systems (see also Schoenung et al. 2003 and EPRI-DOE Storage Handbook 2003)

	Lead Acid	Lithium (Li-ion)	Sodium Sulfur (NaS)	Vanadium Redox Battery
Capital Cost ($/kWh)	100 – 200	500-1500	600	500-800 (expected future incremental costs of ca. 220)
Power related Costs ($/kW)	125-175	175 - 200	150	2125
Maintenance Costs ($/kW a)	5 – 15	10 - 25	20	20
Energy Density (Wh/kg)	30 – 40	150 - 200	100 - 120	25
Lifespan (cycles)	500-800	1200-3000	2500	13,000+
Depth of Discharge	80	80	100	100
Charge/Discharge Efficiency	70 – 90	85	90	85

4.2 Fuel cells

A fuel cell converts energy by using an electrochemical process, similar to a battery. No combustion takes place. The main difference to a battery is the continuous flow of hydrogen (H_2) and oxygen (O_2) that is needed to keep the fuel cell working; and fuel cells cannot store energy like batteries. The key element is the membrane, e.g. molten carbonate, which only allows the H+ ions to travel to the cathode where H+, electrons and O_2 react to form water, the only "waste product" of a fuel cell. The electrons have to take the "detour" through the external circuit which connects the anode and cathode, and this flow of electrons constitutes a direct current. In this way, a maximum voltage of 1.23V per cell can be achieved. Stacking of such cells creates higher voltages. A comprehensive description of fuel cells can be found at Goldstein et al. 2003.

4.2.1 Proton-Exchange Membrane Fuel Cell (PEMFC)

PEMFCs have low operating temperatures of approximately 65-85^{o}C (Goldstein et al. 2003) and are scalable. PEMFCs are small as well as light and typical applications are fuel cell vehicles and stationary distributed generation, i.e. micro-CHPs. One disadvantage is that they need pure hydrogen while some other types of fuel cells can accept hydro-carbon fuels because inner reforming is available. Additionally, the electricity generation efficiency ranges only from 30% to 35% (HHV).

4.2.2 Solid-Oxide Fuel Cell (SOFC)

SOFC is a promising technology for mid-size CHP systems. Easier operation and maintenance are realized by the use of a solid electrolyte. In addition, relatively high electricity generation efficiency of > 45% (HHV) can be achieved and the recovered heat obtained as steam so that high efficiency double effect chillers can be attached (see also section 4.4). The high operational temperature of ca.750°C - 1000°C (Goldstein et al. 2003) enables inner reforming of fuel, i.e. hydro-carbon fuel is automatically reformed to hydrogen inside the fuel cell systems.

4.2.3 Molten Carbonate Fuel Cell (MCFC)

MCFCs use alkali metal carbonates (Li, Na, K) as the electrolyte and have been commercialized for mid-size to large scale distributed generation systems e.g., 300 kW to 2.4 MW. Electric efficiencies of 42% (HHV) can be achieved. The typical operating temperature is 650 °C (Goldstein et al. 2003) and this allows high temperature waste heat utilization.

4.2.4 Phosphoric Acid Fuel Cell (PAFC)

PAFCs are considered to be the most established fuel cell technology and are typically used for on-site CHP systems. The electric efficiency is approximately 35% (HHV) with operation temperatures of approximately 200 °C. The reliability in commercial usage ranges typical from 90% to 95% (Goldstein et al. 2003). PAFCs use expensive materials such as platinum and this keeps installation costs very high, and therefore, PAFCs are being replaced by other cheaper fuel cell types. Additionally, pure hydrogen must be supplied since inner reforming is not available.

Table 3 shows the key performance and economic parameters of stationary fuel cell systems. The lifetime in years is based on 8760 hours/year and depending on the frequency of the usage in the micorgrid, e.g. only peak shaving, the lifetime can increase considerably.

Table 3. Key characteristics of selected stationary fuel cell systems

	PEMFC	SOFC	MCFC	PAFC
Available capacity (kW)	1 - 100	100 - 500	300 - 2400	100 - 500
Total Installation[19] Costs ($/kW)	3800 - 5500	3600	3200 - 5000	4000-5200
Net efficiency (%), (HHV)	30 - 35	45	42	35
lifetime (a)	5	5	10	10

source: Goldstein, L. et al., 2003 and LBNL estimates

4.3 Reciprocating engines

A detailed description of internal combustion engines (ICE) as well as their economic characteristics can be found in Goldstein, L. et al., 2003. For this study, costs as well as performance parameters were provided by Tecogen (see also http://www.tecogen.com/). The 100 kW Tecogen Premium Power Modules (CM-100) modeled support premium power capabilities and sprint features. This unit consists of an asynchronous inverter-based variable speed internal combustion engine genset with combined heat and power (CHP) and power surge capability. The essence of the CERTS Microgrid technology is that smarts added to the on-board electronics of

[19] Including hot water CHP interconnections, electrical equipment, etc. For more information see also Goldstein, L. et al. 2003.

any microgrid device that allows stable and safe islanded operation without the need for complex supervisory controls. This approach allows plug and play development of a microgrid that can potentially provide high PQR with a minimum of specialized site-specific engineering. A notable feature of the CM-100 is its 200 hour limited surge rating of 125 kW. For more information about the parameters used, see section 4.8.

4.4 Absorption chillers

Absorption chillers use heat to provide the energy needed to drive the cooling process - no mechanically driven compressor is used. The heat from direct combustion, waste heat or solar radiation can be used to drive the process. Two different fluids are involved, a refrigerant and absorbent. Absorption chillers use either lithium bromide-water ($LiBr/H_2O$) or ammonia-water (NH_3/H_2O). The $LiBr/H_2O$ system uses lithium bromide as the absorbent and water as the refrigerant and it is the strong affinity of those two substances that makes the cycle work. The ammonia-water system uses water as the absorber and ammonia as the refrigerant.

At extreme low pressure in the evaporator, e.g. 0.8 kPa, the refrigerant boils at ca. 4°C and evaporates, which extracts heat from the building. Then in the absorber the concentrated lithium bromide mixes with the H_2O vapor and the high affinity of those substances creates the dilute lithium bromide solution as well as the low pressure in the evaporator / absorber chamber. The dilute solution is pumped to the generator, which is heated by gas, steam or waste heat, and the refrigerant is driven back out of the absorbent by boiling producing H_2O vapor. Then the vapor is liquefied in the condenser by cooling water and passed on to the evaporator and the cycle starts over again.

A more detailed and simple description of the $LiBr/H_2O$ absorption chiller process can be found at YORK FORM 155.16-EG1 (604) product description.

In general, there are two different types of absorption chillers available:

- single-effect and
- double-effect chillers.

The single-effect cycle refers to the transfer of fluids through the four major components of the refrigeration machine, namely evaporator, absorber, generator and condenser. Hence, the system uses one condenser and one generator. Single-effect absorption chillers use low pressure steam or hot water as the heat source. The thermal efficiency of single-effect absorption systems is low. Although, the technology is simple, the low efficiency has inhibited the cost competitiveness of single-effect systems. Most new single-effect machines are installed in applications where waste heat is readily available.

The double-effect chiller differs from the single-effect in that there are two condensers and two generators. Although the double-effect machines are more efficient than single-effect machines, they have higher initial capital costs, and require input heat above the boiling point of water.

One big advantage of absorption chillers is that they have no moving parts and this increases the reliability and lifetime. Additionally, almost any heat source can be used to drive the generator of a single effect chiller, which creates a potentially flexible approach.

The performance of absorption chillers is defined by the coefficient of performance (COP) as defined by Equation 4. Absorption chiller COPs show a maximum of 1.2 in the case of double-effect types, while electric compressor chillers can provide COPs of 4 to 6.

$$COP = \frac{Output\,(kW)}{Heat\ Input\,(kW)} \quad \textbf{(4)}$$

As shown in Table 4, there can be a huge variation in the investment costs depending on the auxiliary equipment considered. For this study, the investment costs will be in the upper range due to smaller chiller systems. For all further investigations with DER-CAM the higher \$569/kW (\$2 000/RT) number is used, which was gathered from the East Bay Municipal Utility District case study in Oakland (see also Pacific Region CHP Application Center, 2008).

Within DER-CAM, the absorption chiller capacity is always expressed in terms of electricity offset (electric load equivalent), and therefore, the \$569/kW$_{heat}$ translate to \$127/kW$_{electricity}$ assuming a reference electric chiller with a COP of 4.5 (see also Table 7). Knowing the electric demand, DER-CAM is able to calculate the electricity offset due to absorption chillers. In other words, DER-CAM assumes an installed electric chiller[20] in the base case without any installation of DER technologies. This basic electric chiller can be partly or completely replaced by an absorption chiller, if economically attractive, which creates the electricity offset.

Table 4. Key Characteristics of Absorption chillers

Characteristic	***Single-Effect***	***Double-Effect***
COP	0.6-0.7	0.9-1.2
Specific Investment Costs (\$/RT)	365 at 1000 RT[21], 520 at 300 RT, 2000[22] at 180 RT	625 at 300 RT, 1175[23] at 120 RT
Specific O&M Costs (\$/RT yr.)	12 (at 1000 RT) - 27 (at 500 RT)	15 (at 1000 RT) - 30 (at 500 RT)

Source: DOE Electricity Delivery and Energy Reliability and Pacific Region CHP Application Center, 2008

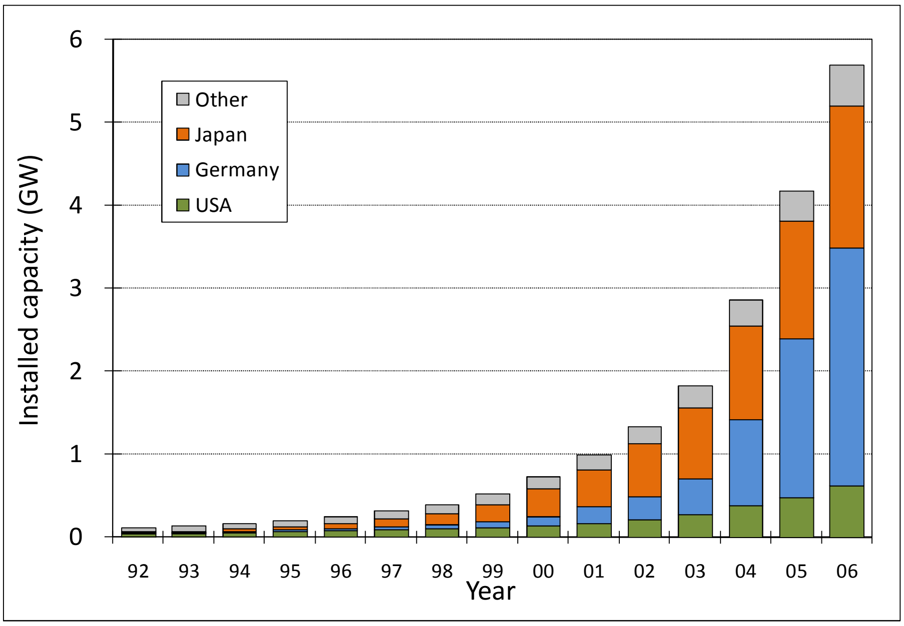
More information on absorption chillers can be found at Advanced Design Guideline Series, 1998, and European Commission Directorate-General for Energy SAVE II Program, 2001.

[20] If the investigated site uses cooling.
[21] 1 RT = 3.517 kW
[22] Based on the East Bay Municipal Utility District case study in Oakland, CA costs are based on year 2002 and 2003, http://www.chpcenterpr.org/PRACLibrary/ProjectProfiles/Index.aspx
[23] Based on the Ritz Carlton case study in San Francisco and 2005\$, http://www.chpcenterpr.org/PRACLibrary/ProjectProfiles/Index.aspx

4.5 Photovoltaics

The three leading International Energy Agency (IEA) countries in adopting PVs are Germany, Japan and the US (IEA PVPS web). In 2006, roughly 5.7 GW of PV was installed in the 18 IEA reporting countries and the adoption curve shows almost exponential growth. Between 2001 and 2006, the total installed capacity increased by 570%. However, the US is lagging but still shows an increase of 370% in the same period (see also IEA PVPS web).

Figure 18. Cumulative installed PV capacity in IEA reporting[24] countries



Source: IEA PVPS web

The most widely used material for solar cells is silicon. Single-crystal silicon and multi-crystalline silicon cells provide the highest efficiency for commercially available technologies and account for 88% of PV modules installed in 2003. Much of the rest is made from amorphous silicon, which is cheaper than the previous mentioned types, but also provides lower efficiency. More information about the efficiency of commercial and test cells can be gathered from Kazmerski Lawrence L. 2006 and NREL b.

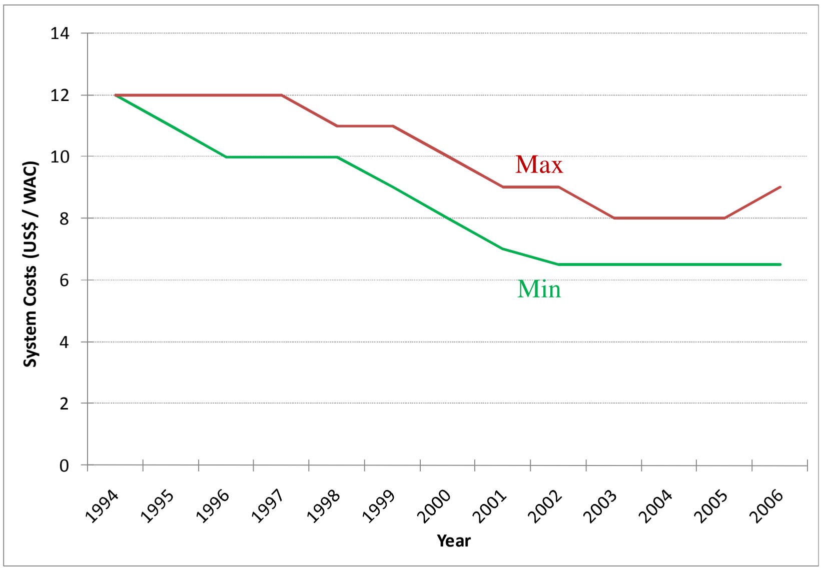
Costs are one of the most important barriers to PV deployment and have decreased by roughly 46% since 1994. The price trend of grid-connected residential PV systems is shown in Figure 19. The current price of single- and multi-crystalline silicon *modules* is approximately \$3.75/WAC (IEA PVPS USA survey report). The *system installation* costs are \$7 to \$9/WAC for roof mounted systems and approximately \$6.50 to \$7.50/WAC for systems bigger than 10 kW.

[24] Reporting IEA countries are Australia, Austria, Canada, Denmark, France, Germany, Great Britain, Israel, Italy, Japan, Mexico, Netherlands, Norway, South Korea, Spain, Sweden, Switzerland, and the United States of America.

The DOE Solar America Initiative targets *module prices* of a $1.25/W from its R&D efforts by 2015 (see also DOE Solar America Initiative), but note that the balance of system costs beyond the modules are considerable.

In the DER-CAM runs, $6 675/kW is used as the current installation cost and $2 670/kW for the heavily subsidized installation cost of the sensitivity run 6 from section 6.

Figure 19. National trends in grid connected residential PV system prices



Source: IEA PVPS USA survey report

4.6 Solar thermal

Solar thermal collectors capture solar radiation and convert it into thermal energy. The heat that is collected may be used immediately or stored. They are classified by IEA as low (<43°C /110°F), medium (43°C/110°F to 82°C/180°F), or high (>82°C /180°F) temperature solar collectors (see also EIA Solar Thermal and Photovoltaic Collector Manufacturing Activities 2006).

The EIA reports for medium and high temperature collectors, which are of interest for absorption chiller and hot water usage, average roughly $200/m^2 (EIA Solar Thermal and Photovoltaic Collector Manufacturing Activities 2006). To account for interconnection/plumbing as well as efficiency, costs of $500/kW[25] are assumed in this research (see also section 4.8).

4.7 CERTS microgrid capabilities

Lasseter Robert, et al. 2002 gives the following definition of a CERTS microgrid: *The Consortium for Electric Reliability Technology Solutions (CERTS) MicroGrid concept assumes an aggregation of loads and microsources operating as a single system providing both power*

[25] Some manufacturer data even suggest higher numbers.

and heat. The majority of the microsources must be power electronic based to provide the required flexibility to insure operation as a single aggregated system. This control flexibility allows the CERTS MicroGrid to present itself to the bulk power system as a single controlled unit that meets local needs for reliability and security.

One of the most important features of the CERTS microgrid is the ability to separate from the macrogrid seamlessly during a grid disturbance, i.e. no disruption to the loads within the micrcorgrid is allowed. Then, when the utility grid returns to normal, the microgrid automatically resynchronizes and seamlessly reconnects. To perform such an operation a universal interconnect device called here the *DER switch* is necessary.

From 2004 to 2006, Northern Power Systems (NPS), the CEC, and the National Renewable Energy Laboratory (NREL) collaborated to create a prototype of a DER switch. Their objective was to consolidate the various power and switching functions as

- power switching
- protective relaying
- metering
- communications, and
- other components,

and incorporate them into a single system with a digital signal processor (DSP).

The DER switch is designed to meet the various relevant standards, such as IEEE 1547[26] and UL 1741,[27] and to minimize custom engineering and site-specific approval processes thereby lowering cost. To maximize applicability and functionality, the switch is also designed to be technology neutral. The controls in the DSP could be used with a circuit breaker, as well as faster semiconductor switching technologies like silicon-controlled rectifier, integrated gate bipolar transistor (IGBT), and integrated gate commutated thyristor (IGCT) technologies, and be applicable to DER assets both conventional synchronous generators or ones with power converters. The full report on the DER switch is Lynch J. et al. 2006.

The main question addressed in this research is: *Does a DER switch and its related CERTS microgrid capabilities change DER adoption?*

[26] IEEE 1547 Standard for Interconnecting Distributed Resources with Electric Power Systems, see also http://grouper.ieee.org/groups/scc21/1547/1547_index.html.

27 Inverters, Converters, Controllers and Interconnection System Equipment for Use with Distributed Energy Resources, see also http://ulstandardsinfonet.ul.com/scopes/1741.html.

4.8 Technology parameters used in the DER-CAM analyses

This work reports results using recently added electrical (conventional lead/acid battery) and thermal storage, capabilities, with both electrical and thermal storage being modeled as inventories. At each hour, energy can either be added up to the maximum capacity, or withdrawn down to a minimum capacity chosen to avoid damaging deep discharge. The rate at which the state of charge can change is constrained, and the state of charge decays hourly. The parameters used for the electrical and thermal storage are shown in following Table 5 (see also Stevens, et al. and Symons, et al.). The menu of available equipment options to DER-CAM for this analysis together with their cost and performance characteristics is shown in Table 6 and Table 7.

Table 5. Energy storage parameters

	Description	electrical	flow battery	thermal
charging efficiency (1)	portion of energy input to storage that is useful	0.9	0.84	0.9
discharging efficiency (1)	portion of energy output from storage that is useful	1[28]	0.84	1
decay (1)	portion of state of charge lost per hour	0.001[29]	0.01[30]	0.01
maximum charge rate (1)	maximum portion of rated capacity that can be added to storage in an hour	0.1	n/a	0.25[31]
maximum discharge rate (1)	maximum portion of rated capacity that can be withdrawn from storage in an hour	0.25	n/a	0.25[32]
minimum state of charge (1)	minimum state of charge as apportion of rated capacity	0.3	0.25	0

source: LBNL estimates, Stevens, et al. and Symons, et al.

While the current set of available technologies is limited, any candidate technology may be included. Technology options in DER-CAM are categorized as either discretely or continuously sized. This distinction is important to the economics of DER because some equipment is subject to strong diseconomies of small scale. Discretely sized technologies are those that would be available to customers only in a limited number of discrete sizes, and DER-CAM must choose an integer number of units, e.g. reciprocating engines have these characteristics. The costs for the

[28] The impact of different discharge levels is subject to further research.

[29] Please note that the decay number used is relatively high due to the fact that the lifetime of lead acid batteries is assumed at the upper end of the lifetime range. At the end of the lifetime the decay increases rapidly. Additionally, the decay increases at higher temperature. However, future investigations should address the impact of different decay numbers.

[30] Preliminary number; future analysis could address the impact of different decay numbers.

[31] Preliminary number; the impact of different maximum charge rates is subject to further investigations.

[32] Preliminary number; the impact of different maximum discharge rates could be the subject to further investigations.

discrete fuel cell[33] technology are interpolated from various studies as described in (Firestone 2004), which is based on data collected by the National Renewable Energy Laboratory (Goldstein et al. 2003). The costs and performance data for the reciprocating engine are based on data provided by Tecogen (see also http://www.tecogen.com/). Continuously sized technologies, on the other hand, are available in such a large variety of sizes that it can be assumed capacity close to the optimal could be acquired. Battery storage costs are roughly consistent with those described by the Electricity Storage Association (see also Electricity Storage Association and chapter 4.1). The installation cost functions for these technologies are assumed to consist of an unavoidable cost (intercept) independent of installed capacity ($) representing the fixed cost of the infrastructure required to adopt such a device, plus a variable cost proportional to capacity ($/kW or $/kWh).

Table 6. Menu of available equipment options, *discrete investments*

	reciprocating engine	fuel cell
capacity (kW)	100	200
sprint capacity (kW)	125	
installed costs ($/kW)	2400	5005
installed costs with heat recovery ($/kW)	3000	5200
variable maintenance ($/kWh)	0.02	0.029
efficiency (%), (HHV)	26	35
lifetime (a)	20	10

Table 7. Menu of available equipment options, *continuous investments*

	electrical storage (lead acid)	thermal storage[34]	flow battery	absorption chiller	solar thermal	Photovoltaics
intercept costs ($)	295	10000	0	20000	1000	1000
variable costs ($/kW or $/kWh)	193[35]	100[36]	220$/kWh and 2125$/kW [37]	127[38]	500[39]	6675[40]
lifetime (a)	5	17	10	15	15	20

33 Reciprocating engines are the most dominant technologies. Investigations show that no fuel cell or micro turbine adoption takes place in our examples due to higher technology costs.

34 Please note that cold thermal storage is not among the set of available technologies, but could be added.

35 $\$/kWh_{electricity}$

36 $\$/kWh_{heat}$

37 Flow batteries are characterized by both the energy content and power rating.

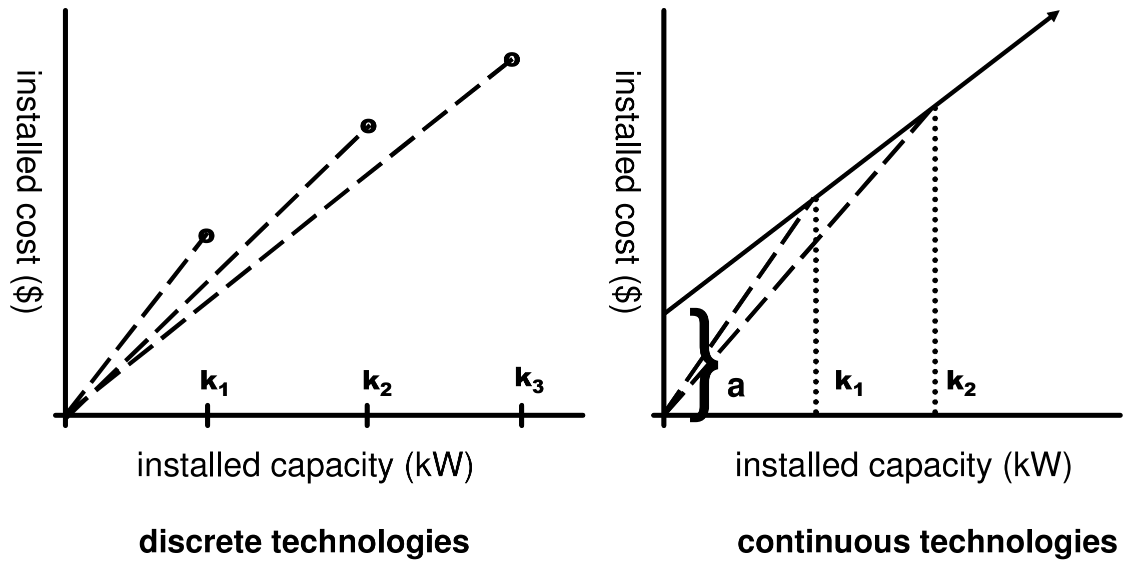
38 abs. chiller capacity is in terms of electricity offset (electric load equivalent).

39 $\$/kW_{of\ recovered\ heat}$

40 $\$/kW_{electricity}$

Please note that both continuous and discrete technologies exhibit economies of scale, but the discrete ones can be more complex and dramatic. Since this particular study focuses on the CM-100, it is clearly critical that it be represented as a discrete technology, but batteries not so. A half of a 100 kW engine makes no sense, and therefore finding the integer choice of gensets that minimizes costs is important. Lead-acid batteries on the other hand, are relatively small and are available in many sizes, so assuming that the exact optimal capacity can be deployed does not detract much from the accuracy of the solution. Please consider Figure 20. The left panel shows a discrete technology with three available sizes, k_1, k_2, and k_3 kW. The cost of larger units is greater but costs per kW decline, as shown by the slopes of the rays to the origin. The right panel shows a continuous technology which can be chosen at any capacity. Nonetheless, note that with an intercept and a constant slope, the costs as shown by the rays to the origin do decline in large sizes.

Figure 20. Discrete versus continuous technologies



5. Tariffs

Actual tariffs for electricity and natural gas for the years 2006, and 2007 were gathered from Pacific Gas and Electric (PG&E), Southern California Edision (SCE), Southern California Gas Company (SoCal), and Consolidated Edison Company of New York (ConEd).

5.1 CA tariffs

5.1.1 Northern California

The California nursing home and data center both purchase electricity and natural gas from PG&E. The electricity tariff has Time-Of-Use (TOU) pricing for both energy and power (demand charge). Demand charges are proportional to the maximum rate of electricity consumption (kW), regardless of the duration or frequency of such consumption over the billing period. Demand charges may be assessed daily (e.g. for some New York DG customers) or

monthly (more common) and may be for all hours of the month or only certain periods (e.g. on, mid, or off peak), or hit just at the hour of peak system-wide consumption.
There are five demand types in DER-CAM applicable to daily or monthly demand charges:

- Non-coincident: incurred by the maximum consumption in any hour.
- On-peak: based only on on-peak hours.
- Mid-peak: based only on mid-peak hours.
- Off-peak: based only on off-peak hours.
- Coincident: based only on the hour of peak system-wide consumption.

PG&E tariffs collect various demand charges based on three summer periods and two winter periods. The PG&E definition of on-peak, mid-peak, and off-peak depends on the season and are specified as follows:

- Summer on-peak: 12:00-18:00 during weekdays
- Summer mid-peak: 08:00-12:00 and 18:00-22:00 during weekdays, all other hours and days: off-peak
- Winter mid-peak: 08:00-22:00 during weekdays, all other hours and days: off-peak.

The demand charge in \$/kW is a significant determinant of distributed generation and electric storage system installations (see also section 6).
A marginal carbon emission factor of 140 g/kWh for electricity purchased from PG&E was assumed (Marnay et al. 2002). This marginal emission factor is used within DER-CAM to determine the carbon emissions from the macrogrid and to be able to estimate the carbon reductions of the microgrid in different investment cases.

Table 8. Energy prices, effective Nov. 2007

electricity	**summer (May – Oct.)**		**winter (Nov. – Apr.)**	
	electricity ($/kWh)	**demand ($/kW)**	**electricity ($/kWh)**	**demand ($/kW)**
on-peak	0.163	15.040		
mid-peak	0.124	3.580	0.116	1.860
off-peak	0.094		0.098	
fixed ($/day)	9.035			

natural gas	
0.035 for summer and 0.037 for winter	$/kWh
1.026 for summer and 1.084 for winter	$/therm
4.955	fixed ($/day)

Source: PG&E

5.1.2 Southern California

Table 9 shows the prices used for the CA school located near Riverside, which are based on SCE electricity rates and SoCal natural gas prices. The definition of on-peak, mid-peak, and off-peak for the SCE territory is as follows:

- Summer on-peak: 12:00-18:00 weekdays
- Summer mid-peak: 08:00-12:00 and 18:00-23:00 weekdays, all other hours and daysare off-peak
- Winter mid-peak: 08:00-21:00 during weekdays, all other hours and days: off-peak.

Table 9. Energy prices, effective July 2007 for electricity and Nov. 2006 for natural gas

electricity	summer (June – Sep.)		winter (Oct. – May)	
	electricity ($/kWh)	**demand ($/kW)**	**electricity ($/kWh)**	**demand ($/kW)**
Non-coincident		9.710		9.710
on-peak	0.113	15.370		
mid-peak	0.093	5.190	0.095	
off-peak	0.068		0.071	
fixed ($/month)	414.980			

natural gas	
0.033	$/kWh
0.967	$/therm
0.411	fixed ($/day)

Source: SCE TOU electricity tariff and SoCal natural gas tariff

A marginal carbon emission factor of 215 g/kWh for electricity purchased from SCE was also obtained from Marnay et al. 2002.

5.2 NYC tariffs

For all investigated New York City sites, the prices in Table 10 were used. One big difference compared to California is the absence of time variability tariffs. No electricity time-of-use tariff is in use, and there is only a seasonal variation in the demand charge. Additionally, the natural gas energy price is higher than in CA, which might discourage DG installation (see also section 6.4).

Table 10. Energy Prices[41], effective April 2007

electricity	summer (June – Sep.)		winter (Oct. – May)	
	electricity ($/kWh)	**demand ($/kW)**	**electricity ($/kWh)**	**demand ($/kW)**
all day long	0.120[42]	14.210[43]	0.120	11.360[44]
fixed ($/month)	71.050			

natural gas	
0.049	$/kWh
1.436	$/therm
0.419	fixed ($/day)

Source: ConEd

A marginal carbon emission factor of 200 g/kWh for electricity purchased from ConEd was assumed (see also Cadmus 1998).

[41] Including all surcharges for service area NYC.
[42] Please note that there is a slight monthly variation in the electricity price depending on the market supply charge and monthly adjustment clause. However, these adjustments do not follow regular monthly patterns and are unpredictable. The variation for the observed year was between 0.10 and 0.13$/kWh.
[43] For the first 300 kW. If the load exceeds 300kW the demand charge decreases by 10%
[44] For the first 300 kW. If the load exceeds 300kW the demand charge decreases by 12%

6. Results

In order to address how carbon emissions and total site energy costs vary when electrical and thermal storage as well as switch capabilities are present, seven DER-CAM runs have been performed:

1. a *do-nothing* case in which all DER investment is disallowed, i.e., the site meets its local energy demands solely by purchases from utilities;
2. an *invest* case that finds the optimal DER investment at current price levels as described in section 4.8;
3. a *low storage and PV price* run, with low storage prices of \$50/kWh for thermal storage, \$60/kWh for electric storage, and \$4175/kW for PV;
4. a *forced investment* run to assess the value of storage systems. Run 3 was repeated forcing the same investments as in the *low storage and PV price* run 3, but in which storage is disallowed;
5. a *low storage, PV, and solar thermal price* run, additionally to the settings of run 3, solar thermal costs are reduced to \$450/kW;
6. a *low storage price and 60% PV price reduction* run, and finally
7. a *switch* run where a certain percentage of the total electric load is considered critical and must be supplied during a macrogrid power failure. For the nursing home, 50% of base and 10% of peak load (defined as any hourly load above the base) must be met; for the school, 25% of base load must be met; and for the data center, the entire load must be met. In these runs, the CERTS microgrid capabilities are applied and the runs were performed with current cost and technology parameters according Table 5, Table 6, and Table 7; no cost reduction / incentive was used. A short description of the CERTS microgrid capabilities can be found in section 4.7.

One important note is that in switch runs, run 7, the reliability and availability of the different technologies such as ICEs, batteries or PVs is important. For example, PV cannot be used as backup during the night, batteries might not be fully charged when a grid failure occurs, and lead-acid batteries can only be discharged to 30% of total battery capacity to avoid battery damaging. These boundaries limit the potential of the different technologies to contribute to sensitive loads during a grid failure. DER-CAM calculates the availability / reliability of storage technologies as well as PV depending on the charge / discharge cycle and solar radiation. The reliability of ICEs and fuel cells was assumed to be 90%. Reliability issues are only considered in the *switch* run.

6.1 CA nursing home results

The major results for these seven runs are shown in Table 11. In the *do-nothing* case (run 1), the nursing home meets all of its electricity demand via utility purchases and heating requirements by burning natural gas. The annual operating cost is \$964 000, and 1 088 t of elemental carbon are emitted each year. In the *invest* case (run 2), technology parameters from Table 5, Table 6 and Table 7 are taken and DER-CAM finds the optimal system.
The optimal system chosen for the site consists of three Tecogen gas engines, a 48 kW absorption chiller, and a 134 kW solar thermal system. Please note that the absorption chiller

capacity is expressed in electricity equivalent of a 4.5 COP electric chiller, and therefore, the 48 kW translates into a 61 RT absorption chiller. At current price levels, neither electrical nor thermal storage is economically attractive. Relative to the *do-nothing* case, the expected annual savings for the optimal DER system is \$38 000/a (ca. 4%) while the elemental carbon emission reduction is 143 t/a (ca. 13%).

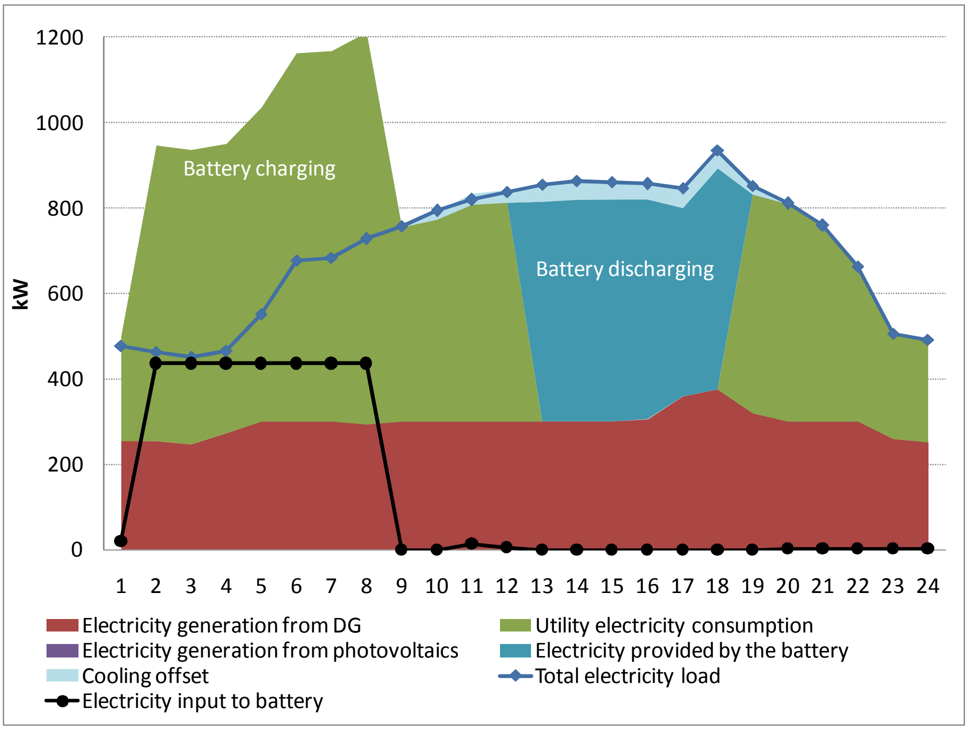
Table 11. Annual results for the northern California nursing home

	run 1	run 2	run 3	run 4	run 5	run 6	run 7
	do-nothing	invest in all technologies	low storage costs and PV incentive of 2.5\$/W	force low storage / PV and solar thermal results	low storage and PV (incentive 2.5\$/W) costs & low solar thermal costs (minus 10%)	low storage and PV costs (PV incentive 60%)	switch run
Equipment							
Tecogen 100 kW with HX (kW)	n/a	300	300	300	300	300	300
switch size (kW)		n/a	n/a	n/a	n/a	n/a	260
abs. chiller (kW in terms of electricity)		48	46	46	85	40	48
solar thermal collector (kW)		134	109	109	443[45]	43	134
PV (kW)		0	0	0	0	517	0
electric storage (kWh)		0	4359	n/a	4148	2082	0
flow battery - energy (kWh)		0	0	0	0	0	0
flow battery - power (kW)		0	0	0	0	0	0
thermal storage (kWh)		0	123	n/a	196	47	0
annual costs (k\$)							
electricity	758.02	429.42	357.41	429.10	369.58	261.83	429.42
NG	205.88	359.14	359.29	360.62	336.06	362.88	359.14
onsite DG technologies	n/a	137.81	199.45	136.66	209.29	285.45	135.50[46]
benefit from switch (\$/kW/a)	n/a	n/a	n/a	n/a	n/a	n/a	<=25
Total	963.90	926.37	916.15	926.39	914.92	910.16	924.06
% savings compared to do-nothing	n/a	3.89	4.95	3.89	5.08	5.58	4.13
annual energy consumption (GWh)							
electricity	5.76	3.23	3.33	3.22	3.45	2.40	3.23
NG	5.70	9.99	10.00	10.03	9.35	10.10	9.99
annual carbon emissions (t/a)							
emissions	1087.74	945.05	959.95	946.31	943.97	833.96	945.05
% savings compared to do-nothing	n/a	13.12	11.75	13.00	13.22	23.33	13.12

[45] Assuming 50% efficiency results in ca. 880 m^2 of solar thermal panel area.
[46] Includes benefits from switch.

Considering low storage prices of $60/kWh for electrical and $50/kWh for thermal storage, the annual operating costs drop by almost 5% (see run 3). However, the elemental carbon reduction is only ca. 12%. This means that the carbon emissions reduction is lower with adoption of electrical and thermal storage than without them (run 2). This finding is supported by run 4, which forces the same results as in the *low storage* cost run 3, but disallows storage adoption. The major driver for electrical storage adoption is the objective to reduce energy costs, and this can be effectively reached by avoiding electricity consumption during on-peak hours. In this run, the battery is charged by cheaper off-peak electricity and displaces utility consumption during on-peak hours (see also Figure 21). The results for run 3 show increased electricity consumption due to charging/discharging inefficiency and decay. Assuming the same marginal carbon emission rate during on-peak and off-peak hours results in additional carbon emissions. Note that this effect could be worse if off-peak electricity were more carbon intensive, e.g. if coal became the marginal fuel.

Figure 21. CA nursing home electricity pattern: July weekday low storage & PV cost (run 3)



As shown in run 6, the combination of PV and electrical storage brings together the positive economic effects of batteries with the positive environmental effects of PV. The annual operating costs drop by ca. 5.60% while the elemental carbon emission reduction is 23.33% compared to the *do-nothing* case run 1. However, a part of the battery capacity is replaced by direct PV usage as indicated in Figure 22 and PV is still not used for battery charging. Figure 21 and Figure 22 also show that at evening peak hours, e.g. 6 pm, an increase in Tecogen capacity above nameplate due to sprint capacity features helps to satisfy the demand. Another important finding for the nursing home is that the number of installed Tecogen reciprocating engines stays constant in all performed runs. The reason for this is that high electricity demand combined with high heat demand makes CHP attractive, see also Figure 5.

Figure 22. CA nursing home electricity pattern: July weekday low storage & 60% PV price reduction (run 6)

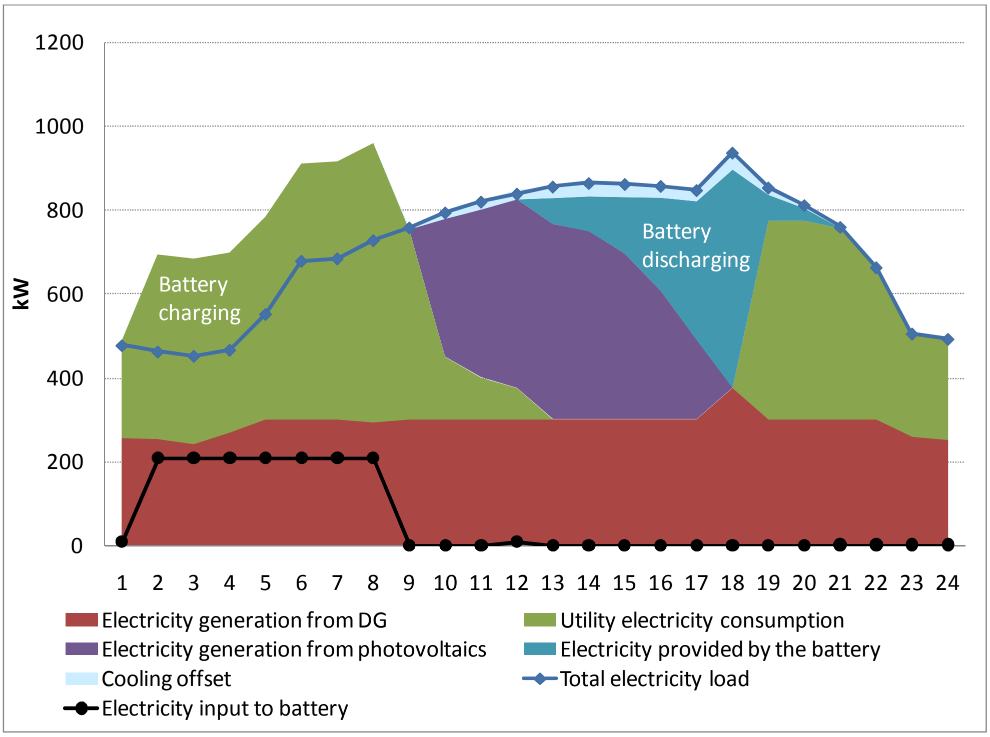
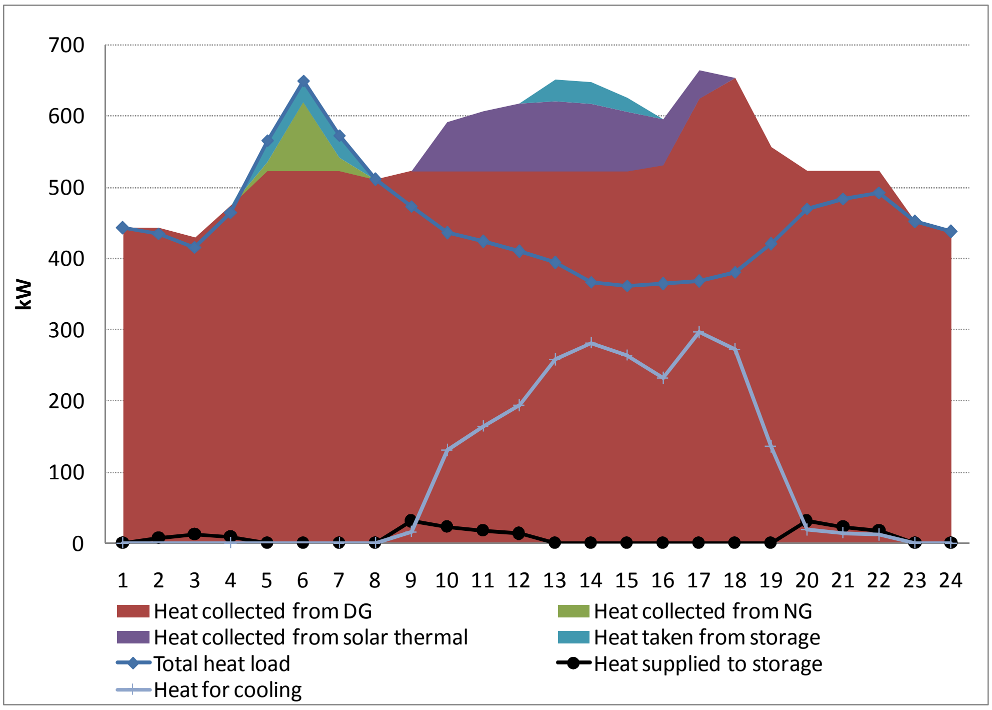


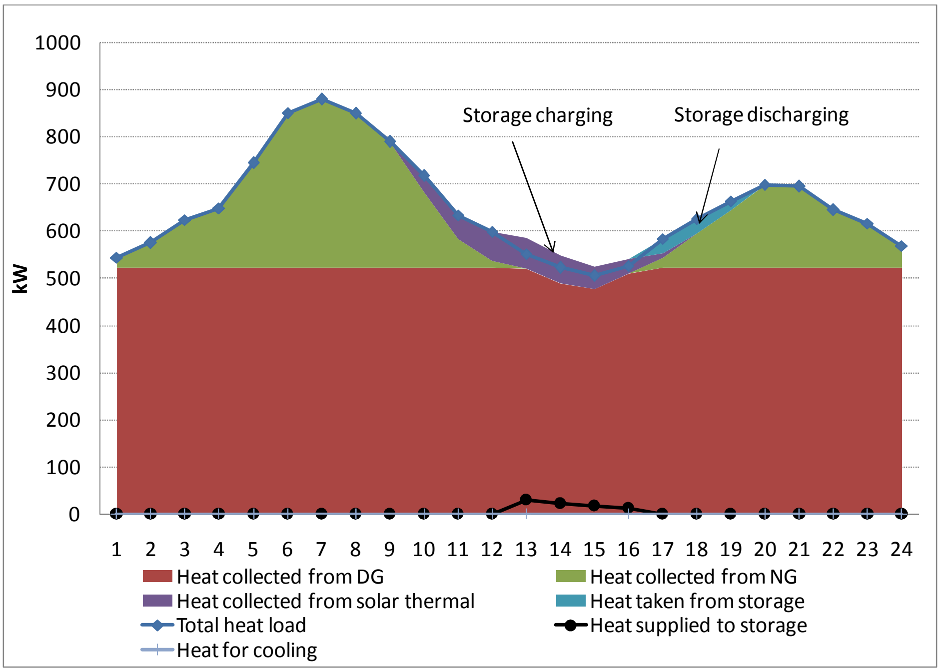
Figure 23. CA Nursing home heat pattern: July Weekday Low Storage & PV Cost (run 3)



Please also note that these results have been estimated assuming perfect reliability of DER equipment. Imperfect reliability would mostly affect the demand charges, but would also have other effects on the value of the project, e.g., the standby charge as back up to DER would have to be provided by the utility (see also section 6.8).

Note that since electric cooling loads can be offset by the absorption chiller, there are four possible ways to meet cooling loads: utility purchases of electricity, on-site generation of electricity, absorption chiller offsets, and stored electricity in batteries. By finding the optimal combination for each hour of the test year, DER-CAM provides the microgrid with an optimal operating schedule for each of its installed technologies (Figure 23 and Figure 24).

Figure 24. CA nursing home heat pattern: Jan. weekday low storage & PV cost (run 3)



Finally, to supply 50% of the base and 10% of the peak remaining load during a macrogrid failure, a switch of ca. 260 kW is necessary. However, the CERTS microgrid capabilities do not change any of the installed DER equipment runs, compared to run 2. The cost effective technologies are already in place. The CERTS microgrid capabilities add costs, but also add benefits to the micorgrid and these are the reasons why the objective function changes (see also Table 11). The incremental costs for the CERTS microgrid capabilities are $25/kW based on Tecogen data. A whole set of different switch runs, with different level of benefits, was performed. The first run with a lower objective function (= annual energy costs) than run 2 was selected. In this way the value of the CERTS microgrid capability can be determined. These sensitivity analyses were performed in $25/kW benefit increments. The essence of this approach is that installed capacity is being made cheaper to represent the benefits it delivers. The implied benefit from CERTS microgrid capabilities for the CA nursing home is quite little, less than $25/kW (see Table 11). One reason why ICEs are favored is the higher availability of 90% compared to a lower availability of batteries. The availability of batteries is calculated internally to 15% based on the optimal charge and discharge cycles. However, those availability factors apply only to *switch* runs, no availability is considered in the other runs.

6.2 CA school results

The same runs as for the northern California nursing home were performed and show a similar pattern; higher carbon emissions with storage due to storage inefficiencies and charging by grid power (see Table 12). However, the major difference between the nursing home and the school is the absence of any internal combustion engines. The low off-peak electricity and heating demand combined with cheap electricity during off-peak hours (compare Table 8 and Table 9) makes the adoption of natural gas engines with CHP unattractive.

The major results for the seven runs are shown in Table 12. In the *do-nothing* case (run 1), the school meets all of its electricity demand via utility purchases and burns natural gas to meet all of its heating requirements. The annual operating cost is $288 000, and 360 t of elemental carbon is emitted each year. In *the invest* case (run 2) technology parameters from Table 5, Table 6 and Table 7 are taken and DER-CAM finds the optimal system.

The optimal system for the site consists of a 139 kW absorption chiller, and a 65 kW solar thermal system. Please note that the absorption chiller capacity is expressed in electricity equivalent of a 4.5 COP electric chiller, and therefore, the 139 kW translate into a 178 RT absorption chiller.

At current price levels, electrical storage, thermal storage, and ICE are all economically unattractive. Relative to the do-nothing case, the expected annual savings for the optimal DER system are $8270/a (ca. 3%) while the elemental carbon emission reduction is 2 t/a (ca. 0.6%). Please note that the absorption chiller uses heat from burning natural gas and solar thermal directly – no waste heat is utilized due to missing Tecogen units.

Considering low storage prices of $60/kWh for electrical and $50/kWh for thermal storage, the annual operating costs drop by almost 13% (see run 3). However, the elemental carbon emission increases by ca. 2%. This finding is also proven by run 4, which forces the same results as in the low storage cost run 3, but disallows storage adoption. Again, as for the nursing home, the major driver for electrical storage adoption is the objective to reduce energy costs, and this is reached by avoiding electricity consumption during on-peak hours and charging the batteries with off-peak electricity (see Figure 25). The installed solar thermal collectors are basically used to provide heat and hot water during the weekdays (Figure 27 and Figure 28). In contrast, thermal storage is mostly used on weekends and charged during weekend days.

Considering lower PV prices *and* low storage prices (run 6), a major decrease in installed battery capacity combined with a 181 kW PV installation is reached. Again, PV is not used to charge batteries, rather, they are charged by cheap off-peak electricity (Figure 26). However, due to PV output, the annual carbon emissions drop by ca. 19% (see Table 12).

Finally, to supply 25% of the base load during a macrogrid failure, a switch of 9.69 kW is necessary. However, the CERTS microgrid capabilities do not overcome the disadvantages of ICEs, and no Tecogen unit is installed. To satisfy the switch constraint within DER-CAM, the installation of 47 kWh of electrical storage is chosen and this provides the PQR benefits. Again, a whole set of different *switch* runs[47], with different levels of benefits, was performed. The first run with a lower objective function (= annual energy costs) than run 2 has been selected. Those sensitivity analyses were performed in $25/kW benefit increments. The implied benefit from CERTS microgrid capabilities for the CA school is very little, less than $25/kW (see Table 12).

Table 12. Annual results for the southern California school

	run 1	run 2	run 3	run 4	run 5	run 6	run 7
	do-nothing	invest in all technologies	low storage costs and PV incentive of 2.5$/W	force low storage / PV and solar thermal results	low storage and PV (incentive 2.5$/W) costs & low solar thermal costs (minus 10%)	low storage and PV costs (PV incentive 60%)	switch run
Equipment							
Tecogen 100 kW with HX (kW)	n/a	0	0	0	0	0	0
Switch size (kW)		n/a	n/a	n/a	n/a	n/a	9.69
abs. chiller (kW in terms of electricity)		139	106	106	106	101	136
solar thermal collector (kW)		65	72	72	94	72	65
PV (kW)		0	0	0	0	181	0
electric storage (kWh)		0	2279	n/a	2279	1518	47
flow battery - energy (kWh)		0	0	0	0	0	0
flow battery - power (kW)		0	0	0	0	0	0
Thermal storage (kWh)		0	41	n/a	16	41	0
annual costs (k$)							
electricity	263.93	245.90	186.96	248.77	186.96	153.24	0.00
NG	24.19	26.51	24.03	24.03	22.61	23.96	26.47
onsite DG technologies	n/a	7.44	40.02	7.36	41.02	71.98	253.49[48]
benefit from switch ($/kW/a)	n/a	n/a	n/a	n/a	n/a	n/a	< 25
Total	288.12	279.85	251.01	280.16	250.59	249.18	279.96
% savings compared to do-nothing	n/a	2.87	12.88	2.76	13.02	13.51	2.83
annual energy consumption (GWh)							
electricity	1.51	1.48	1.54	1.49	1.54	1.19	1.48
NG	0.73	0.80	0.72	0.72	0.68	0.72	0.80
annual carbon emissions (t/a)							
emissions	360.35	358.26	367.73	356.27	365.61	291.34	358.48
% savings compared to do-nothing	n/a	0.58	-2.05	1.13	-1.46	19.15	0.52

[47] Please note that the switch runs were performed with technology parameters from Table 5, Table 6, and Table 7.
[48] Includes benefits from switch.

Figure 25. CA school electricity pattern: May weekday low storage & PV cost (run 3)

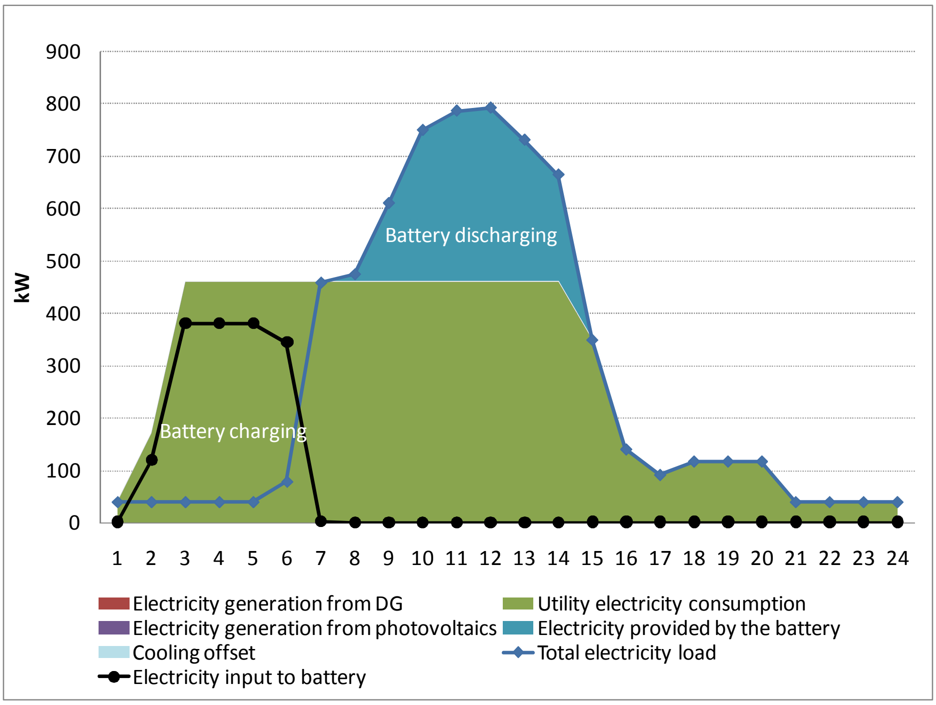


Figure 26. CA school electricity pattern: May weekday low storage & 60% PV price reduction (run 6)

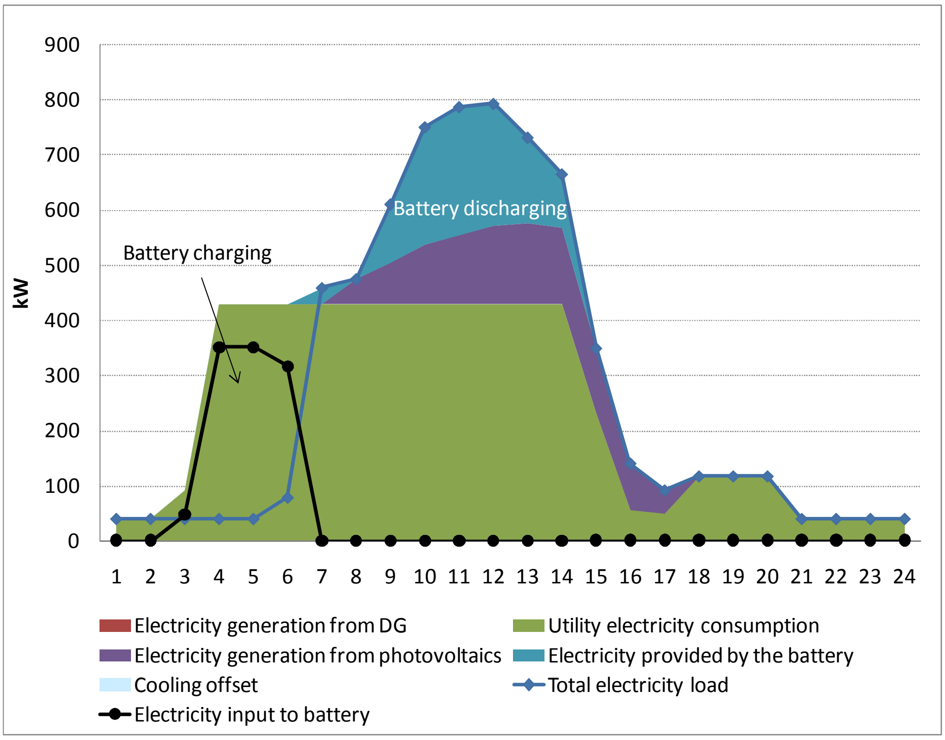


Figure 27. CA school heat pattern: May weekday low storage & PV cost (run 3)

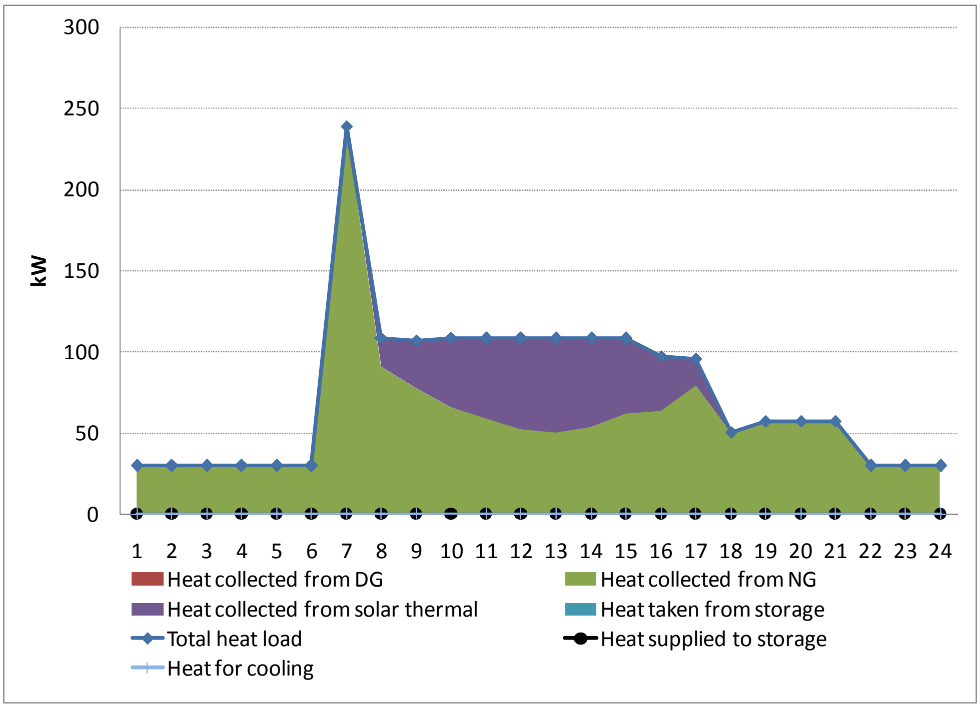
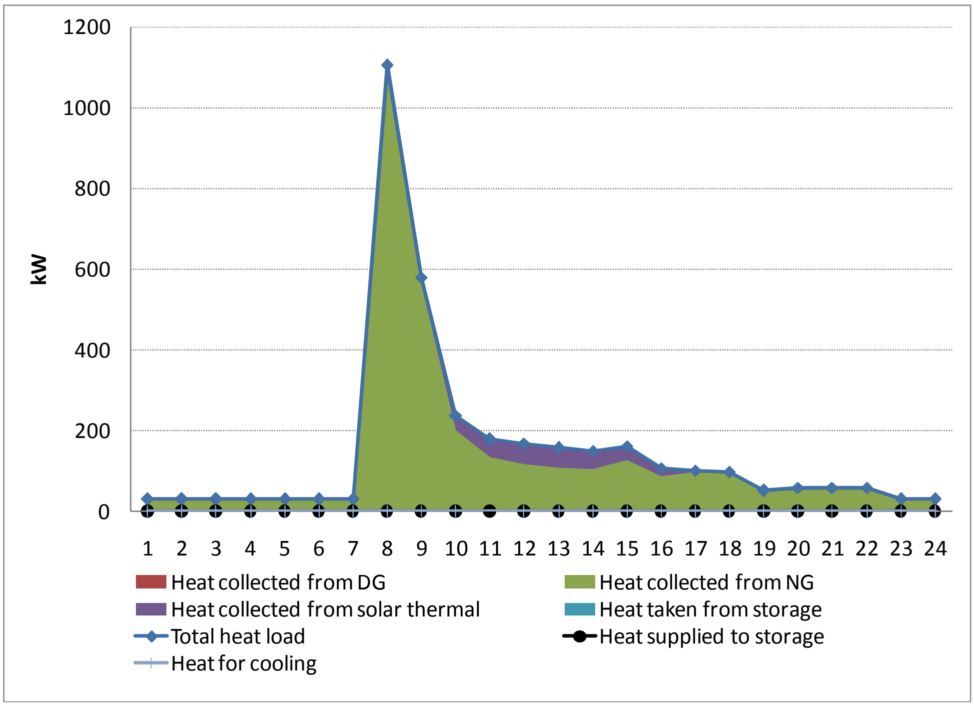


Figure 28. CA school heat pattern: January weekday low storage & PV cost (run 3)



6.3 CA data center results

The runs performed for the data center in the Bay Area show no installation of DG-CHP units, except in the *switch* run. With no heat load, no hot water demand, and an installed economizer which lowers the cooling load especially during the nights, the potential for adoption of DG-CHP for this site is limited.

Table 13. Annual results for the northern California data center

	Run 1	run 2	run 3	run 4	run 5	run 6	run 7
	do-nothing	invest in all technologies	low storage costs and PV incentive of 2.5$/W	force low storage / PV and solar thermal results	low storage and PV (incentive 2.5$/W) costs & low solar thermal costs (minus 10%)	low storage and PV costs (PV incentive 60%)	switch run
Equipment							
Tecogen 100 kW with HX (kW)	n/a	0	0	0	0	0	1600
switch size (kW)		n/a	n/a	n/a	n/a	n/a	1788
abs. chiller (kW in terms of electricity)		141	108	108	108	116	316
solar thermal collector (kW)		0	0	0	0	0	0
PV (kW)		0	0	0	0	1577	0
Electric storage (kWh)		0	13478	n/a	13478	6434	0
flow battery - energy (kWh)		0	0	0	0	0	0
flow battery - power (kW)		0	0	0	0	0	0
thermal storage (kWh)		0	0	n/a	0	0	0
annual costs (k$)							
electricity	1478.36	1459.46	1239.89	1464.53	1239.89	949.11	871.24
NG	1.78	9.73	7.20	5.86	7.20	6.01	322.50
onsite DG technologies	n/a	3.99	195.51	3.54	195.51	467.12	249.36[49]
Benefit from switch ($/kW/a)	n/a	n/a	n/a	n/a	n/a	n/a	125.00
Total	1480.15	1473.18	1442.59	1473.93	1442.59	1422.24	1443.10
% savings compared to do-nothing	n/a	0.47	2.54	0.42	2.54	3.91	2.50
annual energy consumption (GWh)							
electricity	11.42	11.39	11.74	11.41	11.74	8.91	8.44
NG	0.00	0.23	0.15	0.12	0.15	0.12	9.14
annual carbon emissions (t/a)							
emissions	1598.92	1606.13	1650.98	1602.62	1650.98	1253.97	1632.06
% savings compared to do-nothing	n/a	-0.45	-3.26	-0.23	-3.26	21.57	-2.07

[49] Includes benefits from switch.

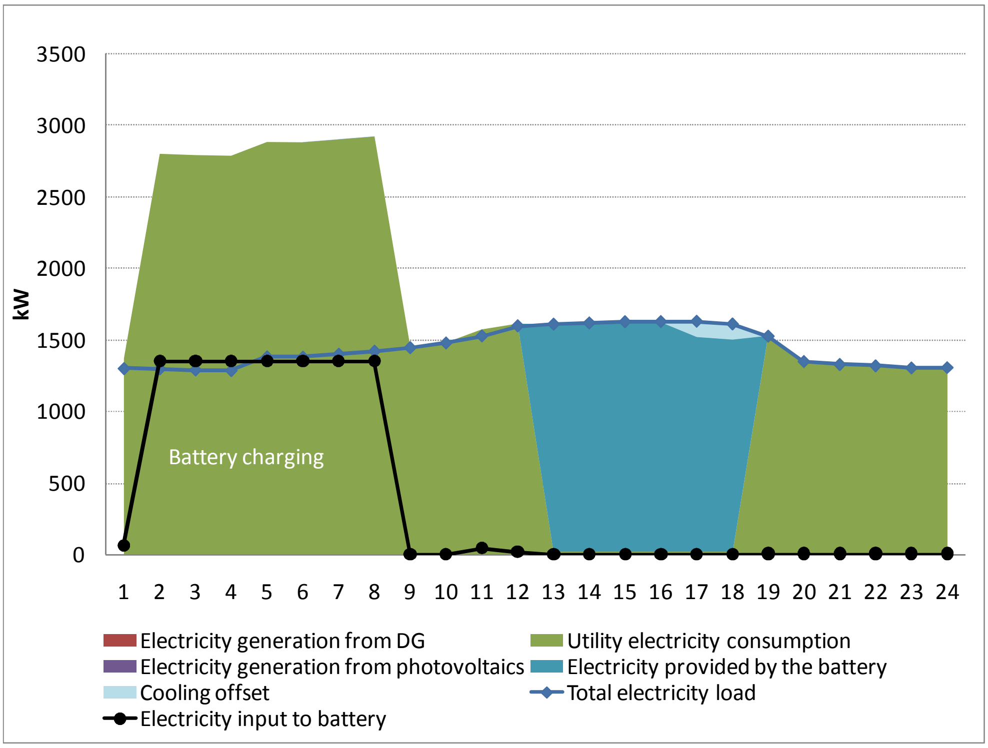
The major results for the seven runs are shown in Table 13. In the *do-nothing* case (run 1), the data center meets all of its electricity demand via utility purchases and burns natural gas to meet all of its heating requirements. The annual operating cost is \$1 480 000, and 1 599 t of elemental carbon is emitted each year. In the *invest* case (run 2) technology parameters from Table 5, Table 6 and Table 7 are taken and DER-CAM finds the optimal system.

The optimal system for the site consists of a 141 kW absorption chiller only. Please note that the absorption chiller capacity is expressed in electricity equivalent of a 4.5 COP electric chiller, and therefore, the 141 kW translate into a 180 RT absorption chiller.

At current price levels, electrical storage, thermal storage, solar thermal collectors, PVs, and ICEs are all economically unattractive. Relative to the *do-nothing* case, the expected annual savings for the optimal DER system is \$7 000/a (ca. 0.5%) while the elemental carbon emissions *increases* by 7 t/a (ca. 0.5%). This increase in emissions is caused by the absorption chiller using heat from burning natural gas directly instead of utilizing waste heat because no Tecogen or fuel cell units were chosen.

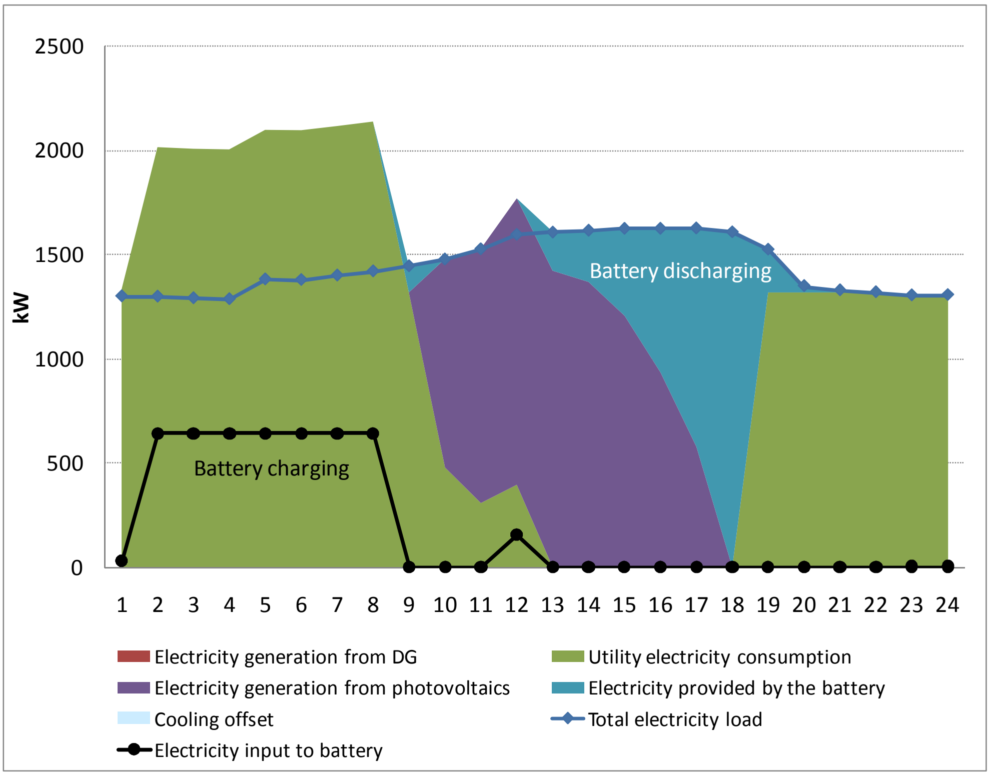
Considering low storage prices of \$60/kWh for electrical and \$50/kWh for thermal storage, the annual operating costs drop by 2.5% (see run 3). However, the elemental carbon emission *increases* by ca. 3%. The combination of burning natural gas and the huge amount of installed battery capacity (ca. 13.5 MWh), combined with the inefficiency of the batteries, increases the carbon emissions. Again, the batteries are charged by off-peak electricity (Figure 29).

Figure 29. CA data center electricity pattern: July weekday low storage & PV cost (run 3)



A positive economic as well as environmental effect can be reached by adding PV to the low storage run. Considering lower PV prices *and* low storage prices (run 6) a major decrease in carbon emissions of ca. 22% is found. Figure 30 shows that almost the entire battery capacity is charged by cheap off-peak electricity. Only at noon when solar radiation hits its maximum is a minor amount of PV electricity used for battery charging.

Figure 30. CA data center electricity pattern: July weekday low storage & 60% PV price reduction (run 6)



The *switch* run[50] for the data center changes the situation completely. Assuming that the data center has a very high critical load of 100%, 16 Tecogen units will be installed. Due to the availability of waste heat from the Tecogen units, the installed absorption chiller capacity increases by 224% compared to run 2. The incremental costs for the CERTS microgrid capabilities are $25/kW based on Tecogen data. A whole set of different switch runs, with different level of benefits, was performed. Again, a run with a lower objective function than run 2 was selected. Those sensitivity analyses were performed in $25/kW benefit increments. The implied benefit from CERTS microgrid capabilities for the CA data center is $125/kW (see Table 13). As already mentioned, the ICEs' high availability makes them favorable over batteries. However, those availability factors apply only to *switch* runs, with no availability is considered in the other runs.

[50] Please note that the switch runs were performed with technology parameters from Table 5, Table 6, and Table 7.

6.4 NYC nursing home results

A major difference for the NYC sites is the almost flat electricity tariff ($/kWh) and the seasonal demand charge ($/kW). This circumstance translates directly in a lower incentive to avoid on-peak power/energy consumption. Additionally, the 25% higher natural gas price ($/kWh) in NYC compared to PG&E service territory has a negative influence on ICE installations and no Tecogen unit is selected by DER-CAM, except in the *switch* run.

As with the CA sites, seven major runs have been performed. The major results for these seven runs are shown in Table 14. In the *do-nothing* case (run 1), the nursing home meets all of its electricity demand via utility purchases and burns natural gas to meet all of its heating requirements. The annual operating cost is $1 195 500, and 1 555 t of elemental carbon are emitted each year. In the *invest* case (run 2) technology parameters from Table 5, Table 6 and Table 7 are taken and DER-CAM finds the optimal system.

The optimal system for the site consists of a 100 kW absorption chiller[51] and a 1438 kW solar thermal system. At current price levels, electrical storage, thermal storage, PVs, and ICEs are all economically unattractive. Relative to the *do-nothing* case, the expected annual savings for the optimal DER system is $34 230/a (ca. 2.9%) while the elemental carbon emission reduction is 116 t/a (ca. 7.5%). Considering the lower NYC solar radiation compared to California, the installation of the huge solar thermal system is very surprising (see also Appendix B). It seems that the high heating demand combined with the absence of DG-CHP units compensates for the lower solar radiation.

Applying lower storage prices of $60/kWh for electrical and $50/kWh for thermal storage, the annual operating costs drop by almost 4% and the elemental carbon reduction is ca. 12.5%. In contrast to the CA nursing home, the adoption of electrical and thermal storage improves the environmental benefits (see also run 3). This finding is proven by run 4, which forces the same results as in the *low storage cost* run 3, but disallows storage adoption. What is so different about the CA nursing home that causes it to show a complete different pattern? It is the *absence* of electrical storage and the *presence* of a big thermal storage system. The flat high electricity tariff of $0.12/kWh prevents almost all electrical storage adoption. The installed battery capacity here is only ca. 7% of the installed battery capacity of the CA nursing home. The reduced battery capacity also reduces the carbon emissions related to battery inefficiencies. Additionally, the big solar thermal system in combination with the huge thermal storage system contributes to the positive environmental effect. The adopted thermal storage system is 39.5 times bigger than in the California nursing home case.

Figure 31 shows a further important impact of the flat electricity tariff: the battery is almost equally charged by off-peak and on-peak times. This shows impressively the power of TOU tariffs on the battery charge/discharge cycle.
Finally, Figure 32 and Figure 33 show the seasonal difference in the heat pattern. During the summer months, the heat storage is used excessively to provide heat during the night, morning, and evening hours. During winter months, almost no heat storage utilization takes place. Figure

[51] In terms of electricity equivalent of a reference electric chiller with a COP of 4.5.

32 also shows the cooling offset by utilization of solar thermal heat, which is used in the absorption chiller.

Considering lower PV prices *and* low storage prices (run 6), no difference to run 3 is reached and PV is not attractive.

Table 14. Annual results for the NYC nursing home

	run 1	run 2	run 3	run 4	run 5	run 6	run 7
	do-nothing	invest in all technologies	low storage costs and PV incentive of 2.5$/W	force low storage / PV and solar thermal results	low storage and PV (incentive 2.5$/W) costs & low solar thermal costs (minus 10%)	low storage and PV costs (PV incentive 60%)	switch run
Equipment							
Tecogen 100kW with HX (kW)	n/a	0	0	0	0	0	200
Switch size (kW)		n/a	n/a	n/a	n/a	n/a	270
abs. chiller (kW in terms of electricity)		100	112	112	134	112	88
solar thermal collector (kW)		1438	2350	2350	2773	2350	1250
PV (kW)		0	0	0	0	0	0
electric storage (kWh)		0	294	n/a	294	294	311
Flow battery - energy (kWh)		0	0	0	0	0	0
Flow battery - power (kW)		0	0	0	0	0	0
thermal storage (kWh)		0	4862	n/a	5470	4862	0
annual costs (k$)							
electricity	845.66	825.89	823.68	816.12	817.27	823.68	636.87
NG	349.84	256.97	171.46	236.35	153.72	171.46	382.28
onsite DG technologies	n/a	78.41	153.46	126.09	164.46	153.46	160.12[52]
benefit from switch ($/kW/a)	n/a	n/a	n/a	n/a	n/a	n/a	<25
Total	1195.50	1161.27	1148.60	1178.56	1135.45	1148.60	1179.27
% savings compared to do-nothing	n/a	2.86	3.92	1.42	5.02	3.92	1.36
annual energy consumption (GWh)							
electricity	6.02	5.90	5.95	5.82	5.90	5.95	4.55
NG	7.14	5.24	3.50	4.82	3.13	3.50	7.80
annual carbon emissions (t/a)							
Emissions	1555.23	1439.26	1361.49	1402.20	1334.08	1361.49	1293.99
% savings compared to do-nothing	n/a	7.46	12.46	9.84	14.22	12.46	16.80

[52] Includes benefits from switch.

Figure 31. NYC nursing home electricity pattern: July weekday low storage & PV cost (run 3)

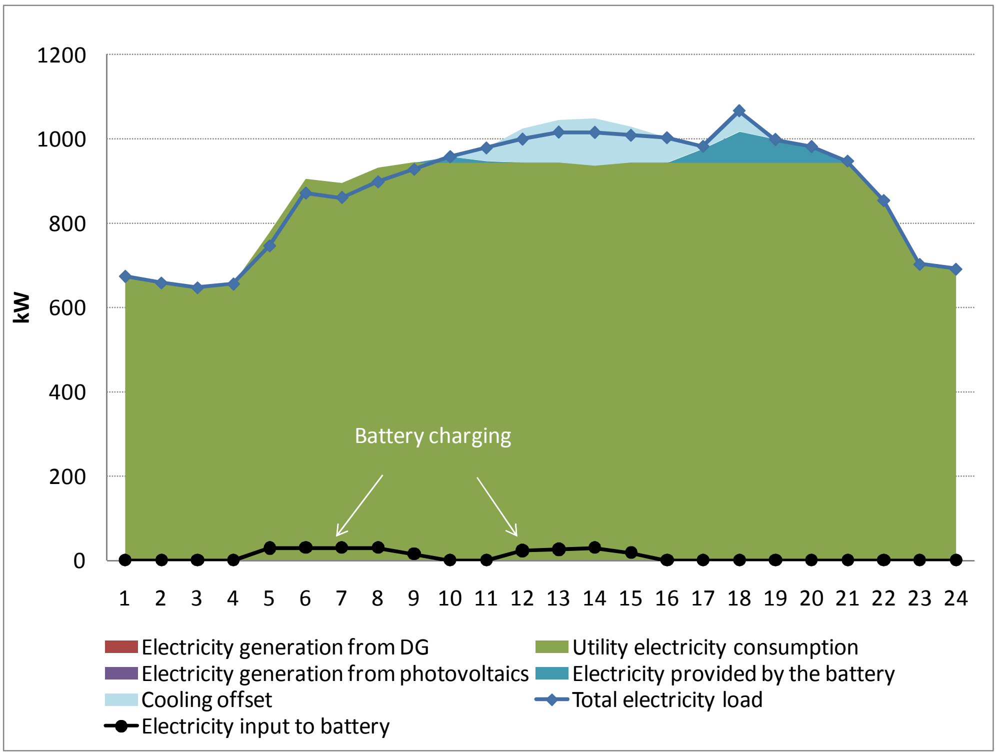


Figure 32. NYC nursing home heat pattern: July weekday low storage & PV cost (run 3)

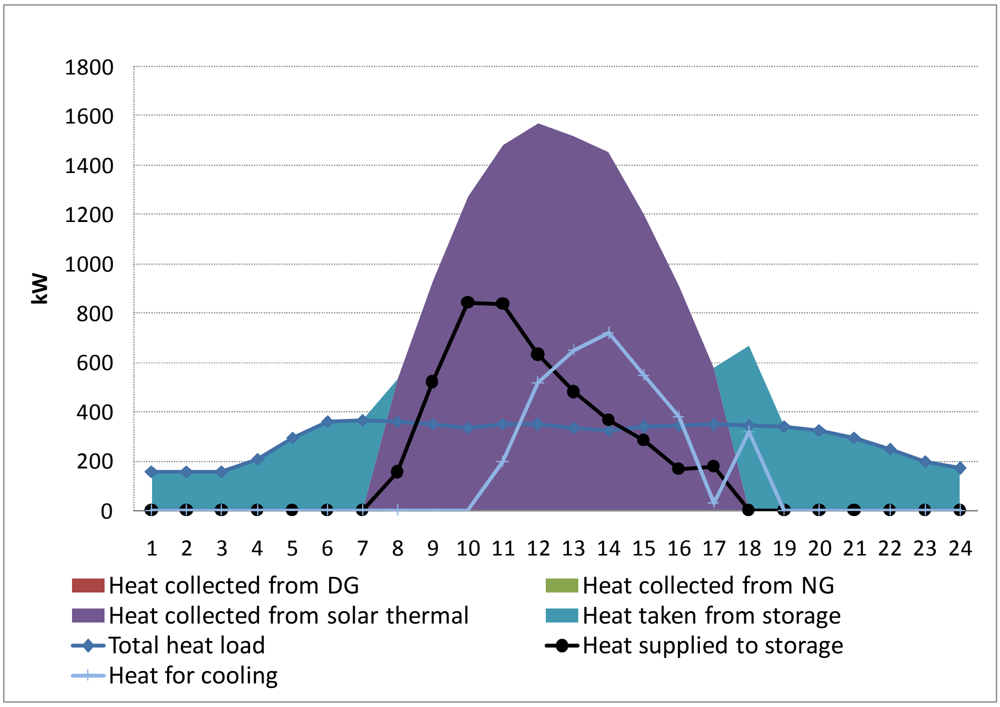
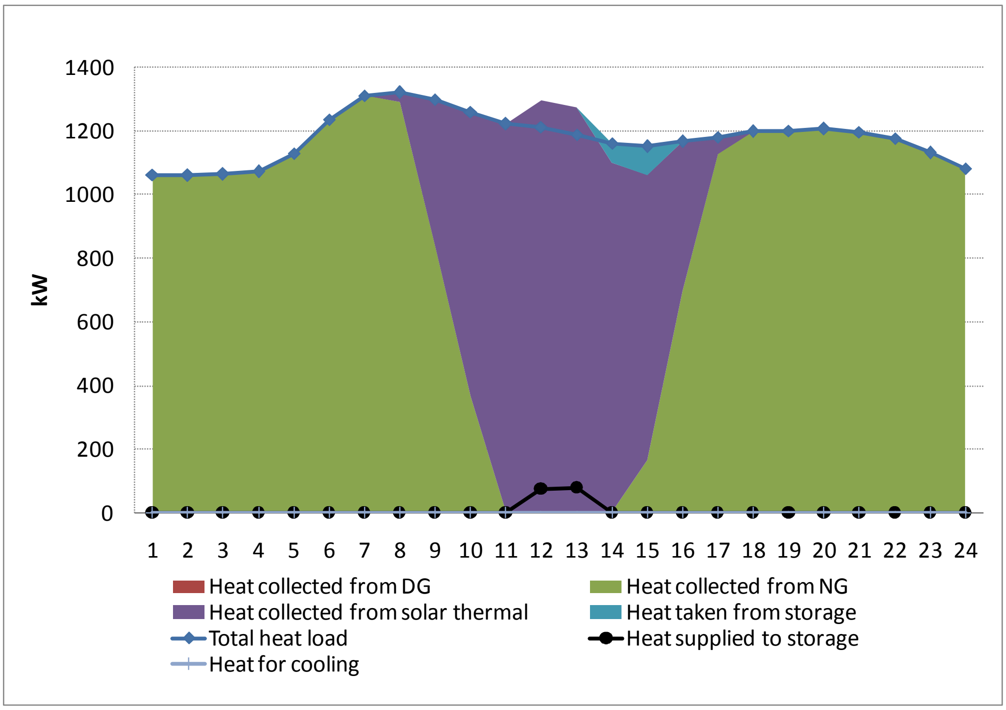


Figure 33. NYC nursing home heat pattern: Jan. weekday low storage and PV cost (run 3)



Finally, to supply 50% of the base and 10% of the peak load during a macrogrid failure, a switch of ca. 270 kW is necessary, and this changes the solution considerably. Two Tecogen units are installed which provide waste heat during the night, morning, and evening hours and reduce the need for thermal storage. Additionally, the *switch* run shows[53] the highest carbon reduction of almost 17% and reduced solar thermal capacities. The implied benefit from CERTS microgrid capabilities for the NYC nursing home is very little, less than $25/kW (see Table 14).

6.5 NYC school results

The NYC school runs show similar results as the CA school, no ICE adoption, not even in the *switch* run.

The major results for the seven runs are shown in Table 15. In the *do-nothing* case (run 1), the school meets all of its electricity demand via utility purchases and burns natural gas to meet all of its heating requirements. The annual operating cost is $258 200, and 271 t of elemental carbon is emitted each year. In the *invest* case (run 2) technology parameters from Table 5, Table 6 and Table 7 are taken and DER-CAM finds the optimal system.

The optimal system for the site consists of a 96 kW absorption chiller and a 103 kW solar thermal system. Again, please note that the absorption chiller capacity is expressed in electricity equivalent of a 4.5 COP electric chiller. At current price levels, electrical storage, thermal storage, and ICEs are all economically unattractive. Relative to the *do-nothing* case, the expected annual savings for the optimal DER system is $4 370/a (ca. 1.7%) while the elemental carbon

[53] Please note that the switch runs were performed with technology parameters from Table 5, Table 6, and Table 7.

emission reduction is 6.95 t/a (ca. 2.6%). Please note that the absorption chiller uses heat from burning natural gas and solar thermal directly – no waste heat is utilized due to the lack of installed Tecogen or fuel cell units.

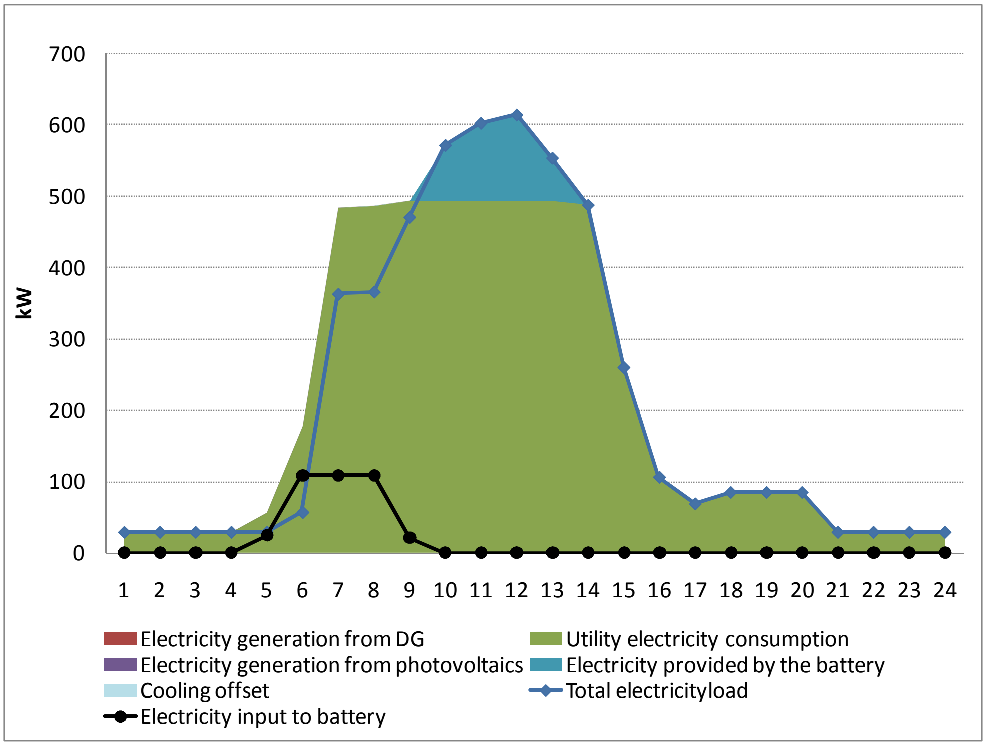
Table 15. Annual results for the NYC school

	run 1	Run 2	run 3	run 4	run 5	run 6	run 7
	do-nothing	invest in all technologies	low storage costs and PV incentive of 2.5$/W	force low storage / PV and solar thermal results	low storage and PV (incentive 2.5$/W) costs & low solar thermal costs (minus 10%)	low storage and PV costs (PV incentive 60%)	switch run
Equipment							
Tecogen 100 kW with HX (kW)	n/a	0	0	0	0	0	0
switch size (kW)		n/a	n/a	n/a	n/a	n/a	7
abs. chiller (kW in terms of electricity)		96	0	0	0	72	96
Solar thermal collector (kW)		103	186	186	204	187	103
PV (kW)		0	0	0	0	166	0
electric storage (kWh)		0	1089	n/a	1089	569	48
Flow battery - energy (kWh)		0	0	0	0	0	0
Flow battery - power (kW)		0	0	0	0	0	0
thermal storage (kWh)		0	441	n/a	443	440	0
annual costs (k$)							
electricity	211.83	204.63	188.50	211.83	188.50	147.45	203.10
NG	46.37	40.37	31.09	35.36	30.16	33.76	40.49
onsite DG technologies	n/a	8.83	27.38	9.79	27.31	62.35	11.02[54]
benefit from switch ($/kW/a)	n/a	n/a	n/a	n/a	n/a	n/a	<25
Total	258.20	253.83	246.97	256.98	245.97	243.56	254.61
% savings compared to do-nothing	n/a	1.69	4.35	0.47	4.74	5.67	1.39
annual energy consumption (GWh)							
electricity	1.12	1.12	1.14	1.12	1.14	0.87	1.12
NG	0.94	0.82	0.63	0.72	0.61	0.69	0.82
annual carbon emissions (t/a)							
emissions	270.65	263.70	258.98	259.57	258.04	208.67	263.92
% savings compared to do-nothing	n/a	2.57	4.31	4.10	4.66	22.90	2.49

[54] Includes benefits from switch.

Considering low storage prices of $60/kWh for electrical and $50/kWh for thermal storage, the annual operating costs drop by 4.35% (see run 3). However, in contrast to the CA school, the elemental carbon emission also decreases. The bigger solar thermal system and heat storage system as well as smaller electrical storage compared to the CA school case reduces the carbon emission by 4.3%. This finding is also proven by run 4, which forces the same results as in the low storage cost run 3, but disallows storage adoption, and shows only a 4.1% drop in carbon emissions. The flat high electricity tariff of $0.12/kWh negatively affects electrical storage adoption. The installed battery capacity is only ca. 48% of the installed battery capacity of the CA school. This reduced battery capacity also reduces the carbon emissions related to battery inefficiencies. Moreover, the battery will be mainly charged in the morning hours to minimize battery loses (Figure 34 and Figure 35). Figure 36 and Figure 37 show higher heat utilization from solar thermal during summer months and weekdays. Additionally, as expected, heat storage is mostly used during summer months.

Figure 34. NYC school electricity pattern: May weekday low storage & PV cost (run 3)



Considering lower PV prices *and* low storage prices (run 6), a major decrease in installed battery capacity combined with a 166 kW PV installation is reached, and a minor part of PV is used to charge the batteries between 7 am and 9 am.

Figure 35. NYC school electricity pattern: May weekday low storage & 60% PV price reduction (run 6)

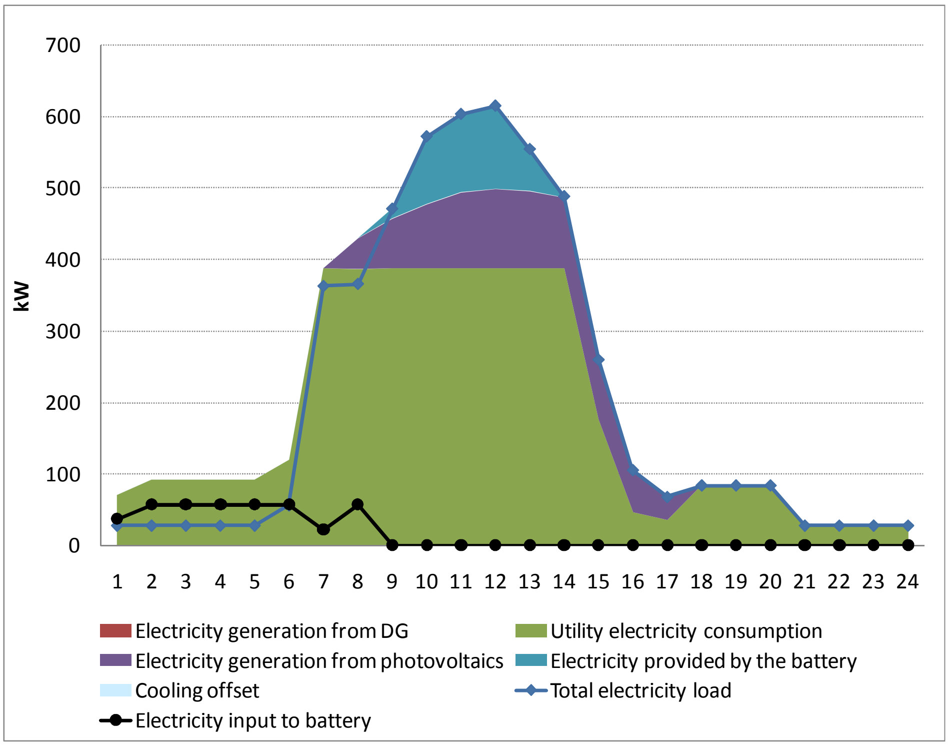


Figure 36. NYC school heat pattern: May weekday low storage & PV cost (run 3)

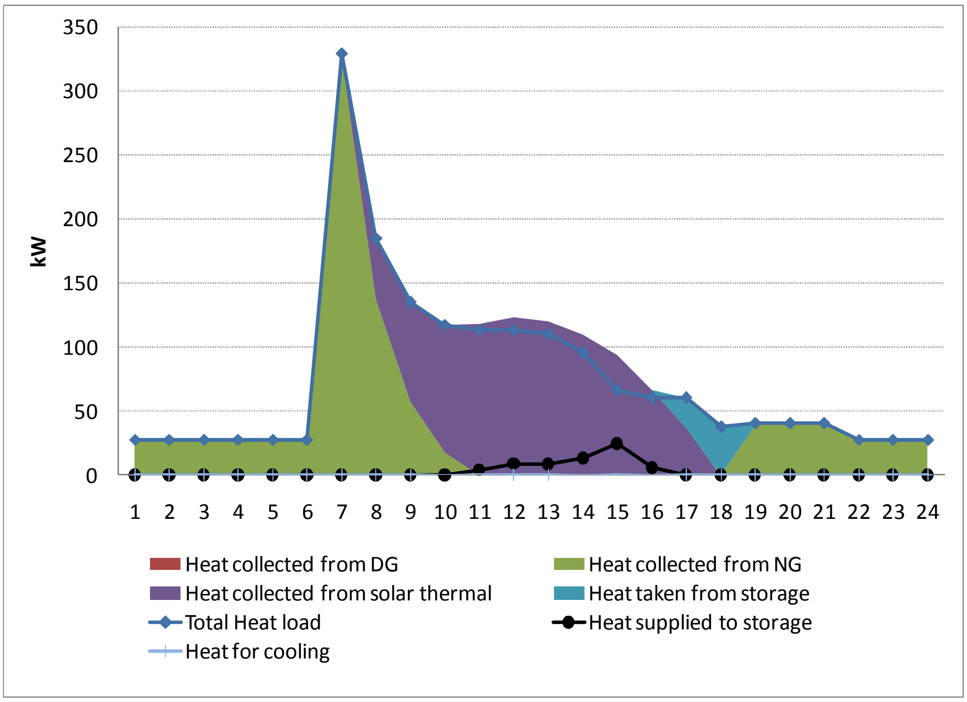
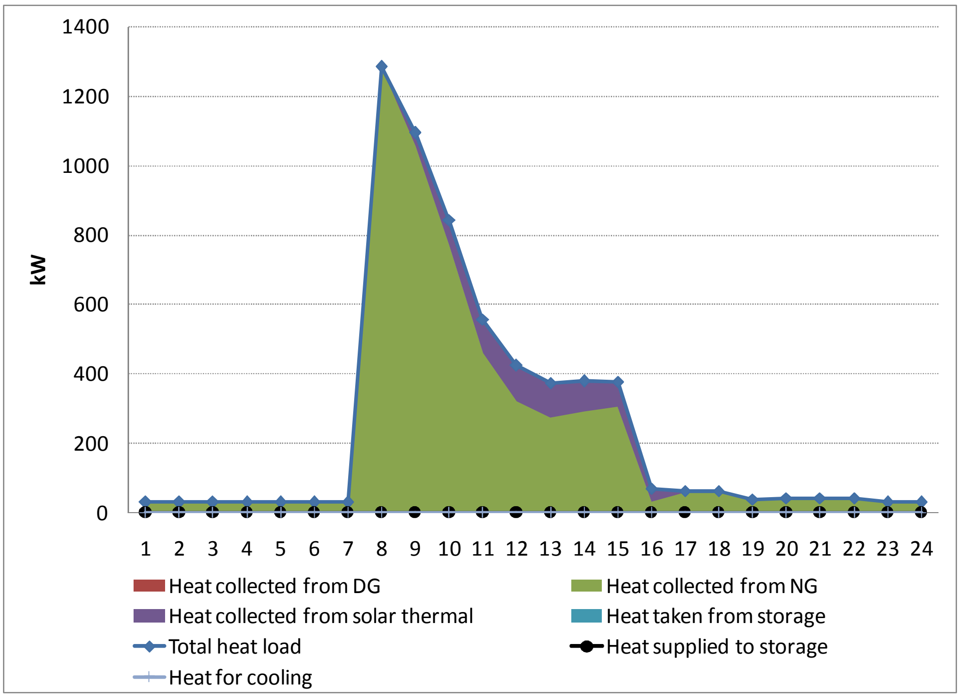


Figure 37. NYC school heat pattern: Jan. weekday low storage and PV cost (run 3)



Finally, to supply 25% of the base load during a macrogrid failure, a switch of ca. 7 kW is necessary. However, the CERTS microgrid capabilities do not change the disadvantages for ICEs. No Tecogen unit is installed due to CERTS microgrid capabilities. To satisfy the switch constraint within DER-CAM, 48 kWh of electrical storage is chosen. Again, a whole set of different *switch* runs[55], with different levels of benefits, was performed. The first run with a lower objective function (= annual energy costs) than run 2 was selected. Those sensitivity analyses were performed in $25/kW benefit increments. The implied benefit from CERTS microgrid capabilities for the CA school is very little, less than $25/kW (see Table 15).

6.6 NYC data center results

The NYC data center results for the performed runs are shown in Table 16 and show no major adoption of DER technologies. The only important adoption takes place for electrical storage and only in the *low storage* runs. Additionally, the adopted storage capacity is limited due to the flat electricity tariff, which discourages load management.

[55] Please note that the switch runs were performed with technology parameters from Table 5, Table 6, and Table 7.

Table 16. Annual results for the NYC data center

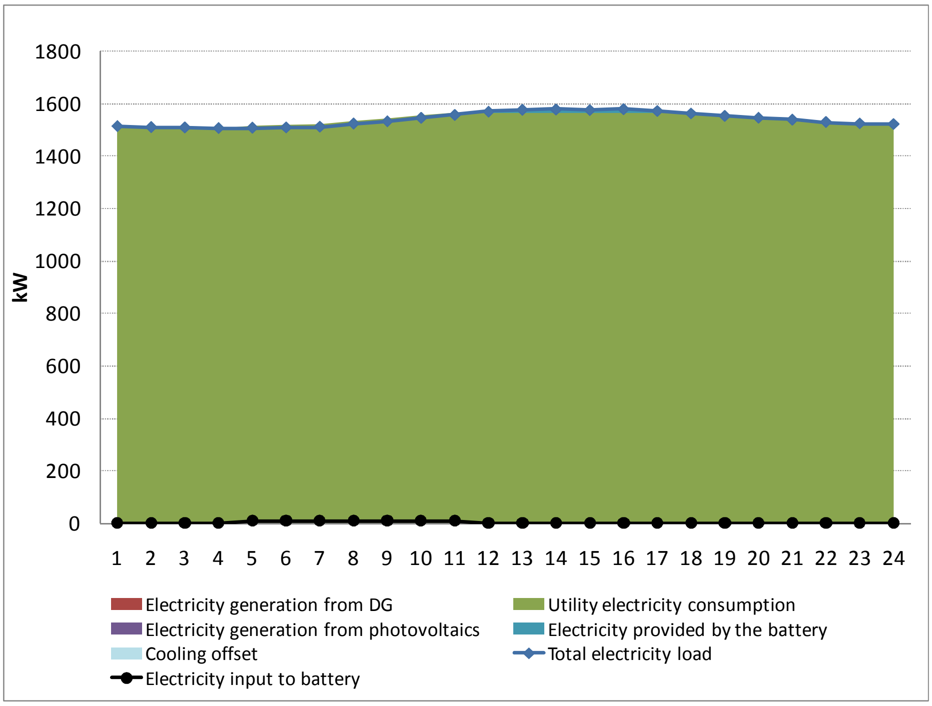
	run 1	run 2	run 3	run 4	run 5	run 6	run 7
	do-nothing	invest in all technologies	low storage costs and PV incentive of 2.5$/W	force low storage / PV and solar thermal results	low storage and PV (incentive 2.5$/W) costs & low solar thermal costs (minus 10%)	low storage and PV costs (PV incentive 60%)	switch run
Equipment							
Tecogen 100 kW with HX (kW)	n/a	0	0	0	0	0	1400
switch size (kW)		n/a	n/a	n/a	n/a	n/a	1591
abs. chiller (kW in terms of electricity)		0	0	0	0	0	0
solar thermal collector (kW)		0	0	0	0	0	0
PV (kW)		0	0	0	0	4	0
Electric storage (kWh)		0	98	n/a	98	94	0
flow battery - energy (kWh)		0	0	0	0	0	8
flow battery - power (kW)		0	0	0	0	0	16
thermal storage (kWh)		0	0	n/a	0	0	0
annual costs (k$)							
electricity	1654.66	1654.66	1652.39	1654.66	1652.39	1651.50	1654.30
NG	0.15	0.15	0.15	0.15	0.15	0.15	0.15
onsite DG technologies	n/a	0.00	1.40	0.00	1.40	2.36	1.24[56]
Benefit from switch ($/kW/a)	n/a	n/a	n/a	n/a	n/a	n/a	200.00
Total	1654.81	1654.81	1653.94	1654.81	1653.94	1654.01	1655.69
% savings compared to do-nothing	n/a	0.00	0.05	0.00	0.05	0.05	-0.05
annual energy consumption (GWh)							
electricity	12.07	12.07	12.07	12.07	12.07	12.07	12.07
NG	0.00	0.00	0.00	0.00	0.00	0.00	0.00
annual carbon emissions (t/a)							
emissions	2414.18	2414.18	2414.78	2414.18	2414.78	2413.52	2414.33
% savings compared to do-nothing	n/a	0.00	-0.03	0.00	-0.03	0.03	-0.01

Even the *switch* run shows no DER *operation*. The DER-CAM switch constraints force the site to adopt 1400 kW of ICEs and a small flow battery capacity, but as can be seen from the table above, the NG demand does not change. In other words, the Tecogen units are only installed to prevent the site during a macorgrid power failure, but during regular macrogrid operation and

[56] Includes benefits from switch.

connection to the micorgrid, the units do not contribute to power supply. A higher availability for flow batteries compared to lead acid batteries results in a flow battery adoption in run 7 (see also section 6, first paragraph). However, a reduction in availability numbers for flow batteries would result in lead acid battery adoption. In other words, this sensitivity just means that electric storage systems, either regular batteries or flow batteries, are needed to satisfy the critical load requirements.

Figure 38. NYC data center electricity pattern: July weekday low storage & PV cost (run 3)



6.7 Carbon tax sensitivity analyses

To estimate the consequence of the external costs, due to carbon emissions, carbon tax sensitivity runs were performed. For the first set of runs, a carbon tax of $150/tC was assumed. This number translates into $40.87/t$CO_2$ (= €26.4[57]/tCO_2) and is roughly the current Carbix CO_2 emission certificate price at the European Energy Exchange in Germany[58]. All runs use actual technology costs and performance parameters from Table 5, Table 6, and Table 7, including the full costs for storage, PV, and solar thermal. Additionally, no DER switch capability is assumed in these runs, and all sensitivity runs use a standard cost minimizing strategy.

Table 17 compares the technology adoption of the carbon tax runs with the equivalent *invest* in all technologies runs (run 2) from the previous sections. All these optimal solutions deliver lower annual energy costs than without DER adoption. With the realistic carbon tax level of $150/tC, major changes appear only for Tecogen, absorption chiller, and solar thermal units. At this level,

[57] Exchange rate of 1.55, June 2008.
[58] http://www.eex.com/en/Market%20Information/Emission%20Rights/EU%20Emission%20Allowances%20%7C%20Spot, values are from June 26th, 2008.

PV, thermal storage, and flow battery adoption does not change compared to the corresponding run 2 from the previous sections. Also, there is no clear pattern except for Tecogen engines. The change in ICE adoption is always zero or positive; if there is a change in ICE adoption it always *increases* in capacity. In contrast, absorption chiller and solar thermal adoption can increase or decrease depending on the site considered. The carbon emissions reductions achieved in these cases are modest, 0-6.5%, and interestingly, the biggest reductions occur in the cases with additional ICE installation, as can be seen in Table 17.

Table 17. Change in installed technologies due to carbon tax of $150/tC compared to run 2 from the previous sections

change	CA nursing home	CA school	CA data center	NYC nursing home	NYC school	NYC data center
Tecogen 100 kW with HX (kW)	0	100	0	100	0	0
static switch size	n/a	n/a	n/a	n/a	n/a	n/a
abs. chiller (kW in terms of electricity)	58	-14	-9	18	2	0
solar thermal collector (kW)	449	-23	0	168	26	0
PV (kW)	0	0	0	0	0	0
electric storage (kWh)	0	39	0	0	0	0
flow battery – energy (kWh)	0	0	0	0	0	0
flow battery – power (kW)	0	0	0	0	0	0
thermal storage (kWh)	0	0	0	0	0	0
carbon emission (t/a)	-17.79	-23.09	-2.28	-92.49	-1.23	0.00
carbon emission (%)	-1.88	-6.45	-0.14	-6.43	-0.47	0.00

To explore the impact of higher carbon tax levels, a carbon tax that is three times higher than the previous level is assumed. The impact of a $450/tC carbon tax on DER technology penetration as well as carbon emissions is shown in Table 18. ICE installation is constant or increases (see Table 18). In the case of the NYC nursing home, ICE adoption increases and solar thermal adoption decreases; however, in all other cases, solar thermal adoption increases and the school sites additionally add thermal storage systems. Despite the high carbon tax, PV is still not chosen at its full price.

The biggest carbon reduction, compared to run 2 without carbon tax, is reached at the NYC nursing home site with much increased ICE adoption. The original disadvantageous conditions for DG-CHP adoption in NYC change to favorable conditions when high carbon taxes are present. This example shows how counterintuitive the results might be depending on the tariff structure, load profile and other constraints. Further, the net carbon emissions reductions remain modest.

Table 18. Change in installed technologies due to carbon tax of $450/tC compared to run 2 from the previous sections

Change	CA nursing home	CA school	CA data center	NYC nursing home	NYC school	NYC data center
Tecogen 100 kW with HX (kW)	0	100	0	400	0	0
static switch size	n/a	n/a	n/a	n/a	n/a	n/a
abs. chiller (kW in terms of electricity)	153	-25	49	23	18	27
solar thermal collector (kW)	1153	64	1131	-401	255	249
PV (kW)	0	0	0	0	0	0
electric storage (kWh)	0	65	0	0	0	0
flow battery - energy (kWh)	0	0	0	0	0	0
flow battery - power (kW)	0	0	0	0	0	0
thermal storage (kWh)	0	453	0	0	431	0
carbon emission (t/a)	-43.23	-41.68	-43.82	-254.75	-14.69	-11.92
carbon emission (%)	-4.57	-11.63	-2.73	-17.70	-5.57	-11.92

Finally, depending on the carbon tax level, the cost minimizing strategy can change for some sites, which makes the investigations even more complicated. For example, at a carbon tax level of $150/tC, the best economic strategy for the CA school is to add a 100 kW ICE, reduce the abs. chiller capacity, reduce the solar thermal capacity, and add more electric storage capabilities (see Table 17). In contrast, at a carbon tax level of $450/tC, the strategy changes and suggests *adding* more solar thermal as well as heat storage capabilities (see Table 18).

The last sensitivity analysis assumes an extreme carbon tax level of $1000/tC and is applied to only the NYC nursing home. The results for this sensitivity run are very surprising because they result in a shift from ICE engines to more efficient fuel cells. Only one 100 kW Tecogen HX unit is installed, but two 200 kW fuel cell units with waste heat utilization are adopted. Thus, in this case the DG-CHP capacity increases by 100 kW compared to the case with $450/tC. In addition, the solar thermal collector capacity surges and reaches a total of 2 672 kW. Because of this huge solar thermal system as well as waste heat utilization, the heat storage capacity reaches 4 977 kW. The abs. chiller capacity increases slightly, but PV is still not attractive because of its high technology costs.

6.8 Standby tariff sensitivity analysis

The standby tariff analysis has been limited to the California nursing home example because it is the most favorable DG-CHP site.

6.8.1 Standby tariffs

The standard PG&E standby tariff shown in Table 19 is used. The reservation charge ($/kW) is based on reservation capacity, i.e., how much power (kW) the customer requests the utility provides as standby. The customer charge ($/meter/day) is a fixed charge for reservation capacity service between 500 kW and 1000 kW. The energy charge ($/kWh) is applicable only when the customer uses standby power from PG&E. If the customer places a reactive demand on PG&E's system in any month in excess of 0.1 kVAR per kW of reservation capacity, then a reactive demand charge will be added to the customer's standby bill, except for customers operating asynchronous generators under net sales contracts.

The definition of on-peak, mid-peak, and off-peak depends on the season and are specified as follows:

- Summer on-peak: 12:00-18:00 during weekdays
- Summer mid-peak: 08:00-12:00 and 18:00-22:00 during weekdays, all other hours and days: off-peak
- Winter mid-peak: 08:00-22:00 during weekdays, all other hours and days: off-peak.

Table 19. Standby tariffs, effective May 2008

PG&E standby rates for less than 2400volts, 500-1000kW capacity		**summer (May – Oct.)**			**winter (Nov – Apr.)**		
		on peak	**mid peak**	**off peak**	**on peak**	**mid peak**	**off peak**
Standby charges	**reservation charge depending on the nameplate of the generator ($/kW and month)**	2.27					
	customer charge ($/meter/day)	13.55					
	energy charge ($/kWh)	0.26	0.16	0.12		0.14	0.12
Other possible charge	reactive demand charge ($/kVAR)	0.15					

Source: PG&E standby tariff

6.8.2 Results

The sensitivity runs suggest that standby tariffs create a slight disadvantage for DER adoption. The optimal DER solutions deliver slightly higher annual energy costs compared to the base case run 1 from Table 20. This disadvantage is caused by the high fixed unavoidable costs of the standby tariff.

To be able to show the impact of standby tariffs on DER adoption, the cost constraint within DER-CAM was relaxed. In regular DER-CAM optimization runs the cost minimizing DER adoption must result in less annual energy costs compared to run 1 *do-nothing*. Otherwise, the adopted system is not considered as a possible solution. This constraint is removed for the standby runs in this chapter. In other words, the $963 900 were not used as cost constraint within DER-CAM and this can result in optimal solutions with higher annual energy costs than in run 1 (see also Table 20). This relaxation is necessary to observe the net effect of the standby charge on adoption, i.e. the tariffs change between the do-nothing and other cases.

Table 20. Annual results for the northern California nursing home using standby tariffs

	run 1	run 2	run 3	run 4	run 5	run 6
	do-nothing	invest in all technologies	low storage costs and PV incentive of 2.5$/W	force low storage / PV and solar thermal results	low storage and PV (incentive 2.5$/W) costs & low solar thermal costs (minus 10%)	low storage and PV costs (PV incentive 60%)
Equipment						
Tecogen 100 kW with HX (kW)	n/a	400	400	400	400	300
abs. chiller (kW in terms of electricity)		56	56	56	56	35
solar thermal collector (kW)		0	0	0	0	0
PV (kW)		0	0	0	0	676
electric storage (kWh)		0	0	n/a	0	68
flow battery - energy (kWh)		0	0	0	0	0
flow battery - power (kW)		0	0	0	0	0
thermal storage (kWh)		0	0	n/a	6	225
annual costs (k$)						
electricity	758.02	394.73	394.74	394.74	394.63	295.57
NG	205.88	422.02	422.01	422.01	422.08	367.84
onsite DG technologies	n/a	168.22	168.22	168.22	168.26	293.50
Total	963.90	984.97	984.97	984.97	984.97[59]	956.92
% savings compared to do-nothing	n/a	-2.19	-2.19	-2.19	-2.19	0.72
annual energy consumption (GWh)						
electricity	5.76	2.60	2.60	2.60	2.60	2.04
NG	5.70	11.75	11.75	11.75	11.75	10.24
annual carbon emissions (t/a)						
Emissions	1087.74	943.89	943.90	943.90	943.88	790.68
% savings compared to do-nothing	n/a	13.22	13.22	13.22	13.23	27.31

[59] The total energy costs for run 5 are slightly different than from run 2, but due to rounding the difference cannot be recognized. Additionally, a difference of only $3 might be just inaccuracy of the GAMS solver. In other words, the objective function (= total energy costs) from run 5 is not significant different than the found objective function from run 2.

The major results for the six runs are shown in Table 20. In the *do-nothing* case (run 1), the nursing home meets all of its electricity demand via utility purchases and heating requirements by burning natural gas based on the regular PG&E tariffs from section 5.1.1 and no standby tariff is used. The annual operating cost is ca. \$964 000, and ca. 1 088 t of elemental carbon is emitted each year. In the *invest* case (run 2), technology parameters from Table 5, Table 6 and Table 7 are taken and DER-CAM finds the optimal system based on the standby tariff from the previous section.

The optimal chosen system for the site consists of four Tecogen gas engines and a 56 kW absorption chiller system. Please note that the absorption chiller capacity is expressed in electricity equivalent of a 4.5 COP electric chiller, and therefore, the 56 kW translates into a 72 RT absorption chiller. However, as can be seen from Table 20, the optimal solution delivers 2.19% *higher* energy costs compared to the *do-nothing* case. In other words, due to the standby tariff, DER adoption is not economically attractive. Relative to the *do-nothing* case, the expected annual savings for the optimal DER system is -\$21 070/a (-2.19%) while the elemental carbon emission reduction is 144 t/a (ca. 13%).

Comparing the results for the CA nursing home from section 6.1, using regular tariffs, with the results using standby tariffs, disadvantages for solar thermal and thermal storage adoption are found. For all performed runs except run 6 (60% PV price reduction and low storage price), DER adoption is not attractive, i.e. the savings compared to the *do-nothing* case are negative. Finally, considering the possible carbon reduction of at least ca. 13%, the hindrance of DER adoption by standby tariffs seems problematic and puts a limitation on carbon reduction potential.

7. Conclusion

In this work the new electrical and thermal storage as well as PQR capabilities of DER-CAM are demonstrated for three commercial sites in California and New York States. The results for the nursing home, school, and data center show a wide range in the complexity of optimal systems and the effects on annual energy costs and carbon emissions.

One major conclusion from the research is that load profiles, tariff structure and available solar radiation have an enormous impact on the site's achievable energy cost as well as carbon emission reduction. Almost every building, in combination with the tariff structure, is unique. The results are often complex and it would not be possible to find the optimal solution with just a trial and error approach. Specifically, storage poses a difficult problem because any decision made in any one time period must consider the effects on all other time periods. Both traditional batteries, such as the familiar lead-acid ones, and flow batteries are considered. Unfortunately, when available at approximately their estimated current full cost, no storage technologies are chosen for any of the test sites, and the same is true for PV.

To be able to show the impact of storage and PV on DER adoption, electricity storage costs are reduced from 193 $/kWh to 60, heat storage is halved from 100 $/kWh to 50, and 60% of PV costs are written down. As shown by the comparison of the California and New York examples in this research, the demand charge reduction is a significant driver for the adoption of electric storage technologies. The PG&E as well as SCE electric tariffs consist of time-of-use tariffs for both electricity ($/kWh) and demand ($/kW), which encourages load management by batteries. However, the high electric demand during on-peak hours, which coincident with the solar radiation, results in peak shaving by the battery and PV. Therefore, to satisfy the site's objective of minimizing energy costs, the batteries have to be charged by grid power during off-peak hours instead of PV during on-peak hours. This circumstance, combined with storage inefficiencies, results in reduced carbon emission reduction potential compared to the case without storage. Comparison of the California and New York nursing home example shows impressive the power of time-of-use tariffs and high demand charges. For example the CA nursing home makes considerable grid electricity purchases over the course of the day, but buys virtually nothing during the on-peak period, 12:00-18:00. The engines, the PV, and the batteries are all used to avoid afternoon grid purchase. In other words, the batteries are used to save cheap off-peak electricity for consumption during the expensive on-peak hours; therefore, the PV and the batteries are in competition to provide this service. The New York nursing home shows a complete different pattern. First of all, the adopted battery capacity is only ca. 7% of the installed battery capacity of the CA nursing home and then the charge / discharge cycle is completely different due to the absence of time-of-use tariffs – the batteries are charged between 04:00 and 16:00.

To model the PQR benefit of the microgrid a certain amount of the building load was assumed to be critical. It is assumed that the nursing home must meet 50% of its base load and 10% of its peak load during a grid failure. The school must meet 25% of its base load and the data center its entire load during a grid failure. The PQR research has been performed via the analysis of the attractiveness of a CERTS Microgrid consisting of multiple nameplate 100 kW Tecogen CM-100. This unit consists of an asynchronous inverter-based variable speed internal combustion engine genset with CHP and power surge capability. The essence of the CERTS Microgrid technology is that smarts added to the on-board electronics of any microgrid device allows stable and safe islanded operation without the need for complex supervisory controls. This approach allows plug and play development of a microgrid that can potentially provide high PQR with a minimum of specialized site-specific engineering. Based on Tecogen data, the PQR features add $25/kW to the CM-100 engines and $100/kW for the DER switch, which separates from the macrogrid seamlessly during a grid disturbance. However, the possibility of supplying energy to sensitive loads during a grid failure also adds benefits to the microgrid. In DER-CAM these benefits are expressed as monetary benefits. These benefits are difficult to find empirically, and therefore, a whole set of PQR runs with variable benefits and fixed PQR costs were performed to determine the PQR benefits with DER-CAM.

The major outcome of the PQR runs is that the consideration of critical loads and PQR can make a huge difference in the DER adoption depending on previously installed equipment. For example, the CA nursing home is already very attractive for DER adoption without any consideration of PQR, and therefore, the consideration of PQR makes no difference in DER adoption. For the NY nursing home, the results are more interesting and show an adoption of 2 CM-100 units to satisfy the critical load condition. In the NY nursing home case, the consideration of PQR makes a considerable difference in DER adoption. In both school examples DER adoption only changes slightly due to the small critical load assumed. No additional CM-100 units are installed. The only changes occur in lead-acid battery adoption. The requirement to satisfy 100% of the data center load during a grid failure results in significant CM-100 adoption. The CA data center adopts 16 and the NY data center 14 units. In contrast without PQR consideration both data centers do not install any CM-100 unit. The found monetary PQR benefits range from less than $25/kW for the nursing home and school examples to $200/kW for the NY data center. In other words the operator / owner of the NY data center must associate $200/kW to the PQR benefit to make the installation of 14 CM-100 units economic attractive.

Also, sensitivity analyses for different carbon tax levels were performed and show that even with carbon tax levels of $1000/tC no PV adoption takes place. At extreme carbon tax levels ICEs get replaced by fuel cells and not by PV due to the high technology costs of PV systems.

Finally, a sensitivity run using stand by tariffs, instead of regular tariffs, proves that standby tariffs hinder DER adoption. Considering the possible carbon reduction of at least ca. 13% for the CA nursing home the hindrance of DER adoption by standby tariffs seems problematic and puts a limitation on carbon reduction potentials.

8. References

Advanced Design Guideline Series (1998): “Absorption Chillers”, Southern California Gas Company, New Buildings Institute, November, 1998.

Cadmus, “Regional Electricity Emission Factors Final Report”, The Cadmus Group, Inc., 1998, Exhibit 6.

ConEd tariffs,
http://www.coned.com/documents/elec/historical/SC09.04_01.2007.271-281a.pdf
http://www.coned.com/documents/gas_tariff/pdf/0004-Firm_Sales_Service.pdf#page=7
http://www.coned.com/rates/elec_MSCMACstatement.asp
http://www.coned.com/rates/elec-historical_rps.asp
http://www.coned.com/rates/elec-historical_sbc.asp

DOE Commercial Building Integration Benchmark Input Table - Draft Version 6, June 22 2007.

DOE Electricity Delivery and Energy Reliability, http://www.eere.energy.gov/de/equipment_costs.html

DOE, EnergyPlus, http://www.eere.energy.gov/buildings/energyplus/weatherdata/4_north_and_central_america_wmo_region_4/1_usa/USA_NY_New.York.City-La.Guardia_TMY.stat

DOE Solar America Initiative, “Solar Energy Industry Forecast: Perspectives on U.S. Solar Market Trajectory”, On-line available: http://www1.eere.energy.gov/solar/solar_america/

EIA Solar Thermal and Photovoltaic Collector Manufacturing Activities 2006, available at http://www.eia.doe.gov/cneaf/solar.renewables/page/solarreport/solar.html

EIA FORM EIA-63A Annual Solar Thermal Collector Manufacturers Survey, available at http://www.eia.doe.gov/cneaf/solar.renewables/page/forms/instr63a.pdf

Electricity Storage Association, Morgan Hill, CA, USA (http://www.electricitystorage.org/tech/technologies_comparisons_capitalcost.htm).

EPRI-DOE Handbook of Energy Storage for Transmission and Distribution Applications, EPRI, Palo Alto, CA, and the U.S. Department of Energy, Washington, DC: 2003. 1001834.

European Commission Directorate-General for Energy SAVE II Program (2001): “Energy Savings by CHCP plants in the Hotel Sector, Absorption chillers”, May 2001

Firestone, R, “Distributed Energy Resources Customer Adoption Model Technology Data”, Berkeley Lab, Berkeley, CA, USA Case Study, Jan. 2004 (available at http://der.lbl.gov).

Goldstein, L., B. Hedman, D. Knowles, S. I. Friedman, R. Woods, and T. Schweizer, “Gas-Fired Distributed Energy Resource Characterizations”, National Renewable Energy Resource Laboratory, Golden, CO, USA Rep. TP-620-34783, Nov. 2003.

Hatziargyriou, N. et al., “Microgrids, An Overview of Ongoing Research, Development, and Demonstration Projects”, IEEE power & energy magazine, July/August 2007.

Huang, Joe, Akbari, H., Rainer, L. and Ritschard, R., “481 Prototypical Commercial Buildings for 20 Urban Market Areas, prepared for the Gas Research Institute”, Chicago IL, also LBL-29798, Berkeley CA, 1991.

IEA PVPS web: IEA Co-operative programe on photovoltaic power systems Task 1, Exchange and dissemination of information on PV Power Systems (PVPS), http://www.iea-pvps.org/.

IEA PVPS USA survey report: IEA Co-operative programme on photovoltaic power systems Task 1, Exchange and dissemination of information on PV Power Systems (PVPS), National survey report of PV power applications in the United Sates of America 2006, published 2007/5/30 revised 2007/8/30

Kazmerski Lawrence L.: “Solar photovoltaics R&D at the tipping point: A 2005 technology overview”, Journal of Electron Spectroscopy and Related Phenomena 150 (2006) 105–135.

Lasseter Robert, Abbas Akhil, Chris Marnay, John Stephens, Jeff Dagle, Ross Guttromson, A. Sakis Meliopoulous, Robert Yinger, and Joe Eto: “White Paper on Integration of Distributed Energy Resources The CERTS MicroGrid Concept”, April 2002.

Lynch J., V. John, S.M. Danial, E. Benedict, I. Vihinen, B. Kroposki, and C. Pink: “Flexible DER Utility Interface System: Final Report”, Technical Report NREL/TP-560-39876, August 2006

Marnay, C. et al., “Estimating Carbon Dioxide Emissions Factors for the California Electric Power Sector”, Lawrence Berkeley National Laboratory Report LBNL 49945, Aug. 2002.

Marnay, C., G. Venkataramanan, M. Stadler, A. Siddiqui, R. Firestone, B. Chandran, “Optimal Technology Selection and Operation of Microgrids in Commercial Buildings”, IEEE Transactions on Power Systems, forthcoming 2008.

Marnay Chris, Michael Stadler, Hirohisa Aki, Brian Coffey, Ryan Firestone, Judy Lai, and Afzal Siddiqui: “Microgrid Selection and Operation for Commercial Buildings in California and New York States“, 4th European PV-Hybrid and Mini-Grid conference, May 29th – May 30th 2008, Glyfada, Athens, Greece.

Marnay Chris, Giri Venkataraman, Michael Stadler, Afzal Siddiqui, Ryan Firestone, Bala Chandran: "Optimal Technology Selection and Operation of Microgrids in Commercial Buildings", IEEE 2007 Power Engineering Society General Meeting, 24-28 June 2007, Tampa, FL, USA.

Microgrid Symposium. For more background on microgrids, please see the presentations from the two Symposiums on Microgrids held at Berkeley, CA, USA in June 2005 and near Montréal, Canada in June 2006 (available at http://der.lbl.gov).

NEDO 2030: Overview of "PV Roadmap Toward 2030" (PV2030), New Energy and Industrial Technology Development Organization (NEDO), 2004 June. Online available: http://www.nedo.go.jp/informations/other/161005_1/gaiyou_e.pdf.

NREL Power Databook. http://www.nrel.gov/analysis/power_databook/docs/pdf/db_chapter02_battery.pdf

NREL PVWATTS, http://rredc.nrel.gov/solar/calculators/PVWATTS/version1/

NREL b, http://www.nrel.gov/pv/thin_film/docs/kaz_best_research_cells.ppt

Pacific Region CHP Application Center, Energy and Resources Group at University of California/Berkeley, United States of America, 2008; http://www.chpcenterpr.org/PRACLibrary/ProjectProfiles/Index.aspx

PG&E commercial tariffs. http://www.pge.com/nots/rates/tariffs/CommercialCurrent.xls

PG&E tariffs. http://www.pge.com/tariffs/pdf/E-19.pdf

PG&E commercial natural gas tariffs. http://www.pge.com/nots/rates/tariffs/GNR2_Current.xls

PG&E natural gas tariffs. http://www.pge.com/tariffs/pdf/G-NR2.pdf

PG&E standby tariff. http://www.pge.com/tariffs/tm2/pdf/ELEC_SCHEDS_S.pdf

Schoenung, Susan M. and William V. Hassenzahl, "Long- vs. Short-Term Energy Storage Technologies Analysis, A Life-Cycle Cost Study", Sandia Report SAND2003-2783 Unlimited Release, August 2003.

Schoenung, S. M., J. M. Eyer, J. J. Iannucci, and S. A. Horgan (1996), "Energy Storage for a Competitive Power Market," Annual Review of Energy and the Environment 21: 347–370.

SCE time of use. http://www.sce.com/NR/sc3/tm2/pdf/ce54-12.pdf

SoCal natural gas tariffs. http://www.socalgas.com/regulatory/tariffs/tm2/pdf/G-10.pdf

Siddiqui, A.S., R. Firestone, S. Ghosh, M. Stadler, C. Marnay, and J.L. Edwards, "Distributed Energy Resources Customer Adoption Modeling with Combined Heat and Power Applications", Lawrence Berkeley National Laboratory Report LBNL 52718, June 2003.

Siddiqui, A. S., C. Marnay, R. M. Firestone, and N. Zhou, "Distributed Generation with Heat Recovery and Storage", J. of E. Engineering, vol. 133, no. 3, pp. 181-210, Sep. 2007.

Stadler, M., R. M. Firestone, D. Curtil, and Chris Marnay, "On-Site Generation Simulation with EnergyPlus for Commercial Buildings", ACEEE Summer Study on Energy Efficiency in Buildings, August 13-18, 2006, Pacific Grove, California, ISBN 0-918249-56-2.

Stadler Michael, Hirohisa Aki, Ryan Firestone, Chris Marnay, & Afzal Siddiqui: "Distributed Energy Resources On-Site Optimization for Commercial Buildings with Electric and Thermal Storage Technologies", ACEEE 2008 Summer Study on Energy Efficiency in Buildings, August 17 – 22, 2008, Pacific Grove, California, ISBN (forthcoming).

Stevens, J. W., G. P. Corey, "A Study of Lead-Acid Battery Efficiency Near Top-of-Charge and the Impact on PV System Design", Sandia National Laboratories.

Symons, P. C., and Butler, P. C., "Introduction to Advancd Batteries for Emerging Applications" Sandia National Laboratory, SAND2001-2022P. http://infoserve.sandia.gov/sand_doc/2001/012022p.pdf

TECOGEN, http://www.tecogen.com/

FuelCellEnergy, http://www.fuelcellenergy.com/files/Vision%2021%20Fact%20Sheet.pdf

VRB Power Systems. http://www.vrbpower.com/technology/faqs.html

YORK FORM 155.16-EG1 (604), "MILLENNIUM YIA Single-Effect Absorption Chillers" http://www.york.com/products/esg/YorkEngDocs/776.pdf

Appendix A. DER-CAM mathematical formulation

This section describes the core mathematical problem solved by DER-CAM. First, the input parameters are listed, and the decision variables are defined. Note that although power units, i.e., kW, are used to measure heat flow over the course of one hour, the actual heat used in that hour is measured in units of energy, i.e., kWh. Therefore, heat flows has been measured in kW in order to enable comparison with power. Next, the optimization problem is described.

Input Parameters

Indices

Name	**Definition**
h	Hours, which belong to $H = \{1,2,\ldots,24\}$
i	Generation technologies, where I = *{the set of technologies selected}*, I_{NG} refers to the set of gas-fired technologies only
m	Months, which belong to $M = \{1,2,\ldots,12\}$
d	Demand types, which belong to D = *{coincident, noncoincident, onpeak, midpeak, offpeak}*
p	Periods, where P = *{on-peak, mid-peak, off-peak}*, e.g., On-peak (hours of the day 12 through 18, inclusive, during summer months, and 18 through 20 during the winter), mid-peak (07 through 11 and 19 through 22 during the summer, and 07 through 17 and 21 through 22 during the winter), or off-peak (01 through 06 and 23 through 24 during all months)
l	Continuous-investment technologies, where L = *{electrical storage ('es'), heat storage ('hs'), flow battery energy ('fe'), flow battery power ('fp'), absorption chiller ('ab'), photovoltaic ('pv'), and solar thermal ('st')}*
t	Day types, which belong to T = *{weekday, peak, weekend}*
u	End uses, which belong to U = *{electricity only ('e'), cooling ('c'), space heating ('s'), water heating ('w'), and natural gas only ('g')}*
k	Gas-fired direct chiller technologies, where K = *{the set of technologies selected}*, and K_{HX}

	is the set of all gas-fired direct chillers with heat exchangers

Customer Data

Name	Description
$Load_{u,m,t,h}$	Customer load (electricity or heat flow) in kW for end use *u* during hour *h*, day type *t* and month *m* (end uses are electricity only ('e'), cooling ('c'), space heating ('s'), water heating ('w'), and natural gas only ('g'))

Market Data

Name	Description
ContractDemandCharge	Contract demand electricity charge for maximum electric-only and cooling loads (US$/kW)
MonthlyFeeElectric	Utility fee for electricity provision (US$/month)
MonthlyFeeNGBasic	Utility fee for basic NG provision (US$/month)
MonthlyFeeNGforDG	Utility fee for DG NG provision (US$/month)
MonthlyFeeNGforABS	Utility fee for absorption chiller NG provision (US$/month)
StandbyCharge	Standby charge for DER investment (US$/(kW-month))
$ElectricityRate_{m,p}$	Volumetric electricity tariff rate for month *m* and period *p* (US$/kWh)
$MonthlyDemandRates_{m,d}$	Monthly demand rate for month *m* and demand type *d* (US$/kW)
$DailyDemandRates_{m,d}$	Daily demand rate for month *m* and demand type *d* (US$/kW)
CTax	Tax on carbon emissions (US$/kg-carbon)

MktCRate	Carbon emissions rate from marketplace generation (kg-carbon/kWh)
NGCarbonEmissionsRate	Carbon emissions rate from burning natural gas to meet heating and cooling loads (kg-carbon/kWh)
$NGBasicPrice_m$	Natural gas price during month *m* (US$/kWh)
$NGforABS_m$	Natural gas price for chillers during month *m* (US$/kWh)
$OtherFuelPrice_i$	Price of fuel associated DG technology *i* (US$/kWh)
$PX_{m,t,h}$	PX market price at which electricity may be sold ($/kWh)

Distributed Energy Resource Technologies Information

Name	**Description**
$Maxp_i$	Nameplate power rating of generation technology *i* (kW)
$Maxp_k$	Nameplate power rating of direct-fired chiller technology *k* (kW)
StaticSwitchParameterValue	Benefit (negative cost) obtained from installing switch ($)
CostM	Variable cost of switch ($/kW)
CostB	Fixed cost of switch ($)
SwitchSize	Size of switch (kW), which is zero if the switch capability is not considered, i.e., this over-rides the constraint in equation (59)
$CapCost_i$	Turnkey capital cost of generation technology *i* (US$/kW)
$CapCost_k$	Turnkey capital cost of direct-fired chiller technology *k* (US$/kW)
$OMFix_i$	Fixed purchase costs of generation technology *i* (US$/(kW-a))

OMFix_k	Fixed annual operation and maintenance costs of direct-fired chiller technology *k* (US$/(kW-a))
FixedCost_l	Fixed annual operation and maintenance costs of continuous technology *l* (US$)
$\text{FixedMaintenance}_l$	Fixed annual operation and maintenance costs of continuous technology *l* (US$/(kW-a))
OMVar_i	Variable operation and maintenance costs of generation technology *i* (US$/kWh)
OMVar_k	Variable operation and maintenance costs of direct-fired chiller technology *k* (US$/kWh)
VariableCost_l	Variable costs of continuous technology *l* (US$/kWh)
E_i	Energy conversion efficiency of generation technology *i* (kWh-electricity/kWh-gas)
COPelectric	Coefficient of performance for electricity
COPabs	Coefficient of performance for absorption chillers
NGChillCOP_k	Coefficient of performance for direct-fired chillers
Annuity_i	Annuity factor for generation technology *i*, where $\text{Annuity}_i = \dfrac{\text{IntRate}}{\left(1 - \dfrac{1}{(1+\text{IntRate})^{\text{Lifetime}_i}}\right)} \forall i$
Annuity_k	Annuity factor for direct-fired chiller technology *k*, where $\text{Annuity}_k = \dfrac{\text{IntRate}}{\left(1 - \dfrac{1}{(1+\text{IntRate})^{\text{Lifetime}_k}}\right)} \forall k$

Annuity_l	Annuity factor for continuous technology *l*, where $\text{Annuity}_l = \frac{\text{IntRate}}{\left(1 - \frac{1}{(1+\text{IntRate})^{\text{Lifetime}_l}}\right)} \forall l$
AnnuitySwitch	Annuity factor for switching equipment
AvailabilityElectricStorage	Average fraction of stored electricity that can be discharged in one day
ElectricityStorageEfficiencyCharge	Fraction of charged electricity into battery that is not lost in energy transfer
ElectricityStorageEfficiencyDischarge	Fraction of electricity discharged from battery that is not lost in energy transfer
ElectricityStorageEfficiencyDecay	Fraction of electricity in battery that is lost in one time period
ElectricityStorageMaxChargeRate	Maximum fraction of remaining battery capacity that can be charged in one time period
ElectricityStorageMaxDischargeRate	Maximum fraction of stored battery capacity that can be discharged in one time period
ElectricityStorageMinStateofCharge	Minimum fraction of battery capacity that should remain
FlowBatteryEfficiencyCharge	Fraction of charged electricity into flow battery that is not lost in energy transfer
FlowBatteryEfficiencyDischarge	Fraction of electricity discharged from flow battery that is not lost in energy transfer
FlowBatteryEfficiencyDecay	Fraction of electricity in flow battery that is lost in one time period
FlowBatteryMinStateofCharge	Minimum fraction of flow battery capacity that should remain

HeatStorageEfficiencyCharge	Fraction of heat sent to storage that is not lost in energy transfer
HeatStorageEfficiencyDischarge	Fraction of discharged heat from storage that is not lost in energy transfer
HeatStorageEfficiencyDecay	Fraction of stored heat that is lost in one time period
HeatStorageMaxChargeRate	Maximum fraction of remaining heat storage capacity that can be charged in one time period
HeatStorageMaxDischargeRate	Maximum fraction of stored heat that can be discharged in one time period
Lifetime_i	Expected lifetime of generation technology *i* (a)
Lifetime_k	Expected lifetime of direct-fired chiller technology *k* (a)
Lifetime_l	Expected lifetime of continuous technology *l* (a)
MinLoad_i	Minimum level at which generation technology *i* can operate (kW)
ReliabilityDER	Average fraction of time DER equipment is available and not subject to outage
SprintCap_i	Maximum level at which generation technology *i* can operate (kW)
α_i	Units of heat (kW) produced from one kW of electricity by generation technology *i*
α_k	Units of heat (kW) produced from one kW of electricity by direct-fired chiller technology *k*
MaxAnnualHours_i	Maximum number of hours of operation allowed per annum for generation technology *i*

Other Parameters

Name	**Description**
IntRate	Interest rate on DER investments (%), which we assume to be 7.5% per annum
$N_{m,t}$	Number of days of type *t* in month *m*
$\mathrm{SolarInsolation}_{m,h}$	Fraction of maximum solar insolation incident upon location during hour *h* in month *m*
$\mathrm{AvailabilitySolarDay}_{m}$	Average hourly fraction of maximum solar insolation incident upon location in month *m*
AvailabilitySolar	Average hourly fraction of maximum solar insolation incident upon location throughout the test year
β_u	Units of heat (kW) produced from one kW of natural gas for end use *u*
MinEff	Minimum natural gas system energy efficiency
BaseCaseCost	Total energy cost without DER investment ($)
MaxPaybackPeriod	Length of payback period (a)
FracBase	Fraction of base electric-only load classified as sensitive
FracPeak	Fraction of peak electric-only load classified as sensitive

Decision Variables

Name	**Description**
$DERInvestment_i$	Number of units of generation technology *i* installed by the customer
$ElectricityPurchase_{m,t,h}$	Amount of electricity purchased by customer during hour *h*, type of day *t*, and month *m* (kWh) (this variable is derived from other variables, but listed

	here for clarity)
$GenL_{i,m,t,h}$	Generated power by technology *i* during hour *h*, type of day *t*, and month *m* to supply the customer's load (kWh)
$GenX_{i,m,t,h}$	Generated power by technology *i* during hour *h*, type of day *t*, and month *m* to sell to the grid (kWh)
$NGforHeat_{m,t,h}$	Purchased natural gas used for heating during hour *h*, type of day *t*, and month *m* for heat (kWh)
$NGforNGChill_{m,t,h}$	Purchased natural gas used for chiller during hour *h*, type of day *t*, and month *m* for heat (kWh)
$SwitchPurchase$	Binary decision variable for purchasing switching equipment
$HeatStorageOutput_{m,t,h}$	Gross stored heat released during hour *h*, type of day *t*, and month *m* (kW)
$NGChillPurchQuantity_{k}$	Number of natural gas direct-fired absorption chillers purchased of type *k*
$Purchase_{\ell}$	Binary decision variable of continuous investment technology *l* purchased
$Capacity_{\ell}$	Capacity of continuous investment technology *l* purchased (kW)
$NGChillAmount_{k,m,t,h}$	Offset cooling load during hour *h*, type of day *t*, and month *m* by using absorption chiller *k* (kW)
$TotalEnergyCost$	Sum of DER, NG, electricity purchase, switch parameter, and heat storage costs ($)
$DERCurrentlyOperating_{i,m,t,h}$	Number of units of generation technology *i* running during hour *h*, type of day *t*, and month *m*
$CoolingbyAbsorption_{m,t,h}$	Cooling load met by continuous absorption chiller during hour *h*, type of day *t*, and month *m*

$CoolingbyElectric_{m,t,h}$	Cooling load met by electricity during hour *h*, type of day *t*, and month *m*
$CoolingbyNGChill_{m,t,h}$	Cooling load met by absorption chiller during hour *h*, type of day *t*, and month *m*
$SprintAmount_{i,m,t,h}$	Total output above rated capacity by generation technology *i* during hour *h*, type of day *t*, and month *m* (kW)
$ElectricityProvided_{m,t,h}$	Total electricity supply during hour *h*, type of day *t*, and month *m* (kWh)
$ElectricityGeneration_{m,t,h}$	Total electricity supply from on-site thermal electricity generation during hour *h*, type of day *t*, and month *m* (kWh)
$ElectricityPV_{m,t,h}$	Total electricity supply from on-site photovoltaic generation during hour *h*, type of day *t*, and month *m* (kWh)
$ElectricityfromBattery_{m,t,h}$	Total net electricity supply from batteries during hour *h*, type of day *t*, and month *m* (kW)
$ElectricityfromFlowBattery_{m,t,h}$	Total net electricity supply from flow batteries during hour *h*, type of day *t*, and month *m* (kW)
$ElectricityStored_{m,t,h}$	Total electricity stored in batteries during hour *h*, type of day *t*, and month *m* (kW)
$ElectricityStorageInput_{m,t,h}$	Net electricity sent to batteries for storage during hour *h*, type of day *t*, and month *m* (kW)
$ElectricityStorageOutput_{m,t,h}$	Gross electricity released from batteries during hour *h*, type of day *t*, and month *m* (kW)
$ElectricityStorageLosses_{m,t,h}$	Electricity lost from batteries during hour *h*, type of day *t*, and month *m* (kW)
$FlowBatteryStored_{m,t,h}$	Total electricity stored in flow batteries during hour *h*, type of day *t*, and month *m* (kW)

$FlowBatteryInput_{m,t,h}$	Net electricity sent to flow batteries for storage during hour *h*, type of day *t*, and month *m* (kW)
$FlowBatteryOutput_{m,t,h}$	Gross electricity released from flow batteries during hour *h*, type of day *t*, and month *m* (kW)
$FlowBatteryLosses_{m,t,h}$	Electricity lost from flow batteries during hour *h*, type of day *t*, and month *m* (kW)
$ElectricityConsumed_{m,t,h}$	Total electricity demand during hour *h*, type of day *t*, and month *m* (kW)
$ElectricityforCooling_{m,t,h}$	Cooling load met by electricity during hour *h*, type of day *t*, and month *m* (kW)
$ElectricityforStorage_{m,t,h}$	Gross electricity sent to batteries for storage during hour *h*, type of day *t*, and month *m* (kW)
$ElectricityforFlowBattery_{m,t,h}$	Gross electricity sent to flow batteries for storage during hour *h*, type of day *t*, and month *m* (kW)
$HeatProvided_{m,t,h}$	Supply of heat available during hour *h*, type of day *t*, and month *m* (kW)
$HeatfromNG_{m,t,h}$	Net heat from burning natural gas during hour *h*, type of day *t*, and month *m* (kW)
$HeatfromSolar_{m,t,h}$	Net heat from solar thermal during hour *h*, type of day *t*, and month *m* (kW)
$HeatfromStorage_{m,t,h}$	Net heat released from storage during hour *h*, type of day *t*, and month *m* (kW)
$HeatfromNGChill_{m,t,h}$	Net heat from direct-fired absorption chillers during hour *h*, type of day *t*, and month *m* (kW)
$HeatStored_{m,t,h}$	Total heat stored during hour *h*, type of day *t*, and month *m* (kW)

$HeatStorageInput_{m,t,h}$	Net heat sent to storage during hour *h*, type of day *t*, and month *m* (kW)
$HeatStorageLosses_{m,t,h}$	Heat lost from storage during hour *h*, type of day *t*, and month *m* (kW)
$HeatforCooling_{m,t,h}$	Gross heat for cooling during hour *h*, type of day *t*, and month *m* (kW)
$HeatforStorage_{m,t,h}$	Gross heat for storage during hour *h*, type of day *t*, and month *m* (kW)
$HeatConsumed_{m,t,h}$	Demand for heat during hour *h*, type of day *t*, and month *m* (kW)
AnnualDGElectricity	Total electricity generated on-site during test year (kWh)
AnnualDGRecHeat	Total recovered heat used to meet heat loads (kWh)
AnnualNGforDG	Total natural gas purchases for on-site generation (kWh)
AnnualizedCapitalCost	Annualized capital cost of discrete generation technologies, continuous technologies, direct chillers, and switch parameters ($)
UpfrontCapitalCost	Total capital cost of discrete generation technologies, continuous technologies, direct chillers, and switch parameters ($)

Problem Formulation

It is assumed that the site acquires the residual electricity that it needs beyond its self-generation from the utility at the regulated tariff. The mathematical formulation of the problem follows:

min

$$TotalEnergyCost = \sum_{m \in M} \text{ContractDemandCharge} \cdot \max_{m \in M, t \in T, h \in H} \left\{ \text{Load}_{'e',m,t,h} + \text{Load}_{'c',m,t,h} \right\}$$

$$+ \sum_{m \in M} \text{MonthlyFeeElectric}$$

$$+\sum_{m\in M}\sum_{i\in I}\left(DERInvestment_{i}\cdot \mathrm{Maxp_i} + Capacity_{,pv'}\right)\cdot \mathrm{StandbyCharge}$$

$$+\sum_{m\in M}\sum_{p\in P}\sum_{t\in T}\sum_{h\in p} ElectricityPurchase_{m,t,h}\cdot \mathrm{N_{m,t}}\cdot \mathrm{ElectricityRate_{m,p}}$$

$$+\sum_{m\in M}\sum_{d\in D}\mathrm{MonthlyDemandRates_{m,d}}\cdot \max_{t\in T, h\in d}\left\{ElectricityPurchase_{m,t,h}\right\}$$

$$+\sum_{m\in M}\sum_{t\in T}\sum_{d\in D}\mathrm{DailyDemandRates_{m,d}}\cdot \mathrm{N_{m,t}}\cdot \max_{h\in d}\left\{ElectricityPurchase_{m,t,h}\right\}$$

$$+\sum_{m\in M}\sum_{t\in T}\sum_{h\in H} ElectricityPurchase_{m,t,h}\cdot \mathrm{MktCRate}\cdot \mathrm{N_{m,t}}\cdot \mathrm{CTax}$$

$$-\sum_{i\in I}\sum_{m\in M}\sum_{t\in T}\sum_{h\in H} GenX_{i,m,t,h}\cdot \mathrm{N_{m,t}}\cdot \mathrm{PX_{m,t,h}}$$

$$-SwitchPurchase\cdot \mathrm{StaticSwitchParameterValue}\cdot \mathrm{SwitchSize}$$

$$+\sum_{m\in M}\sum_{t\in T}\sum_{h\in H}\sum_{i\in I_{NG}}\left(GenL_{i,m,t,h}+GenX_{i,m,t,h}\right)\cdot \frac{1}{\mathrm{E_i}}\cdot \mathrm{N_{m,t}}\cdot \begin{pmatrix}\mathrm{NGBasicPrice_m} \\ +\,\mathrm{NGCarbonEmissionsRate}\cdot \mathrm{CTax}\end{pmatrix}$$

$$+\sum_{m\in M}\sum_{t\in T}\sum_{h\in H} NGforHeat_{m,t,h}\cdot \mathrm{N_{m,t}}\cdot \begin{pmatrix}\mathrm{NGBasicPrice_m} \\ +\,\mathrm{NGCarbonEmissionsRate}\cdot \mathrm{CTax}\end{pmatrix}$$

$$+\sum_{m\in M}\sum_{t\in T}\sum_{h\in H}\sum_{k\in K} NGforNGChill_{k,m,t,h}\cdot \mathrm{N_{m,t}}\cdot \left(\mathrm{NGforABS_m}+\mathrm{NGCarbonEmissionsRate}\cdot \mathrm{CTax}\right)$$

$$+\sum_{m\in M}\left(\mathrm{MonthlyFeeNGBasic}+\mathrm{MonthlyFeeNGforDG}+\mathrm{MonthlyFeeNGforABS}\right)$$

$$+\sum_{m\in M}\sum_{t\in T}\sum_{h\in H}\sum_{i\notin I_{NG}}\left(GenL_{i,m,t,h}+GenX_{i,m,t,h}\right)\cdot \frac{1}{\mathrm{E_i}}\cdot \mathrm{N_{m,t}}\cdot \mathrm{OtherFuelPrice_i}$$

$$+\sum_{i\in I} DERInvestment_{i}\cdot \mathrm{Maxp_i}\cdot \mathrm{CapCost_i}\cdot \mathrm{Annuity_i}$$

$$+\sum_{k\in K} NGChillPurchaseQuantity_k \cdot \mathrm{Maxp_k} \cdot \mathrm{CapCost_k} \cdot \mathrm{Annuity_k}$$

$$+\sum_{\ell\in L} \left(Purchase_\ell \cdot \mathrm{FixedCost}_\ell + Capacity_\ell \cdot \mathrm{VariableCost}_\ell\right) \cdot \mathrm{Annuity}_\ell$$

$$+ SwitchPurchase \cdot \left(\mathrm{SwitchSize} \cdot \mathrm{CostM} + \mathrm{CostB}\right) \cdot \mathrm{AnnuitySwitch}$$

$$+\sum_{m\in M}\sum_{i\in I} DERInvestment_i \cdot \mathrm{Maxp_i} \cdot \frac{\mathrm{OMFix_i}}{12}$$

$$+\sum_{m\in M}\sum_{\ell\in L} Capacity_\ell \cdot \mathrm{FixedMaintenance}_\ell$$

$$+\sum_{m\in M}\sum_{k\in K} NGChillPurchaseQuantity_k \cdot \mathrm{Maxp_k} \cdot \frac{\mathrm{OMFix_k}}{12}$$

$$+\sum_{m\in M}\sum_{i\in I}\sum_{t\in T}\sum_{h\in H} \left(GenL_{i,m,t,h} + GenX_{i,m,t,h}\right) \cdot \mathrm{N_{m,t}} \cdot \mathrm{OMVar_i}$$

$$+\sum_{m\in M}\sum_{k\in K}\sum_{t\in T}\sum_{h\in H} NGChillAmount_{k,m,t,h} \cdot \mathrm{N_{m,t}} \cdot \mathrm{OMVar_k} \tag{A1}$$

Subject to:

$$DERCurrentlyOperating_{i,m,t,h} \le DERInvestment_i \quad \forall i,m,t,h \tag{A2}$$

$$GenL_{i,m,t,h} + GenX_{i,m,t,h} \ge DERCurrentlyOperating_{i,m,t,h} \cdot \mathrm{Maxp_i} \cdot \mathrm{MinLoad_i} \quad \forall i \notin I_{PV}, m,t,h \tag{A3}$$

$$GenL_{i,m,t,h} + GenX_{i,m,t,h} \le DERCurrentlyOperating_{i,m,t,h} \cdot \mathrm{SprintCap_i} \quad \forall i \notin I_{PV}, m,t,h \tag{A4}$$

$$CoolingbyAbsorption_{m,t,h} \le Capacity_{'ab'} \quad \forall m,t,h \tag{A5}$$

$$SprintAmount_{i,m,t,h} \ge \left(GenL_{i,m,t,h} + GenX_{i,m,t,h}\right) - \mathrm{Maxp_i} \cdot DERCurrentlyOperating_{i,m,t,h} \quad \forall i,m,t,h \tag{A6}$$

$$\sum_{m\in M}\sum_{t\in T}\sum_{h\in H} Sprint\,Amount_{i,m,t,h}\cdot \mathrm{N}_{\mathrm{m,t}} \le \left(\mathrm{SprintCap_i} - \mathrm{Maxp_i}\right)\cdot \mathrm{SprintHours_i}\cdot DERInvestment_i \quad \forall i \tag{A7}$$

$$ElectricityProvided_{m,t,h} = ElectricityPurchase_{m,t,h} + ElectricityGeneration_{m,t,h} + ElectricityPV_{m,t,h} + ElectricityfromBattery_{m,t,h} + ElectricityfromFlowBattery_{m,t,h} \;\forall m,t,h \tag{A8}$$

$$ElectricityStored_{m,t,h} = ElectricityStored_{m,t,h-1} + ElectricityStorageInput_{m,t,h} - ElectricityStorageOutput_{m,t,h} - ElectricityStorageLosses_{m,t,h} \;\forall m,t,h \tag{A9}$$

$$FlowBatteryStored_{m,t,h} = FlowBatteryStored_{m,t,h-1} + FlowBatteryInput_{m,t,h} - FlowBatteryOutput_{m,t,h} - FlowBatteryLosses_{m,t,h} \;\forall m,t,h \tag{A10}$$

$$ElectricityConsumed_{m,t,h} = \mathrm{Load}_{\mathrm{'e',m,t,h}} + ElectricityforCooling_{m,t,h} + ElectricityforStorage_{m,t,h} + ElectricityforFlowBattery_{m,t,h} \;\forall m,t,h \tag{A11}$$

$$ElectricityProvided_{m,t,h} = ElectricityConsumed_{m,t,h} \;\forall m,t,h \tag{A12}$$

$$ElectricityGeneration_{m,t,h} = \sum_{i\notin I_{PV}}\left(GenL_{i,m,t,h} + GenX_{i,m,t,h}\right)\forall m,t,h \tag{A13}$$

$$ElectricityPV_{m,t,h} \le Capacity_{'pv'}\cdot \mathrm{SolarInsolation_{m,h}} \;\forall m,t,h \tag{A14}$$

$$ElectricityStorageInput_{m,t,h} = ElectricityforStorage_{m,t,h}\cdot \mathrm{ElectricityStorageEfficiencyCharge} \;\forall m,t,h \tag{A15}$$

$$FlowBatteryInput_{m,t,h} = ElectricityforFlowBattery_{m,t,h}\cdot \mathrm{FlowBatteryEfficiencyCharge} \;\forall m,t,h \tag{A16}$$

$$ElectricityfromBattery_{m,t,h} = ElectricityStorageOutput_{m,t,h}\cdot \mathrm{ElectricityStorageEfficiencyDischarge} \;\forall m,t,h \tag{A17}$$

$$ElectricityfromFlowBattery_{m,t,h} = FlowBatteryOutput_{m,t,h}\cdot \mathrm{FlowBatteryEfficiencyDischarge} \;\forall m,t,h \tag{A18}$$

$$ElectricityStorageLosses_{m,t,h} = ElectricityStored_{m,t,h-1}\cdot \mathrm{ElectricityStorageEfficiencyDecay} \;\forall m,t,h \tag{A19}$$

$$FlowBatteryLosses_{m,t,h} = FlowBatteryStored_{m,t,h-1} \cdot \text{FlowBatteryEfficiencyDecay} \; \forall m,t,h \tag{A20}$$

$$ElectricityStorageInput_{m,t,h} \leq \left(Capacity_{'es'} - ElectricityStored_{m,t,h-1}\right) \cdot \text{ElectricityStorageMaxChargeRate} \; \forall m,t,h \tag{A21}$$

$$ElectricityStorageOutput_{m,t,h} \leq ElectricityStored_{m,t,h-1} \cdot \text{ElectricityStorageMaxDischargeRate} \; \forall m,t,h \tag{A22}$$

$$ElectricityStored_{m,t,h} \leq Capacity_{'es'} \; \forall m,t,h \tag{A23}$$

$$ElectricityStored_{m,t,h} \geq Capacity_{'es'} \cdot \text{ElectricityStorageMinStateofCharge} \; \forall m,t,h \tag{A24}$$

$$FlowBatteryInput_{m,t,h} \leq Capacity_{'fp'} \; \forall m,t,h \tag{A25}$$

$$FlowBatteryOutput_{m,t,h} \leq Capacity_{'fp'} \; \forall m,t,h \tag{A26}$$

$$FlowBatteryStored_{m,t,h} \leq Capacity_{'fe'} \; \forall m,t,h \tag{A27}$$

$$FlowBatteryStored_{m,t,h} \geq Capacity_{'fe'} \cdot \text{FlowBatteryMinStateofCharge} \; \forall m,t,h \tag{A28}$$

$$\text{Load}_{\text{'c',m,t,h}} = CoolingbyElectric_{m,t,h} + CoolingbyAbsorption_{m,t,h} + CoolingbyNGChill_{m,t,h} \; \forall m,t,h \tag{A29}$$

$$CoolingbyElectric_{m,t,h} = ElectricityforCooling_{m,t,h} \; \forall m,t,h \tag{A30}$$

$$CoolingbyNGChill_{m,t,h} = \sum_{k \in K} NGChillAmount_{k,m,t,h} \; \forall m,t,h \tag{A31}$$

$$NGforNGChill_{m,t,h} = \sum_{k \in K} NGChillAmount_{k,m,t,h} \cdot \frac{\text{COPelectric}}{\text{NGChillCOP}_\text{k}} \; \forall m,t,h \tag{A32}$$

$$CoolingbyAbsorption_{m,t,h} = HeatforCooling_{m,t,h} \cdot \frac{\text{COPabs}}{\text{COPelectric}} \; \forall m,t,h \tag{A33}$$

$$HeatProvided_{m,t,h} = HeatfromNG_{m,t,h} + HeatfromDG_{m,t,h} + HeatfromSolar_{m,t,h} + HeatfromStorage_{m,t,h} + HeatfromNGChill_{m,t,h} \; \forall m,t,h \tag{A34}$$

$$HeatStored_{m,t,h} = HeatStored_{m,t,h-1} + HeatStorageInput_{m,t,h} - HeatStorageOutput_{m,t,h} - HeatStorageLosses_{m,t,h} \ \forall m,t,h \tag{A35}$$

$$HeatConsumed_{m,t,h} = \mathrm{Load}_{'s',m,t,h} + \mathrm{Load}_{'w',m,t,h} + HeatforCooling_{m,t,h} + HeatforStorage_{m,t,h} \ \forall m,t,h \tag{A36}$$

$$HeatConsumed_{m,t,h} = HeatProvided_{m,t,h} \ \forall m,t,h \tag{A37}$$

$$HeatfromNG_{m,t,h} = NGforHeat_{m,t,h} \cdot \beta_{'s'} \ \forall m,t,h \tag{A38}$$

$$HeatfromDG_{m,t,h} \le \sum_{i\in I} \alpha_{\mathrm{i}} \cdot \left(GenL_{i,m,t,h} + GenX_{i,m,t,h}\right) \forall m,t,h \tag{A39}$$

$$HeatfromSolar_{m,t,h} \le Capacity_{'st'} \cdot \mathrm{SolarInsolation}_{\mathrm{m,h}} \ \forall m,t,h \tag{A40}$$

$$HeatfromStorage_{m,t,h} = HeatStorageOutput_{m,t,h} \cdot \mathrm{HeatStorageEfficiencyDischarge} \ \forall m,t,h \tag{A41}$$

$$HeatfromNGChill_{m,t,h} = \sum_{k\in K_{HX}} \alpha_{\mathrm{k}} \cdot NGChillAmount_{k,m,t,h} \ \forall m,t,h \tag{A42}$$

$$HeatStorageInput_{m,t,h} = HeatforStorage_{m,t,h} \cdot \mathrm{HeatStorageEfficiencyCharge} \ \forall m,t,h \tag{A43}$$

$$HeatStorageLosses_{m,t,h} = HeatStored_{m,t,h-1} \cdot \mathrm{HeatStorageEfficiencyDecay} \ \forall m,t,h \tag{A44}$$

$$HeatStored_{m,t,h} \le Capacity_{'hs'} \ \forall m,t,h \tag{A45}$$

$$HeatStorageOutput_{m,t,h} \le Capacity_{'hs'} \cdot \mathrm{HeatStorageMaxDischargeRate} \ \forall m,t,h \tag{A46}$$

$$HeatStorageInput_{m,t,h} \le Capacity_{'hs'} \cdot \mathrm{HeatStorageMaxChargeRate} \ \forall m,t,h \tag{A47}$$

$$\sum_{m\in M}\sum_{t\in T}\sum_{h\in H} DERCurrentlyOperating_{i,m,t,h} \cdot \mathrm{N}_{\mathrm{m,t}} \le DERInvestment_i \cdot \mathrm{MaxAnnualHours}_{\mathrm{i}} \ \forall i \tag{A48}$$

$$AnnualDGElectricity = \sum_{i\in I_{NG}}\sum_{m\in M}\sum_{t\in T}\sum_{h\in H} \left(GenL_{i,m,t,h} + GenX_{i,m,t,h}\right) \cdot \mathrm{N}_{\mathrm{m,t}} \tag{A49}$$

$$AnnualDGRecHeat = \sum_{m\in M}\sum_{t\in T}\sum_{h\in H} HeatfromDG_{m,t,h} \cdot \mathrm{N}_{\mathrm{m,t}} \tag{A50}$$

$$AnnualNGforDG = \sum_{i \in I_{NG}} \sum_{m \in M} \sum_{t \in T} \sum_{h \in H} \left(GenL_{i,m,t,h} + GenX_{i,m,t,h} \right) \cdot \frac{1}{\mathrm{E_i}} \cdot \mathrm{N_{m,t}} \tag{A51}$$

$$AnnualDGElectricity + AnnualDG\mathrm{Re}cHeat \geq AnnualNGforDG \cdot \mathrm{MinEff} \tag{A52}$$

$$\begin{aligned} AnnualizedCapitalCost = & \sum_{i \in I} DERInvestment_i \cdot \mathrm{Maxp_i} \cdot \mathrm{CapCost_i} \cdot \mathrm{Annuity_i} \\ & + \sum_{k \in K} NGChillPurchaseQuantity_k \cdot \mathrm{Maxp_k} \cdot \mathrm{CapCost_k} \cdot \mathrm{Annuity_k} \\ & + \sum_{\ell \in L} \left(Purchase_\ell \cdot \mathrm{FixedCost}_\ell + Capacity_\ell \cdot \mathrm{VariableCost}_\ell \right) \cdot \mathrm{Annuity}_\ell \\ & + SwitchPurchase \cdot \left(\mathrm{SwitchSize} \cdot \mathrm{CostM} + \mathrm{CostB} \right) \cdot \mathrm{AnnuitySwitch} \end{aligned} \tag{A53}$$

$$AnnualSavings = \mathrm{BaseCaseCost} - \left(TotalEnergyCost - AnnualizedCapitalCost \right) \tag{A54}$$

$$\begin{aligned} UpfrontCapitalCost = & \sum_{i \in I} DERInvestment_i \cdot \mathrm{Maxp_i} \cdot \mathrm{CapCost_i} \\ & + \sum_{k \in K} NGChillPurchaseQuantity_k \cdot \mathrm{Maxp_k} \cdot \mathrm{CapCost_k} \\ & + \sum_{\ell \in L} \left(Purchase_\ell \cdot \mathrm{FixedCost}_\ell + Capacity_\ell \cdot \mathrm{VariableCost}_\ell \right) \\ & + SwitchPurchase \cdot \left(\mathrm{SwitchSize} \cdot \mathrm{CostM} + \mathrm{CostB} \right) \end{aligned} \tag{A55}$$

$$AnnualSavings \geq \frac{UpfrontCapitalCost}{\mathrm{MaxPaybackPeriod}} \tag{A56}$$

$$Capacity_\ell \leq 100000 \cdot Purchase_\ell \tag{A57}$$

$$\begin{aligned} \mathrm{SwitchSize} = & \min_{m \in M, t \in T, h \in H} \left\{ \mathrm{Load_{'e',m,t,h}} \cdot \mathrm{FracBase} \right\} \\ & + \left(\max_{m \in M, t \in T, h \in H} \left\{ \mathrm{Load_{'e',m,t,h}} \right\} - \min_{m \in M, t \in T, h \in H} \left\{ \mathrm{Load_{'e',m,t,h}} \right\} \right) \cdot \mathrm{FracPeak} \end{aligned} \tag{A58}$$

$$\mathrm{AvailabilitySolarDay_m} = \frac{\sum_{h \in H} \mathrm{SolarInsolation_{m,h}}}{24} \quad \forall m \tag{A59}$$

$$\mathrm{AvailabilitySolar} = \frac{\sum_{m \in M} \mathrm{AvailabilitySolarDay_m}}{12} \tag{A60}$$

$$\text{AvailabilityElectricStorage} \tag{A61}$$
$$= \text{ElectricityStorageMaxDischargeRate} \cdot \frac{\left(24 - \frac{1}{\text{ElectricityStorageMaxChargeRate}}\right)}{24}$$

$$\sum_{i \in I}\left(DERInvestment_i \cdot \text{ReliabilityDER} \cdot \text{SprintCap}_{\text{i}}\right) + \text{AvailabilitySolar} \cdot Capacity_{'pv'} + Capacity_{'fp'} \tag{A62}$$
$$+ \text{AvailabilityElectricStorage} \cdot Capacity_{'es'} \geq \text{SwitchSize}$$

Appendix B. Solar data

To obtain solar data for DER-CAM, PVWATTS from NREL has been used (see also NREL PVWATTS). Originally designed to gather information for PV system output for different places, PVWATTS can be also used to gather solar radiation data for DER-CAM. DER-CAM assumes a maximum solar radiation of 1000W/m^2, which is the same number as used for testing PV panels. Thus, to obtain the fraction of solar insolation for different places and fixed alignment of the panels PVWATTS can be used. Setting the AC Rating to 1kW, PVWATTS delivers the fraction of max. solar radiation for a chosen site. Please note that this procedure is independent from the efficiency of the solar panel. The efficiency would simply increase the area of the solar panels. Assuming the same alignment of the solar thermal panel it can be used for solar thermal systems also. Thus, the fraction of solar radiation delivered from PVWATTS can be used within DER-CAM for both PV and solar thermal systems.

Northern California, Oakland

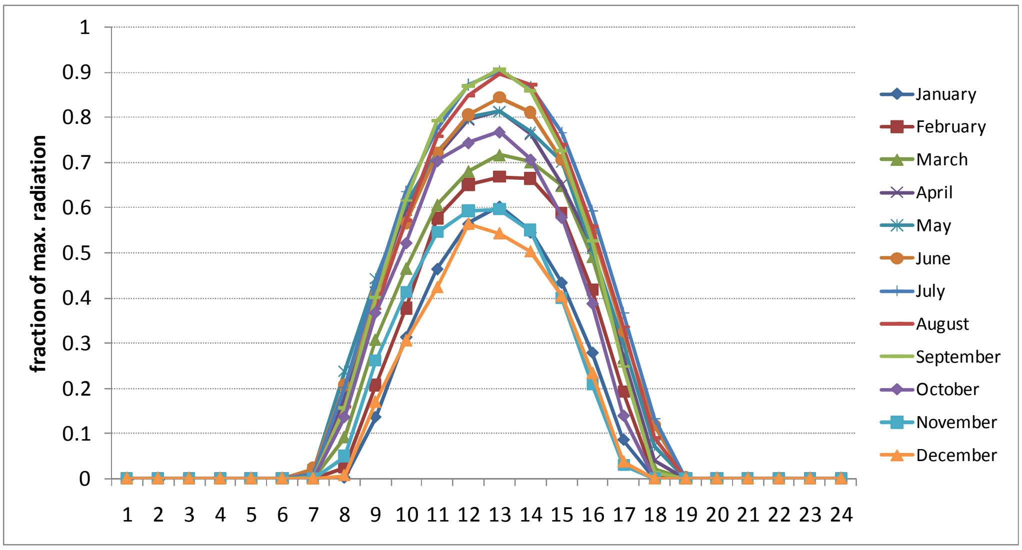
San Francisco is used as an approximation for Oakland.

Table 21. Settings for PVWATTS to obtain the fraction of max. radiation for Oakland

PVWATTS: Hourly PV Performance Data	
City:	SAN_FRANCISCO
State:	CA
Lat (deg N):	37.62
Long (deg W):	122.38
Elev (m):	5
Array Type:	“Fixed Tilt”
Array Tilt (deg):	37.6
Array Azimuth (deg):	180.0
DC Rating (kW):	1.3
DC to AC Derate Factor:	0.770
AC Rating (kW):	1.0

Source: NREL PVWATTS

Figure 39. Fraction of max. solar radiation for San Francisco



Southern California, Riverside

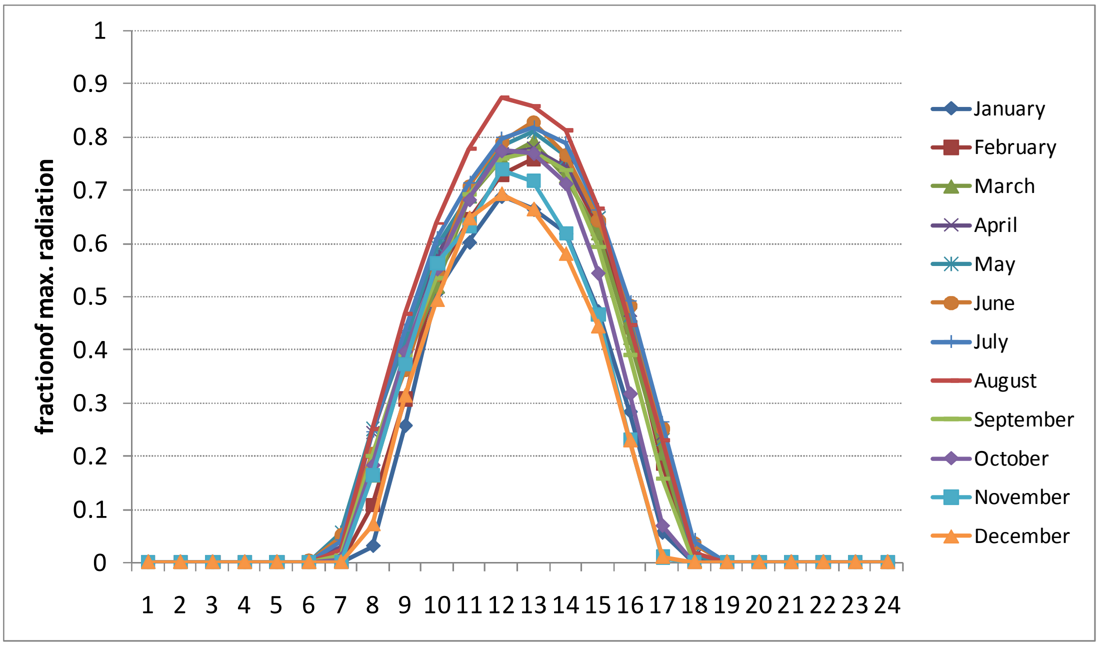
Los Angeles is used as approximation for Riverside.

Table 22. Settings for PVWATTS to obtain the fraction of max. radiation for Riverside

PVWATTS: Hourly PV Performance Data	
City:	LOS_ANGELES
State:	CA
Lat (deg N):	33.93
Long (deg W):	118.40
Elev (m):	32
Array Type:	"Fixed Tilt"
Array Tilt (deg):	33.9
Array Azimuth (deg):	180.0
DC Rating (kW):	1.3
DC to AC Derate Factor:	0.770
AC Rating (kW):	1.0

Source: NREL PVWATTS

Figure 40. Fraction of max. solar radiation for Los Angeles



<u>New York City</u>

Table 23. Settings for PVWATTS to obtain the fractionof max. radiation for New York City

PVWATTS: Hourly PV Performance Data	
City:	NEW_YORK_CITY
State:	NY
Lat (deg N):	40.78
Long (deg W):	73.97
Elev (m):	57
Array Type:	"Fixed Tilt"
Array Tilt (deg):	40.8
Array Azimuth (deg):	180.0
DC Rating (kW):	1.3
DC to AC Derate Factor:	0.770
AC Rating (kW):	1.0

source: NREL PVWATTS

Figure 41. Fraction of max. solar radiation for New York City