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ABSTRACT

The addition of storage technologies such as flow batteries, conventional batteries, and heat storage can improve the economic as well as environmental attractiveness of on-site generation (e.g., PV, fuel cells, reciprocating engines or microturbines operating with or without CHP) and contribute to enhanced demand response. In order to examine the impact of storage technologies on demand response and carbon emissions, a microgrid's distributed energy resources (DER) adoption problem is formulated as a mixed-integer linear program that has the minimization of annual energy costs as its objective function. By implementing this approach in the General Algebraic Modeling System (GAMS), the problem is solved for a given test year at representative customer sites, such as schools and nursing homes, to obtain not only the level of technology investment, but also the optimal hourly operating schedules. This paper focuses on analysis of storage technologies in DER optimization on a building level, with example applications for commercial buildings. Preliminary analysis indicates that storage technologies respond effectively to time-varying electricity prices, i.e. by charging batteries during periods of low electricity prices and discharging them during peak hours. The results also indicate that storage technologies significantly alter the residual load profile, which can contribute to lower carbon emissions depending on the test site, its load profile, and its adopted DER technologies.

Introduction

In this paper, a microgrid is defined as a cluster of electricity sources and (possibly controllable) loads in one or more locations that are connected to the traditional wider power system, or macrogrid, but which may, as circumstances or economics dictate, disconnect from it and operate as an island, at least for short periods (see Microgrid Symposium 2005, 2006, and Hatziargyriou, N. et al.). The successful deployment of microgrids will depend heavily on the economics of distributed energy resources (DER), in general, and upon the early success of small

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clusters of mixed technology generation, grouped with storage, and controllable loads. If clear economic, environmental, and utility system benefits from such early projects are realized, momentum can propel the adoption of added microgrid capabilities as well as precipitate the regulatory adjustments necessary to allow widespread microgrid introduction.

The potential benefits of microgrids are multi-faceted, but from the *adopters'* perspective, there are two major groupings: 1) the cost, efficiency, and environmental benefits (including possible emissions credits) of combined heat and power (CHP), and 2) the power quality and reliability (PQR) benefits of on-site generation and control. At the same time, it should be noted that growth in electricity demand in developed countries centers on the residential and commercial sectors in which CHP applications particularly have not hitherto been well developed.

This paper reports on the latest efforts intended to insert storage (both electrical and thermal) capabilities into the microgrid analysis on a building level. In previous work, the Berkeley Lab has developed the Distributed Energy Resources Customer Adoption Model (DER-CAM), (Siddiqui et al. 2003). Its optimization techniques find both the combination of equipment and its operation over a typical year that minimize the site's total energy bill, typically for electricity plus natural gas purchases, as well as amortized equipment purchases. The chosen equipment and its schedule should be economically attractive to a single site or to members of a microgrid consisting of a cluster of sites, and it should be subsequently analyzed in more engineering and financial detail (Stadler et al. 2006).

Electrical and thermal storage is added as an option to the menu of technology choices, and this capability is demonstrated by the analysis of two commercial buildings in California. A nursing home in the San Francisco Bay Area and a southern California school are investigated to assess the economic and environmental attractiveness of distributed generation with storage.

The Distributed Energy Resources - Costumer 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 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 the building cooling problem; that is, results reflect the benefit of displacement of electricity demand 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 structure and rates, and DG investment options. The following technologies are currently considered in the DER-CAM model:[3]

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[2] Three different day-long 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.

- natural gas-fired reciprocating engines, gas turbines, microturbines, and fuel cells;
- photovoltaics and solar thermal collectors;
- electrical storage, 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 in 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, storage and cooling equipment, required to meet the site's following end-use loads at each time step:

- 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;
- natural gas-only loads, e.g. mostly cooking that can only be met by natural gas.

Figure 1. Schematic of the Energy Flow Model used in DER-CAM[5]
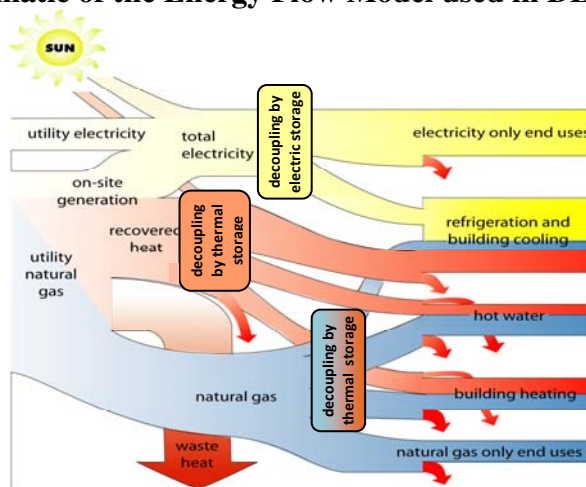
The outputs of DER-CAM include the optimal DG and storage adoption and an hourly operating schedule, as well as the resulting costs, fuel consumption, and carbon emissions (Figure 2).

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[3] Despite the wide variety of technologies considered in DER-CAM, we use a subset of technologies in this work to keep the results clear. See also section "DER Equipment Including Storage Technologies".

[4] DER-CAM's objective function to minimize the total energy costs can be changed easily to a carbon minimizing or other strategy.

[5] Please note that thermal storage contains also heat for absorption chillers, and therefore, Figure 1 considers cold thermal storage indirectly.

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 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 and transfer are obeyed. The recently added storage constraints are essentially inventory balance constraints that state that 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 any energy charged minus any energy discharge minus 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 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 Siddiqui et al. 2007.

Figure 2. High-Level Schematic of Information Flow in DER-CAM
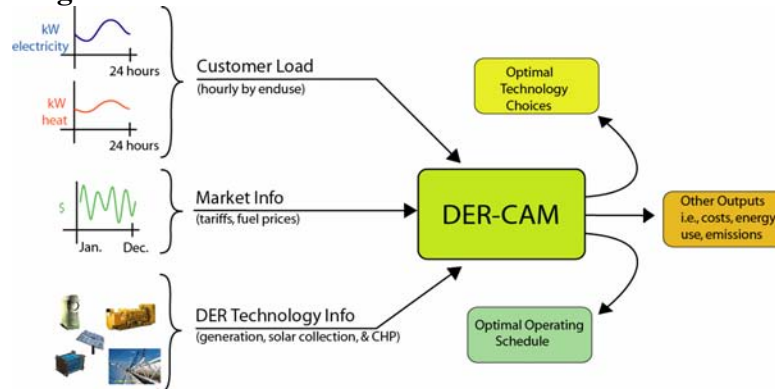
Figure 3. MILP Solved by DER-CAM[6]

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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
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DER Equipment Including Storage Technologies[7]

This paper reports results using recently added electrical, i.e. a conventional lead/acid battery, and thermal storage, capabilities, with both electrical and thermal storage being viewed 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 models are shown in following Table 1 (see also Stevens et al. and Symons et al.).

Table 1. Energy Storage Parameters

	description	electrical	flow battery[8]	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[9]	0.01	0.01

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[6] Not all constraints are shown (e.g. flow batteries have more different constraints than electric storages).

[7] Only active storage systems are considered. No thermal effects of the building shell are taken into account.

[8] Flow batteries differ from conventional rechargeable batteries in one significant way: the power and energy ratings of a flow battery are independent of each other. This is made possible by the separation of the electrolyte and the battery stack. Flow batteries can be rapidly 'recharged' by replacing the electrolyte liquid stored in an external tank.

[9] Please note that our decay number 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 will address the impact of different decay numbers.

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

The menu of available equipment options to DER-CAM for this analysis together with their cost and performance characteristics is shown in Table 2 and 3.

Table 2. Menu of Available Equipment Options, *Discrete Investments*

	reciprocating engine	fuel cell
capacity (kW)	100	200
sprint capacity	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

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. The costs for the discrete fuel cell[10] 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. Continuously sized technologies are available in such a large variety of sizes that it can be assumed capacity close to the optimal could be acquired, e.g. battery storage, the costs for which are roughly consistent with those described by the Electricity Storage Association (see also Electricity Storage Association). The installation cost functions for these technologies are assumed to consist of an unavoidable cost (intercept) independent of installed capacity ($) representing the fixed cost of the infrastructure required to adopt such a device, plus a variable cost proportional to capacity ($/kWh or $/kW).

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[10] 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 costs.

Table 3. Menu of Available Equipment Options, *Continuous Investments*

	electrical storage	thermal storage[11]	flow battery	absorption chiller	solar thermal	photovoltaics
intercept costs ($)	295	10000	0	20000	1000	1000
variable costs ($/kW or $/kWh)	193[12]	100[13]	220 / 2125[14]	127[15]	500[16]	6675[17]
lifetime (a)	5	17	10	15	15	20

Results

Optimal DER Equipment for a Northern California Nursing Home

A numerical example was completed of a northern California Nursing Home in the Bay Area operating during 2007. This facility has a peak total electrical load of 958 kW. Table 4 shows the prices used, which are based on local Pacific Gas and Electric (PG&E) rates. Natural gas prices for the region were also obtained from PG&E tariffs. A marginal carbon emission factor of 140 g/kWh for electricity purchased from PG&E was assumed (Marnay et al. 2002). Finally, the carbon emission factor for each DG unit is calculated by dividing the natural gas emission factor of 49 g/kWh by the appropriate higher heating value (HHV) efficiency. For example, the carbon emission factor is 188 g/kWh for the 100 kW reciprocating engine. From the data, DER is not necessarily more energy or carbon efficient than central station power. For example, simple cycle on-site generation of electricity using reciprocating engines at this site would be more carbon intensive than procurement from PG&E; however, using waste heat to offset thermal or electrical loads can improve the overall carbon efficiency.

In order to address how carbon emissions and total site energy costs change when electric and thermal storage is present, six DER-CAM runs were performed: 1. a *do nothing* case in which all DER investment is disallowed, i.e., the nursing home meets its local energy demands solely by purchases; 2. an *invest* case, which finds the optimal DER investment; 3. a *low storage and PV price* run; 4. to assess the value of storage systems, a run was performed forcing the same investments as in the low storage price run 3, but in which storage is disallowed; 5. a *low storage, PV, and solar thermal price* run; and 6. a *low storage price and 60% PV price reduction* run.

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

[12] $/kWh$_{electricity}$

[13] $/kWh$_{heat}$

[14] Flow batteries are characterized by both the energy content and power rating.

[15] abs. chiller capacity is in terms of electricity offset (electric load equivalent).

[16] $/kW$_{of recovered heat}$

[17] $/kW$_{electricity}$

Table 4. Input Energy Prices effective Nov. 2007

Electricity	Summer (May – Oct.)		Winter (Nov. – Apr.)	
	electricity ($/kWh)	demand ($/kW)	electricity ($/kWh)	demand ($/kW)
on-peak	0.16	15.04		
mid-peak	0.12	3.58	0.12	1.86
off-peak	0.09		0.10	
fixed ($/day)	9.04			

Natural Gas	
0.04	$/kWh
4.96	fixed ($/day)

Sources: PG&E commercial tariffs, PG&E tariffs, PG&E commercial, and PG&E natural gas tariffs.
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 major results for these six runs are shown in Table 5. 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 $964 000, and 1088 t of elemental carbon are emitted each year. In the *invest in all technologies* case (run 2) technology parameters from Table 1, 2, and 3 are taken and DER-CAM finds the optimal system. The optimal system for the site consists of three Tecogen gas engines, a 48 kW absorption chiller, and a 134 kW solar thermal system. At current price levels, neither electric nor thermal storage is economically attractive. Relative to the *do nothing* case, the expected annual savings for the optimal DER system are $38000/a (ca. 4%) while the elemental carbon emissions reduction is 143 t/a (ca. 13%). Considering low storage prices of $50/kWh for thermal and $60/kWh for electric storage, the annual operating costs drop by almost 5% (see run 3). However, the elemental carbon reduction is only ca. 12%. This means that elemental carbon emission reduction is lower with adoption of electric and thermal storages than without it (run 2). This finding is proven by run 4, which forces the same results as in the low storage cost run 3, but disallows storage adoption. The major driver for electric storage adoption is the objective to reduce energy costs, and this can be very effectively reached by avoiding electricity consumption during on-peak hours. In this example, the battery is charged by very cheap off-peak electricity and displaces utility consumption during on-peak hours (see also Figure 6). 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.

However, 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 5.60% while the elemental carbon emission reduction is 23.35% 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 7 and PV is not used for battery charging.

Table 5. Annual Results for the Northern California Nursing Home[18]

|	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$/W	force low storage / PV results	low storage costs and PV incentive of 2.5$/W & low solar thermal costs (minus 10% of original costs)	low storage costs and 60% PV price reduction
equipment						
Tecogen 100 kW with heat exchanger (kW)	n/a	300	300	300	300	300
abs. Chiller (kW in terms of electricity)		48	46	46	85	40
solar thermal collector (kW)		134	109	109	443	43
PV (kW)		0	0	0	0	517
electric storage (kWh)		0	4359	n/a	4148	2082
thermal storage (kWh)		0	123	n/a	196	47
annual total costs (k$)						
total	964	926	916	926	915	910
% savings compared to do nothing	n/a	3.94	4.98	3.94	5.08	5.60
annual energy consumption (GWh)						
electricity	5.76	3.23	3.33	3.22	3.45	2.40
NG	5.70	9.99	10.00	10.03	9.35	10.10
annual elemental carbon emissions (t/a)						
emissions	1088	945	960	946	944	834
% savings compared to do nothing	n/a	13.14	11.76	13.05	13.24	23.35

Another important finding for the nursing home is that the number of installed Tecogen reciprocating engine stays constant in all performed runs. The reason for this is the CHP favorable heat and electricity load (see also Figure 4). High electricity demand combined with high heat demand makes CHP very attractive.

Please also note that these results are 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., on the standby charge as back up to DER would have to be provided by the utility.

Besides the optimal investment plan, DER-CAM provides the microgrid with an optimal schedule for each installed technology, which we illustrate using the low storage cost run 3 and run 6 (see Figures 5 through 7). 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.

[18] Flow batteries are never chosen, and therefore, omitted in table 5.

Figure 4. Total Heat and Electricity Demand for the Nursing Home on January and July Weekdays
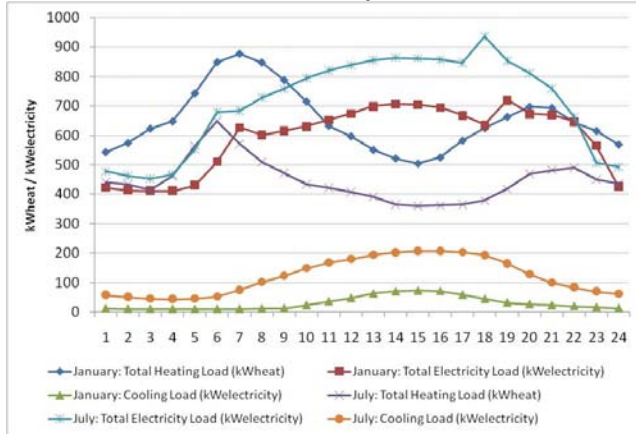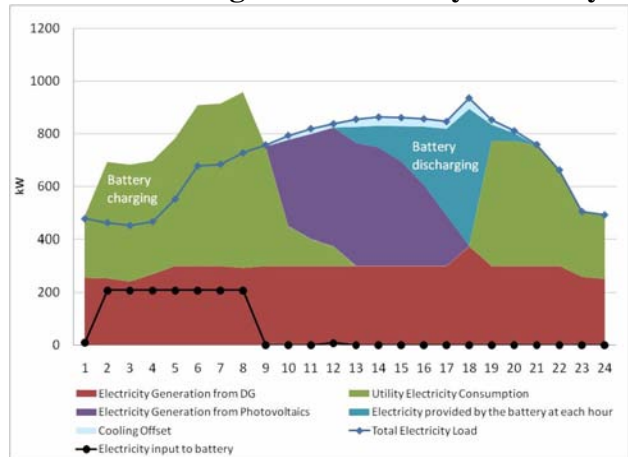

Figure 5. Low Storage and PV Price (run 3) Diurnal Heat Pattern for the Nursing Home on a January Weekday
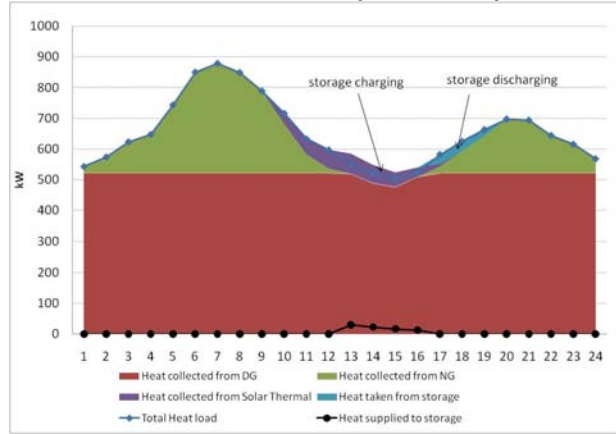
Figure 6. Low storage and PV Price (run 3) Diurnal Electricity Pattern for the Nursing Home on a July Weekday
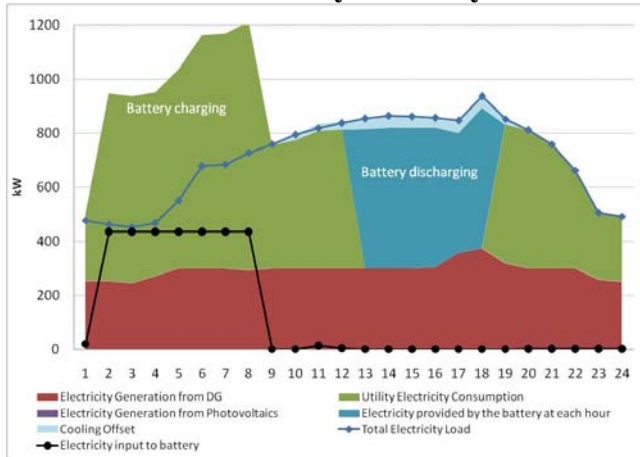
Figure 7. Low Storage Price and 60% PV Price Reduction (run 6) Diurnal E. Pattern for the Nursing Home on a July Weekday

Optimal DER Equipment for a Southern California School

A numerical example was also completed of a southern California school in the Los Angeles area operating in 2007. This facility has a peak total electrical load of 884 kW. Table 6 shows the prices used, which are based on local Southern Californian Edison (SCE) rates. Natural gas prices for the region were obtained from SoCal gas. A marginal carbon emission factor of 215 g/kWh for electricity purchased from SCE was assumed (Marnay et al. 2002).

The same runs as for the northern California nursing home were performed and confirm the higher carbon emissions with storage due to storage inefficiencies and charging by grid

10

power (see also Table 7). However, the major difference between the nursing home and the school is the absence of any internal combustion engine. The low off-peak electricity and heating demand combined with cheap electricity during off-peak hours (compare Tables 4 and 6) makes the adoption of natural gas engines with CHP unattractive.

Table 6. Input Energy Prices (Nov. 2006 for Natural Gas and July 2007 for Electricity)

Electricity	Summer (June – Sep.)		Winter (Oct. – May)	
	electricity ($/kWh)	demand ($/kW)	electricity ($/kWh)	demand ($/kW)
non-coincident		9.71		9.71
on-peak	0.12	15.37		
mid-peak	0.09	5.19	0.10	
off-peak	0.07		0.07	
fixed ($/month)	414.98			

Natural Gas	
0.03	$/kWh
0.41	fixed ($/day)

Sources: SCE time of use and SoCal natural gas tariffs.
Summer on-peak: 12:00-18:00 during weekdays,
Summer mid-peak: 08:00-12:00 and 18:00-23:00 during weekdays, all other hours and days: off-peak;
Winter mid-peak: 08:00-21:00 during weekdays, all other hours and days: off-peak;

Table 7. Annual Results for the Southern California School

|	run 1	run 2	run 3	run 4	run 5	run 6[19]
	do nothing	invest in all technologies	low storage costs and PV incentive of 2.5$/W	force low storage / PV results	low storage costs and PV incentive of 2.5$/W & low solar thermal costs (minus 10% of original costs)	low storage costs and 60% PV price reduction
equipment						
Tecogen 100 kW with HX (kW)		0	0	0	0	0
abs. Chiller (kW in terms of electricity)		139	106	106	101	101
solar thermal collector (kW)	n/a	65	72	72	94	72
PV (kW)		0	0	0	0	181
electric storage (kWh)		0	2279	n/a	2279	1518
thermal storage (kWh)		0	41	n/a	116	41
annual total costs (k$)						
total	288	280	251	280	251	249
% savings compared to do nothing	n/a	2.77	12.85	2.78	12.85	13.54
annual elemental carbon emissions (t/a)						
emissions	360	358	368	356	366	291
% savings compared to do nothing	n/a	0.56	-2.17	1.11	-1.66	19.17

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[19] Please note that we do not consider society costs in our analysis.

11

Both numerical examples show that electric storage adoption is driven by economic decisions to minimize total energy costs by avoiding on-peak grid purchases. To avoid higher carbon emissions, the storage systems have to be charged by renewable energy sources such as PV or solar thermal. However, this possibility depends strongly on the load profile as well as solar insolation and economic parameters, i.e., the electricity tariff structure. Due to this finding, the off-peak operation of high-efficiency CHP natural gas units might help to decrease the off-peak carbon emission levels to eliminate the impact of storage inefficiencies (see also the hotel example in Marnay et al. 2008). Further investigations of a wider variety of building types will be performed in the future.

Figure 8. Low Storage and PV Price (run 3) Diurnal Electricity Pattern for the School on a May Weekday
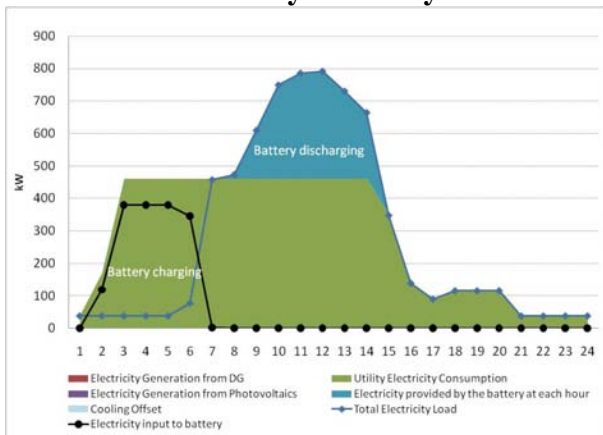
Figure 9. Low Storage and 60% PV Price Reduction (run 6) Diurnal E. Pattern for the School on a May Weekday
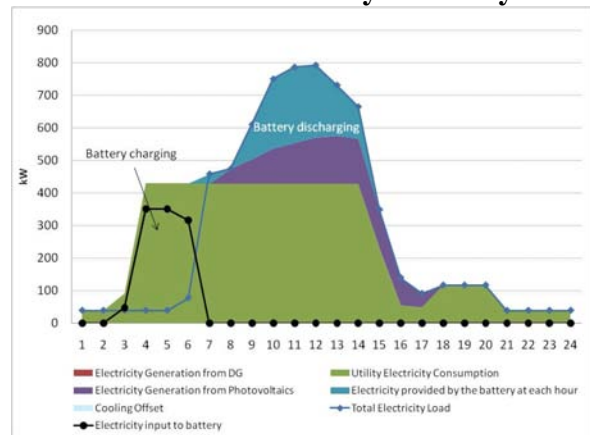
Conclusions

In this paper the new electrical and thermal storage capabilities of DER-CAM are demonstrated for two California commercial sites. The results 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 investigations is that heat, electric load profile, tariff structure, available solar insolation, and installed DG equipment (PV, solar thermal, natural gas driven reciprocating engines, etc.) 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. As shown for the nursing home and school example in this work, the demand charge reduction is a significant driver for the adoption of electric storage technologies. However, the high electric demand during on-peak hours, which coincident with the solar insolation, 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 higher carbon emissions for the nursing home and the school example than without storages. However,

12

different load profiles (high energy consumption in the evening) can result in a storage charging by efficient (i.e CHP units) or renewable energy sources that compensate for the storage inefficiencies. Thus, a wide variety of building types will be investigated in the future to derive load profile and tariff structure pattern which combines the positive economic effects of storage with the positive environmental effects of high efficient low carbon intensive technologies.

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14