LBNL-1973E

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Optimal Technology Investment and Operation in Zero-Net-Energy Buildings with Demand Response

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Environmental Energy Technologies Division

June 2009

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.

Disclaimer

To be presented at the 22nd Annual Western Conference, Advanced Workshop in Regulation and Competition, June 17-19, 2009, Hyatt Regency, Monterey, California, USA

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Michael Stadler[2], Afzal Siddiqui[3], Chris Marnay[4], Hirohisa Aki[5], and Judy Lai[6]

Abstract

The US Department of Energy has launched the Zero-Net-Energy (ZNE) Commercial Building Initiative (CBI) in order to develop commercial buildings that produce as much energy as they use. Its objective is to make these buildings marketable by 2025 such that they minimize their energy use through cutting-edge energy-efficient technologies and meet their remaining energy needs through on-site renewable energy generation. We examine how such buildings may be implemented within the context of a cost- or carbon-minimizing microgrid that is able to adopt and operate various technologies, such as photovoltaic (PV) on-site generation, heat exchangers, solar thermal collectors, absorption chillers, and passive / demand-response technologies. We use a mixed-integer linear program (MILP) that has a multi-criteria objective function: the minimization of a weighted average of the building's annual energy costs and carbon / CO_2 emissions. The MILP's constraints ensure energy balance and capacity limits. In addition, constraining the building's energy consumed to equal its energy exports enables us to explore how energy sales and demand-response measures may enable compliance with the CBI. Using a nursing home in northern California and New York with existing tariff rates and technology data, we find that a ZNE building requires ample PV capacity installed to ensure electricity sales during the day. This is complemented by investment in energy-efficient combined heat and power equipment, while occasional demand response shaves energy consumption. A large amount of storage is also adopted, which may be impractical. Nevertheless, it shows the nature of the solutions and costs necessary to achieve ZNE. For comparison, we analyze a nursing home facility in New York to examine the effects of a flatter tariff structure and different load profiles. It has trouble reaching ZNE status and its load reductions as well as efficiency measures need to be more effective than those in the CA case. Finally, we illustrate that the multi-criteria frontier that considers costs and carbon emissions in the presence of demand response dominates the one without it.

Keywords: CO_2 emissions, distributed generation, energy management, microgrid, storage, zero-net energy buildings, zero-carbon

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

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1. Introduction

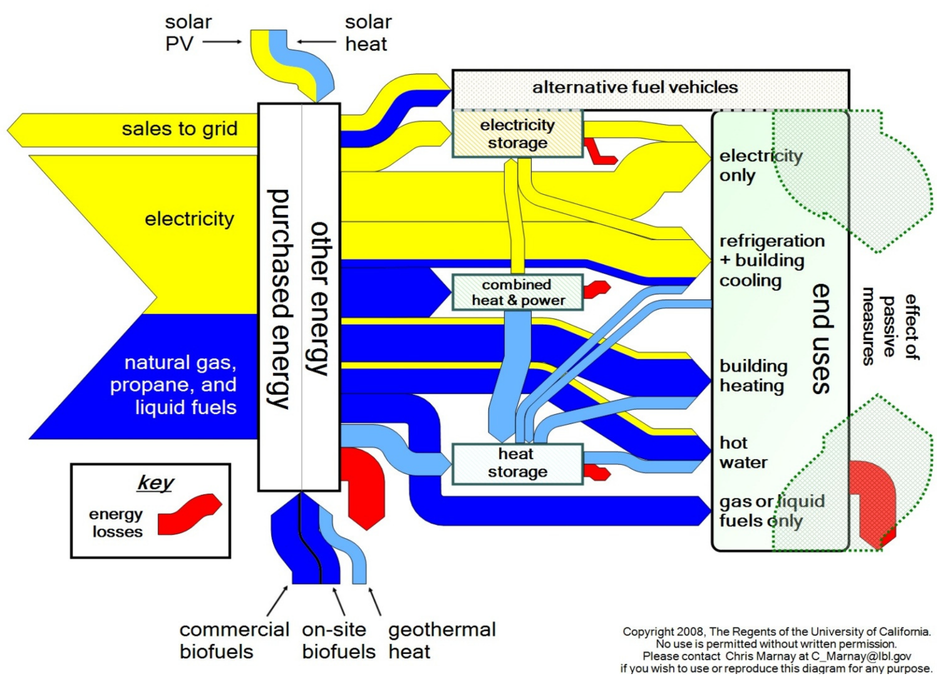
Due to increasing energy consumption in industrialized countries and concerns about climate change, the traditional centralized paradigm for organizing the production and distribution of power may face competition from a more decentralized layout. Aided by deregulation of electricity industries worldwide, which facilitates the relaying of price signals to promote economically efficient energy consumption and production, small-scale, on-site generation with combined heat and power (CHP) applications is becoming more attractive to commercial entities. There is also a movement towards more heterogeneous power quality and reliability (PQR), which is easier to implement via a dispersed network of loads and resources (Marnay (2008)). Although distributed generation (DG) units are less efficient at converting primary fuel sources to electricity than central power plants, their closer proximity to end-use loads prevents transmission losses and enables CHP applications to re-use much of the waste heat. Thus, the use of such distributed energy resources (DER) may be more energy efficient overall than relying on central power plants.

To date, however, the penetration of DER has been modest largely due to regulatory barriers, the relatively high capital cost of DER equipment, and the complexity of analyzing energy flows in a commercial building or a microgrid, which is a localized network of energy loads and sources operating in a semi-autonomous manner from the wider macrogrid. The first impediment refers to features of utility policy, ranging from poorly defined and enforced interconnection standards to retrograde tariff components such as standby charges and exit fees, and the lack of exposure to real-time prices. In terms of the economics and energy flows, there is a strong connection since the optimal installation and operation of DER equipment will have to be synchronized with the energy flows, something that is not possible without recourse to mathematical programming. The Sankey diagram in Figure 1 captures the complexity of the problem faced by a typical commercial entity: on the right-hand side are its end-use loads, while the available energy resources are on the left-hand side. For example, in order to meet its electricity-only load, the commercial entity can simply purchase electricity from the utility at the tariff rate or it can install DG units. However, for a load such as cooling, not only can electricity purchases and on-site generation be utilized, but also recovered heat from DG units in operation or heat from solar thermal systems. As a result, an optimal dispatch for all on-site DER equipment is not trivial even in a deterministic setting as we have here. Furthermore, features such as energy storage and demand–side measures (DSM) complicate the picture. Hence, a mixed-integer linear program (MILP) that minimizes energy costs or carbon emissions, the DER Customer Adoption Model (DER-CAM), has been developed at Berkeley Lab. It solves the investment and operational problem of a typical commercial entity given various market and technological data, considering the supply as well as the passive side, e.g., building quality.

In previous work, DER-CAM was used to determine optimal DER investment and operational decisions for various commercial sites and regulatory regimes. For example, we investigated how the availability of CHP equipment interacts with a carbon tax to determine whether CO_2 emissions may be reduced drastically (Siddiqui (2005)). More recent work has examined the impact of storage equipment on minimized costs, energy efficiency, and CO_2 emissions (Marney et al. (2008), Stadler et al. (2008), Siddiqui et al. (2007)). Thus, even though the perspective of DER-CAM is that of a small commercial entity, it may be used to test how policy changes may affect production and consumption of energy in a deregulated environment.

Following this approach, we examine how zero-net energy buildings (ZNEBs) may be implemented in California and New York. This endeavor is directly relevant now because of the U.S. Department of Energy's zero-net energy commercial building initiative (CBI), which was launched on August 5, 2008 with the objective of developing commercial buildings by 2025 that produce as much energy as they consume. By directly mentioning the minimization of energy use via innovative technologies and demand response, the CBI's vision of a ZNEB is something that can be implemented in DER-CAM. Hence, in this paper, a typical commercial building is restricted to comply with the CBI, even though this restriction may come at a high cost.

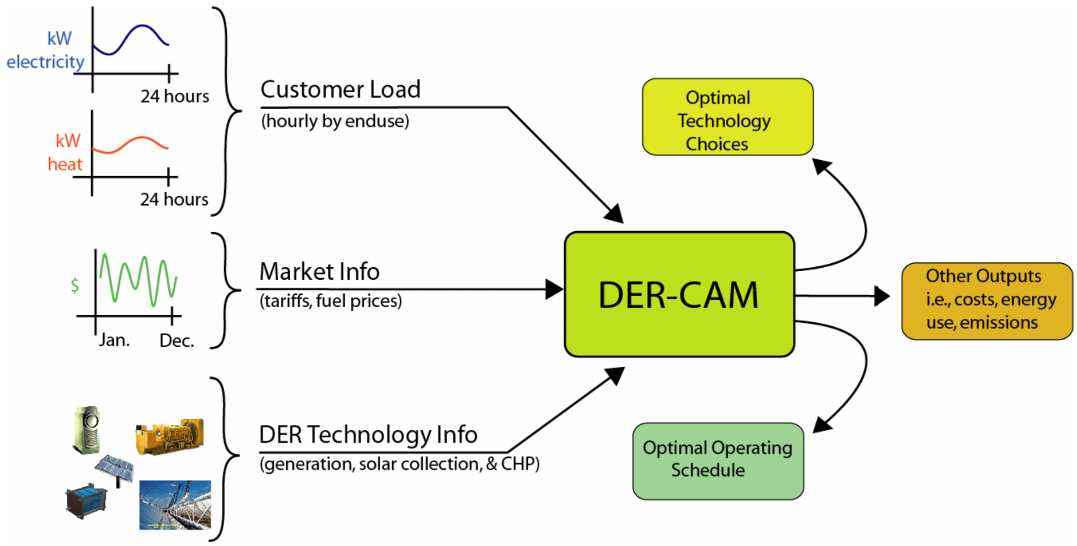
Figure 1. Sankey diagram of energy flows



2. Problem Formulation

As noted in Section 1, the DER investment and operation problem of a typical commercial entity lends itself to analysis via a MILP. The resulting program, DER-CAM, implemented in the General Algebraic Modeling System (GAMS), is amenable to the investigation of various policies over a test year, such as carbon taxes, efficiency standards, and, in this paper, the ZNEB proposed by the CBI. Regardless of the particular research objective, DER-CAM has a common structure with a cost-minimizing (or, as we shall illustrate, a multi-criteria) objective function and standard constraints on energy production, flows, and consumption (Siddiqui et al. (2005), Stadler et al. (2008b)). Thus, it takes input data on DER and DSM equipment, end-use loads, and energy prices in order to provide optimal adoption and dispatch of DER equipment and DSM as outputs (see Figure 2). Other outputs, such as the level of carbon emissions and energy efficiency, are also calculated.

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



The annual energy costs, minimized by DER-CAM, include electricity and fuel purchases from the utility, amortized capital costs of any DER equipment and DSM applied, ongoing operating and maintenance (O&M) expenses of the equipment, less the revenue from any sales, e.g., from photovoltaic (PV) output. Some of the key constraints in the model include:

- energy balancing, i.e., for each type of end-use, total consumption in a given time period must equal total production, withdrawal from storage (essentially inventory balance), and purchases less any displacement, e.g., via DSM or recovered heat
- output capacity, i.e., the total electricity produced is restricted by the amount of installed capacity and, in the case of PV or solar thermal equipment, by available solar insolation
- heat flows, i.e., the useful recovered heat is limited by the amount of waste heat generated and the efficiency of CHP equipment
- amount of energy available for storage and discharge depends on the characteristics of batteries and heat reservoirs, such as minimum and maximum levels of charge along with charging and discharging rates
- investor constraints, such as a minimum payback period, which may reflect risk aversion on part of typical commercial users; and
- regulatory constraints, such as ZNEB requirements or carbon taxes.

In addition, DER-CAM is able to handle the often complex structures of most utility tariffs, which exhibit multiple load periods and demand charges. The intuitive structure of the mathematical formulation is presented in Figure 3.

Figure 3. Representative MILP solved by DER-CAM

```
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
```

An innovative aspect of the current work, besides the inclusion of DSM and the CBI's ZNEB constraint, is the multi-criteria objective function. Instead of simply minimizing the annual energy costs, the commercial entity may specify an objective function that is a weighted average of its costs and carbon emissions, i.e.,

$$\min\left\{ \mathrm{w}\frac{Cost}{\mathrm{MaxCost}} + (1-\mathrm{w})\frac{Carbon}{\mathrm{MaxCarbon}} \right\} \tag{1}$$

Here, w is a parameter between zero and one that weighs the objective function, e.g., $w = 0$ is a case of pure carbon minimization, and MaxCost and MaxCarbon are parameters that are simply used to make the objective function dimension-less. For our research, we use the maximal costs as well as the maximal carbon emissions found in a set of optimization runs. Please note that any other definition of MaxCost and MaxCarbon could be used. Finally, *Cost* and *Carbon* are the annualized energy costs (in \$/a) and carbon emissions (in t/a), respectively. If we want to find the cheapest possible ZNEB, we assume $w = 1$ for the optimization runs. For the multi-objective frontier w can vary between 0 and 1.

The ZNEB constraint, which forces the building to sell the same amount of energy as it purchases, is also worth highlighting.

$$\frac{(Electricity\ Purchased - Electricity\ from\ PV\ Exported - Electricity\ from\ other\ Onsite\ Generation)}{\mathrm{MacrogridEfficiency}} \tag{2}$$

$$+ NG\ Consumed = 0;\quad \text{on an annual basis}$$

We assume that the energy-conversion efficiency (MacrogridEfficiency) and the carbon emissions rate of the macrogrid are given by the average marginal efficiency of the control area in which the commercial entity is located. Due to fluctuations in the merit-order supply stack, this assumption will not hold on an hourly basis, but we use it as a rough estimate of the offset fuel consumption from on-site production of energy. The ZNEB constraint (Equation 2) indicates that the net fuel consumed in the generation of electricity, whether through on- or off-site means, plus the total amount of natural gas used for heating is equal to zero. In the first term of the constraint, the numerator includes the total amount of electricity purchased minus the total electricity exported from both PV and thermal on-site production. Dividing the net consumption of electricity (in kWh_e) by the average macrogrid efficiency (in kWh_e/kWh) converts the quantity to net fuel consumption (in kWh). Since the second term of the constraint, the annual consumption of natural gas for meeting heating end-uses or other natural gas loads, is likely to be positive, the commercial entity must be a net exporter of electricity. As we shall see from the case study, this requirement is quite demanding.

3. Data

3.1. Test Site

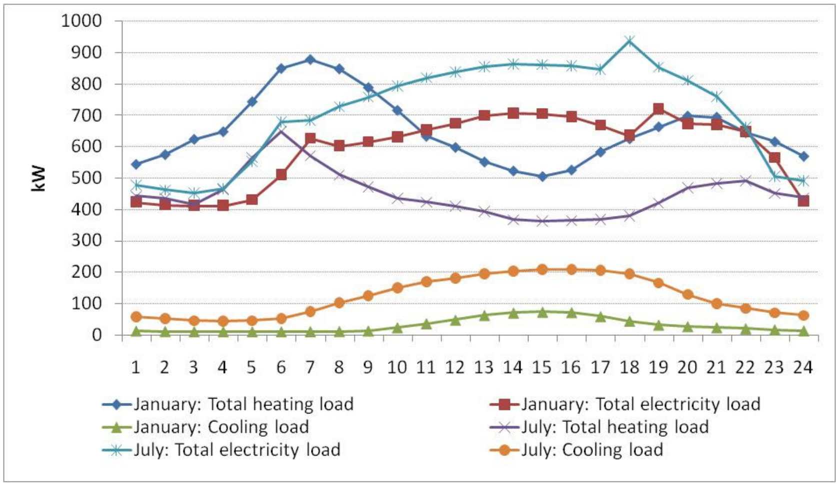
In order to illustrate the implementation of the ZNEB from the perspective of a commercial entity, two nursing home case studies were performed; one located in the Bay Area of northern California (CA) and the other located in New York City (NYC). Both sites are characterized by relatively stable seasonal demand, and therefore, only January and July profiles are shown in Figure 4. 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).

The same CA nursing home was transferred to Consolidated Edison Company of New York (ConEd) service territory in NYC. To consider the impact of the colder winter and hotter summer climate, the load profiles were adjusted by temperature data (see also Stadler et al. (2008)).

As can be seen in Figure 4, the night heating load for the CA nursing home is roughly 60% of the peak. Additionally, during daytime hours, recovered heat from on-site generation 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, since the electricity demand coincides with the total heat demand, this favors the installation of DG units with CHP. Additionally, the deleterious effects of any desynchronous electricity and heating loads may be mitigated via the use of storage facilities. In this case study, 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.

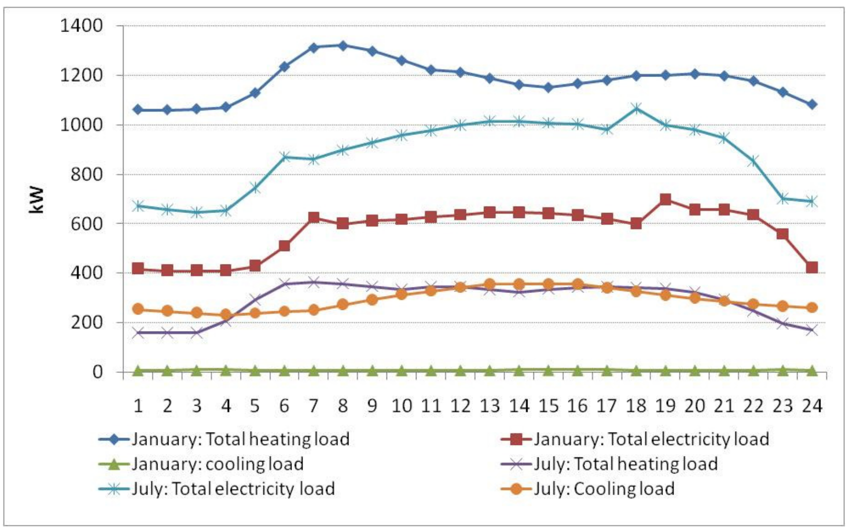
The NYC nursing home shows less or no cooling demand in winter months, but higher heating demand, which is very stable during the day. The combination of high heating and electricity demand makes the NYC nursing home also a prime candidate for CHP applications. How these CHP technologies interact with electric and heat storage systems (which act as load shifting options) and with other DSM measures will be shown in the following sections.

Figure 4. CA nursing home January and July weekday electricity[7] and total heat (space + water heating)[8] demand



source: Stadler et al. 2008

Figure 5. NYC nursing home January and July weekday electricity and total heat (space + water heating) demand



source: Stadler et al. 2008

3.2. Technologies

The newest technologies added to DER-CAM are *abstract* DSMs that capture the effect of efficiency measures, e.g., building quality changes and demand reduction measures due to behavioral changes, among others. Additionally, DER-CAM considers storage systems, and this enables load-shifting measures in the optimization runs.

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

Efficiency and behavioral measures are defined as *abstract* "low," "mid," and "high" measures, which represent a set of possible real technologies (see Table 1 and 2). The measures are characterized by the:

- costs of reducing 1 kW of load ($/kW)
- maximum potential of load reduction (%), e.g., the maximum contribution is limited by the U-value in case of new building insulation.
- annual time limit for the measure, e.g., in case of behavioral changes the lighting effect in an office building is limited to work hours.

Please note that the parameters from Table 1 and 2 are just estimates to show the impact of DSM within DER-CAM. The DSM input parameters depend on the building type simulated and will also change with the type of DSM considered. For this work, the real DSM options linked to those abstract parameters are not that important.

Table 1. DSM input parameters for electricity[9]

electricity	variable cost ($/kW)	max. contribution (% of total load in any hour)	max. hours (hours)
low	0.00	30	4380
mid	0.06	10	8760
high	1.00	5	760

source: LBNL assumptions

Table 2. DSM input parameters for heating

heating	variable cost ($/kW)	max. contribution (% of total load in any hour)	max. hours (h)
low	0.00	30	1095
mid	0.03	20	8760
high	0.05	10	8760

source: LBNL assumptions

Many building simulation tools, e.g., EnergyPlus, require specification of the demand response schedules. Since they require specification of occupancy and behavioral changes, such tools can never find the optimal schedule of DSM measures to reach ZNEB levels. In contrast, the flexible approach of DER-CAM (see also Figure 6) allows picking the optimal operating hours for measures to minimize costs, carbon emissions, or other objectives, and delivers optimal schedules.

Recently, electrical (conventional lead/acid battery) and thermal storage capabilities were added to DER-CAM. 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.

[9] Batteries and heat storage are modeled more realistically at this point and parameters are shown in Table 3.

The parameters used for the electrical and thermal storage are shown in Table 3 (Stevens et al. (1996) and Symons et al. (2001)). The menu of available equipment options to DER-CAM for this analysis together with their cost and performance characteristics is shown in
Table **4** and Table 5.

Figure 6. DSM approach within DER-CAM (M1, M2, and M3 are different measures)

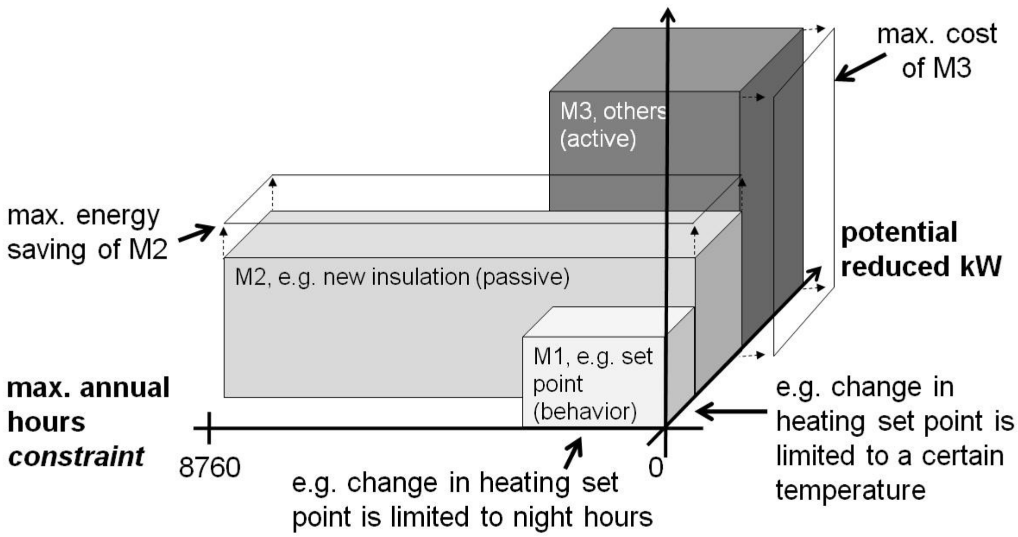


Table 3. Energy storage parameters

	description	electrical	flow battery	thermal
charging efficiency	portion of energy input to storage that is useful	0.9	0.84	0.9
discharging efficiency	portion of energy output from storage that is useful	1[10]	0.84	1
decay	portion of state of charge lost per hour	0.001[11]	0.01[12]	0.01
maximum charge rate	maximum portion of rated capacity that can be added to storage in an hour	0.1	n/a	0.25[13]
maximum discharge rate	maximum portion of rated capacity that can be withdrawn from storage in an hour	0.25	n/a	0.25[14]
minimum state of charge	minimum state of charge as a portion of rated capacity	0.3	0.25	0

source: LBNL estimates, Stevens et al. (1996), and Symons et al. (2001)

[10] The impact of different discharge levels is subject to further research.
[11] 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.
[12] Preliminary number; future analysis could address the impact of different decay numbers.
[13] Preliminary number; the impact of different maximum charge rates is subject to further research.
[14] Preliminary number; the impact of different maximum discharge rates could be the subject to further research.

Table 4. 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 5. Menu of available equipment options, *continuous investments*

	electrical storage (lead acid)	thermal storage[15]	flow battery	absorption chiller	solar thermal	photovoltaics
intercept costs ($)	295	10000	0	20000	1000	1000
variable costs ($/kW or $/kWh)	193[16]	100[17]	220$/kWh and 2125$/kW [18]	127[19]	500[20]	6675[21]
lifetime (a)	5	17	10	15	15	20

While the current set of available technologies is limited, any candidate technology may be included. Technology options in DER-CAM are categorized as being 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 discrete fuel cell[22] 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 Electricity

[15] Please note that cold thermal storage is not among the set of available technologies, but could be added.
[16] $/kWh$_{electricity}$
[17] $/kWh$_{heat}$
[18] Flow batteries are characterized by both the energy content and power rating.
[19] Abs. chiller capacity is in terms of electricity offset (electric load equivalent).
[20] $/kW$_{of\ recovered\ heat}$
[21] $/kW$_{electricity}$
[22] Reciprocating engines are the most dominant technologies at this point. Research shows that no fuel cell or micro turbine adoption takes place in our examples due to higher technology costs.

Storage Association). The installation cost functions for these technologies are assumed to consist of an unavoidable cost (intercept) independent of installed capacity ($) representing the fixed cost of the infrastructure required to adopt such a device, plus a variable cost proportional to capacity ($/kW or $/kWh).

3.3. Tariffs for the California Example

The California nursing home purchases both electricity and natural gas from PG&E. As is typical among utilities, 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., in New York state for some 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.

Table 6. Energy prices PG&E, 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

The demand charge in $/kW is a significant determinant of distributed generation and electric storage system installations (Stadler et al. (2008)). A marginal carbon emission factor of 140 gC/kWh$_e$ for electricity purchased from PG&E along with a macrogrid energy-conversion efficiency of 34% 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.

3.4. Tariffs for the NYC Example

Table 7 shows the Consolidated Edison Company of New York (ConEd) tariffs used for the NYC nursing home example. A marginal carbon emission factor of 200 gC/kWh$_e$ for electricity purchased from ConEd was assumed (see also Cadmus (1998)).

Table 7. Energy prices, effective April 2007

electricity	summer (June – Sep.)		winter (Oct. – May)	
	electricity ($/kWh)	**demand ($/kW)**	**electricity ($/kWh)**	**demand ($/kW)**
all day long	0.12[23]	14.21[24]	0.12	11.36[25]
fixed ($/month)	71.05			

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

Source: ConEd

4. Results

In order to address how carbon emissions and total site energy costs vary when electrical, thermal storage, efficiency as well as load reduction measures are present, five DER-CAM runs have been performed:

1. a *do-nothing* case in which all DER investments and DSM adoption are disallowed, i.e., the site meets its local energy demands solely by purchases from utilities; furthermore, no ZNEB constraint is considered
2. an *invest* case that finds the optimal DER and DSM adoption at current price levels as described in Section 3; again, no ZNEB constraint is considered
3. a *low cost invest* case that finds the optimal DER and DSM adoption with low storage prices of $50/kWh for thermal storage, $60/kWh for electric storage, and $2670/kW for PV; no ZNEB constraint is considered
4. a *ZNEB invest* case that finds the optimal DER and DSM adoption at current price levels as described in Section 3, considering the ZNEB constraint
5. a *ZNEB low storage and low PV price* run, with low storage prices of $50/kWh for thermal storage, $60/kWh for electric storage, and $2670/kW for PV; both the ZNEB constraint and DSM are considered.

Since we want to find the cheapest ZNEB solution for the nursing homes, the weight factor (w) from the multi-objective approach from Section 2 is set to 1 (pure cost optimization). Additionally, a footprint constraint limits the amount of installed PV and solar thermal to 30 000m^2 (roughly total floorspace of the building) to make the results more realistic.

[23] 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.
[24] For the first 300 kW. If the load exceeds 300kW the demand charge decreases by 10%
[25] For the first 300 kW. If the load exceeds 300kW the demand charge decreases by 12%

4.1. ZNEB Results for the CA Nursing Home

The annualized results for the nursing home are summarized in Table 8, and they indicate the type of DER equipment adopted, annual energy costs and consumption, and annual carbon emissions.

Table 8. Annualized results for the northern California nursing home (*w* = 1)

	run 1	run 2	run 3	run 4	run 5
	do-nothing	invest in all technologies	low cost invest	ZNEB invest in all technologies	ZNEB low storage and low PV price
equipment					
100 kW reciprocating engine with heat exchanger (kW)	n/a	300	200	0	200
abs. chiller (kW in terms of electricity displaced)	n/a	0	0	238	0
solar thermal collector (kW)	n/a	0	0	3952	0
PV (kW)	n/a	0	358	2408	3162
electric storage (kWh)	n/a	0	1427	0	1514
thermal storage (kWh)	n/a	0	0	9897	0
annual costs (k$)					
total	963.90	721.29	707.17	1782.61	829.32
% savings compared to do-nothing	n/a	25.17	26.67	**-84.94**	**13.96**
annual utility energy consumption (GWh)					
electricity	5.76	2.13	2.08	3.41	2.33
NG	5.70	8.91	7.76	0.004	7.48
energy sales (GWh)					
electricity	n/a	n/a	n/a	3.41	4.87
annual carbon emissions (t/a), *does not contain carbon offset due to electricity sales*					
emissions	1087.74	737.37	673.40	477.83	694.75
% savings compared to do-nothing	n/a	32.21	38.09	**56.07**	36.13

We note that run 2 provides the adoption of 300 kW of on-site generation with a heat exchanger. No absorption chillers, energy storage, or solar-based technologies are installed. Absent any ZNEB legislation, this result is the closest to what we would expect today if the nursing home took a strictly cost-minimizing approach while also considering DSM. We find that compared to run 1, in which all of the nursing home's energy needs are met via the utility, there is a significant reduction in both costs and carbon emissions[26] of 25% and 32%, respectively. In effect, by relying more on gas-fired DER equipment, the nursing home swaps purchases of electricity from the utility for more natural gas purchases. However, if load shift measures (electric and heat storage) and PV were made much cheaper (run 3), then a considerable amount of PV and electric storage systems would be installed and the annual carbon emission reduction reaches 38%.

If we include the ZNEB constraint in run 4, then we find that at current technology costs, the nursing home would face a near doubling of its energy bill (an increase of ca. 85%) since it would be largely dependent on expensive solar-based equipment and energy storage technologies. Nevertheless, the results indicate that the desired objective of a ZNEB is achieved by reducing natural gas purchases to almost nothing. The extensive use of renewable energy technologies also provides a drastic reduction in carbon emissions, i.e., 56% relative to the *do-nothing* case. Figure 7 illustrates how the ZNEB constraint and the concomitant reduction in carbon emissions are attained: modest demand (load) reduction (see Figure 7) throughout the day and some cooling offset by absorption cooling, but mostly extensive PV generation and sales. In this example the same amount of electricity is sold as purchased from the utility. The optimal dispatch for meeting the heating load would be similarly reliant on solar thermal heating. Hence, we can infer from this case study that, while meeting the ZNEB constraint is feasible via existing technologies, its cost may be prohibitively too high for current implementation.

On the other hand, if subsidies for PV technology and both electric and thermal storage are provided, then the ZNEB constraint is not prohibitively expensive for the nursing home. Table 8 shows an adoption of a 200 kW on-site, gas-fired generation system with CHP along with electric storage and PV. Consequently, the energy bill is reduced by nearly 15% relative to the *do-nothing* case, while carbon emissions decrease by almost 36%. Compared to Figure 7, the optimal dispatch in Figure 8 provides for more load shifting via the battery and some on-site generation via the gas-fired DG system. Please note that the batteries will be charged mostly by cheaper off-peak electricity and not by PV. PV is used for electricity sales. Also, in run 5, more electricity is sold than purchased from the utility, and this can lead to financial losses to the building under current net-metering conditions in CA. However, due to the subsidies of $4005/kW for PV and $133/kWh for batteries in run 5, the effective cost of carbon emissions reduction is ca. $950/tC[27], which is significantly higher than the current price of carbon at the EEX in Germany, $65/tC[28].

[26] Carbon emissions here include not only those produced locally at the site of the nursing home, but also those from off-site electricity purchases, which are calculated via the average macrogrid efficiency measure.
[27] This number also considers the carbon offset due to PV electricity sales to the grid.
[28]http://www.eex.com/en/Market%20Data/Trading%20Data/Emission%20Rights/EU%20Emission%20Allowances%20|%20Spot/spot-eua-table/2009-04-29, values are from April 29, 2009.

Figure 7. Optimal schedule for meeting the electricity load on a July weekday (run 4)

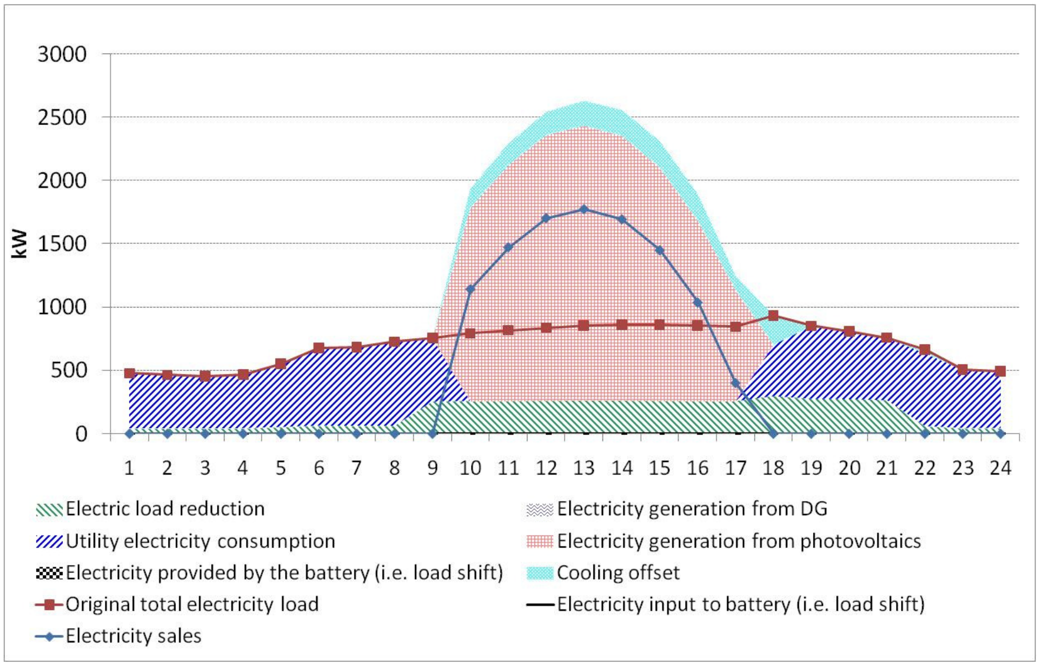
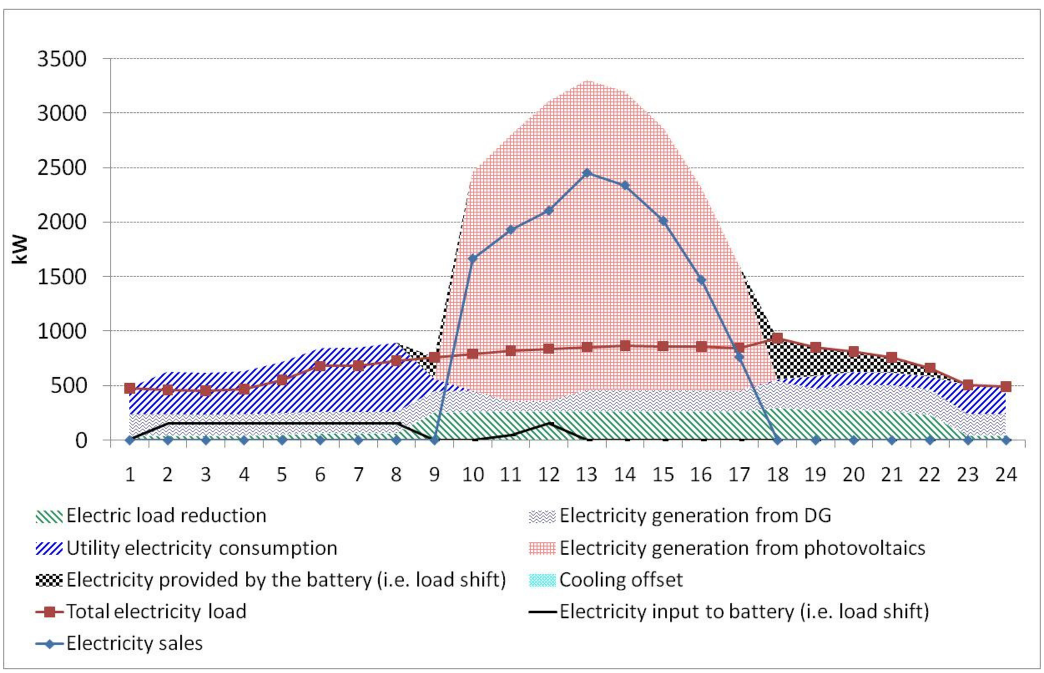


Figure 8. Optimal schedule for meeting the electricity load on a July weekday (run 5)



4.2. ZNEB Results for the NYC Nursing Home

Table 9 shows the result for the NYC nursing home. The first interesting difference to the CA nursing home is the missing PV installation and the huge solar thermal and heat storage system adoption in run 3 (low storage and PV costs). Despite having less solar radiation compared to

California, more solar thermal is adopted. The reason for this can be partly seen in the higher natural gas tariff combined with the almost constant demand charge as well as flat electricity tariffs. A major driver for DG / CHP and battery adoption is the possibility to avoid on-peak demand charges as well as high on-peak prices. Since natural gas is very expensive and the possibility to avoid expensive on-peak electricity is limited due to the flat tariff, no CHP system will be installed. However, the NYC nursing home has a huge heating load, which can be supplied by solar thermal.

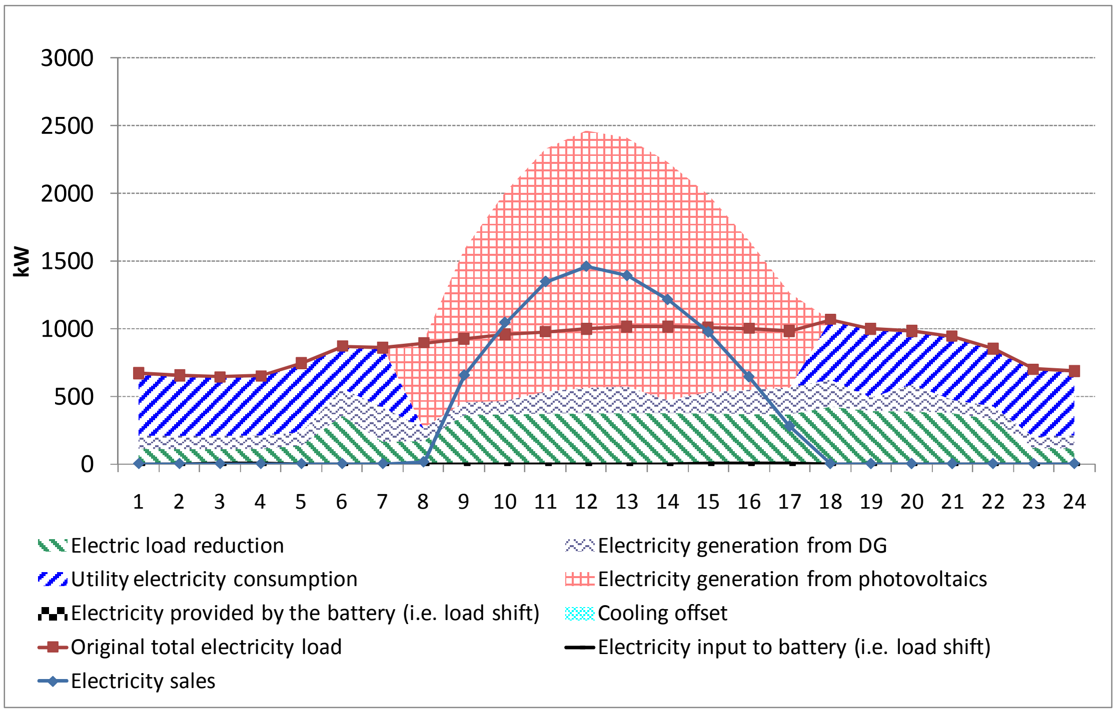
Table 9. Annualized results for the NYC nursing home (*w* = 1)

	run 1	run 2	run 3	run 4	run 5	run 4a	run 5a
	do-nothing	invest in all technologies	low cost invest	ZNEB invest in all technologies	ZNEB low storage and low PV price	***relaxed*** ZNEB invest in all technologies	***relaxed*** ZNEB low storage and low PV price
equipment							
100 kW reciprocating engine with heat exchanger (kW)	n/a	0	0	not feasible with chosen assumptions / settings		300	300
abs. chiller (kW in terms of electricity displaced)		0	0			0	0
solar thermal collector (kW)		906	1734			252	0
PV (kW)		0	0			2775	2840
electric storage (kWh)		0	412			0	28
thermal storage (kWh)		0	4250			490	716
annual costs (k$)							
Total	1195.50	926.94	912.19	not feasible with chosen assumptions / settings		2043.76	1094.18
% savings compared to do-nothing	n/a	22.46	23.70			**-70.95**	**8.48**
annual utility energy consumption (GWh)							
electricity	6.02	4.64	4.65	not feasible with chosen assumptions / settings		1.06	0.95
NG	7.14	3.81	2.34			6.82	7.73
energy sales (GWh)							
electricity	n/a	n/a	n/a	not feasible		3.38	3.58
annual carbon emissions (t/a), *does not contain carbon offset due to electricity sales*							
emissions	1555.23	1115.58	1045.73	not feasible with chosen assumptions / settings		548.90	571.96
% savings compared to do-nothing	n/a	28.27	32.76			**64.71**	**63.22**

The next interesting finding is that the NYC nursing home is not able to comply with the ZNEB constraint within DER-CAM if using the DSM input data from section 3.2. The higher loads in combination with the restricted DSM result in infeasible conditions. To show results for run 4 and run 5, the ZNEB constraint within DER-CAM was relaxed by increasing the DSM potential (run 4a and run 5a). In other words, the NYC nursing home needs to increase the efficiency levels more than the CA nursing home. The max. contribution of the "mid" measures from Table 1 and 2 had to be increased from 10 to 27% and from 20 to 38%.

Figure 9 shows the consequences of the relaxed ZNEB constraint. The NYC nursing home operates the on-site internal combustion engines all day long and also sells electricity to the market during the day.

Figure 9. NYC nursing home, optimal schedule for meeting the electricity load (run 5a)



4.3. Cost Minimization versus CO_2 Minimization

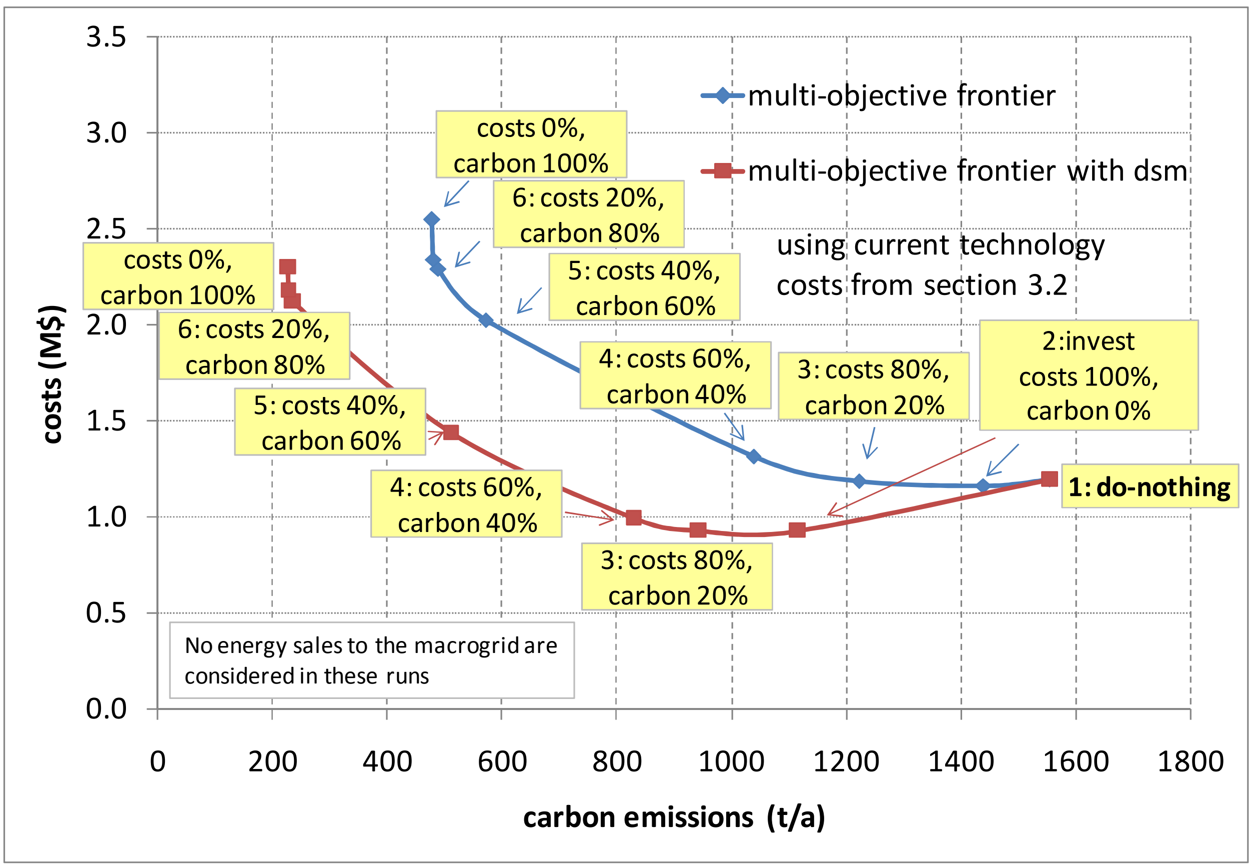
In the zero-carbon (ZC) building runs, we vary the weight factor (*w*) in the objective function, thereby creating a frontier with different annual energy costs and carbon emissions. Furthermore, no electricity sales to the macrogrid and ZNEB requirements are considered, and current technology costs from Section 3.2 are used.

With the multi-objective approach from Section 2, a set of different optimization runs for the NYC nursing home without DSM (top-right blue curve in Figure 10) and with DSM (bottom red curve in Figure 10) are performed. Every optimization run is characterized by a specific weight factor *w*, where the starting point is the *do-nothing* case (run 1) from the previous section. Point

2 is characterized by *w* = 1 (pure cost optimization), and for the bottom frontier (red curve), this represents run 2 from Table 9. For the top-right blue curve, frontier point 2 shows less reduction in both cost and carbon emissions than point 2 from the multi-objective frontier with DSM. This is not surprising since DSM offers also "free" behavioural changes.

With decreasing *w*, which means increasing focus on carbon emissions, the annual energy costs increase and the carbon emissions go down. However, as can be seen from Figure 10, it is not possible to reach zero carbon. Without demand reduction measures the carbon emissions level off at ca. 470 t/a, and the annual energy costs explode to reach levels 213% higher than the *do-nothing* case[29]. Also, with demand reduction measures, as described in section 3.2, the NYC nursing home cannot reach zero-carbon status, even at price levels ca. 200% higher than the actual energy costs (*do-nothing* case). The carbon emissions level off at ca. 220 t/a considering DSM. To reach 220 t/a, the amount of installed PV, solar thermal, and both electric and heat storage systems increases considerably, which results in tremendous annual energy costs. For example, point 6 from the bottom frontier (red line) with DSM requires 300 kW of reciprocating engines, 198 kW[30] of absorption chillers, 6456 kWh of electric storage, 6476 kWh of heat storage, 2097 kW of PV, and 2858 kW of solar thermal capacity.

Figure 10. Multi-objective frontier for the NYC nursing home



[29] Electricity sales would not help against the high annual energy costs since there is a footprint constraint in the model, and due to that constraint, no additional PV or solar thermal is possible, which could be used for sales.
[30] In terms of electricity displaced. 198 kW_e translates to 251 refrigeration tons.

5. Conclusions

The ongoing deregulation of the energy sector and concerns about climate change are providing incentives for small-scale, on-site generation with CHP applications and energy storage to become more attractive to commercial investors. Indeed, such DER equipment has the potential to provide tangible benefits to consumers in terms of lower energy bills. Nevertheless, the high capital costs of such equipment and the complexity of energy flows within a microgrid may inhibit the adoption of DER unless an optimization perspective is taken. Using DER-CAM, we are able to model a typical commercial entity's DER investment and operation problem as a MILP that takes data on market prices, technology characteristics, end-use loads, and regulatory rules as inputs. Although the perspective of DER-CAM is that of a small (relative to the entire macrogrid) user, it may be employed to examine the effects of wider energy policies, such as carbon taxes and energy efficiency requirements.

In this paper, DER-CAM is used to illustrate how the CBI's ZNEB requirement may be implemented. The commercial entity is constrained to sell as much energy as it purchases, which in our case study of a northern California and NYC nursing home results in adoption of PV panels and storage systems. Consequently, natural gas purchases for heating purposes are driven to near zero, while electricity purchases from the utility and NG purchases for on-site generation are significantly offset by sales back to the grid and efficiency measures. On the other hand, the nursing home's energy bill soars due to the adoption of costly equipment. However, subsidies on these renewable energy and storage technologies would make ZNEB attainable to the site at a modest increase (or even decrease) in the energy bill. Next, in a ZC example, we illustrate that there is a trade-off between cost and carbon emissions, and that zero-carbon status may be achieved only at a sharp increase in the energy bill, assuming that currently available equipment is used. Here, the importance of DSM is paramount because the last tranche of reduction in carbon emissions, possibly attained via a combination of PV-generated power and electrical storage, seems to be prohibitively expensive.

For future work in this area, we would like to address not only the cost in the objective function, but also the risk of a commercial entity that faces stochastic energy prices and possibly unreliable equipment. We envisage a risk-hedging strategy that constructs a portfolio of physical equipment as well as financial instruments in order to deliver an innovative solution for more sustainable provision and consumption of energy. As with the current study, the impact of any policy dispensations could be investigated, this time from the perspective of a risk-averse microgrid entity. We believe that such an example is essential in illustrating the challenges from (and possible remedies for) climate change and price volatility.

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