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Control of Greenhouse Gas Emissions by Optimal DER Technology Investment and Energy Management in Zero-Net-Energy Buildings[1]

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Abstract

The U.S. Department of Energy has launched the commercial building initiative (CBI) in pursuit of its research goal of achieving zero-net-energy commercial buildings (ZNEB), i.e. ones 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-efficiency technologies and meet their remaining energy needs through on-site renewable energy generation. This paper examines how such buildings may be implemented within the context of a cost- or CO_2-minimizing microgrid that is able to adopt and operate various technologies: photovoltaic modules (PV) and other on-site generation, heat exchangers, solar thermal collectors, absorption chillers, and passive/demand-response technologies. A mixed-integer linear program (MILP) that has a multi-criteria objective function is used. The objective is minimization of a weighted average of the building's annual energy costs and 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 ZNEB objective. Using a commercial test site in northern California with existing tariff rates and technology data, we find that a ZNEB requires ample PV capacity installed to ensure electricity sales during the day. This is complemented by investment in energy-efficient combined heat and power (CHP) 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 a ZNEB. Additionally, the ZNEB approach does not necessary lead to zero-carbon (ZC) buildings as is frequently argued. We also show a multi-objective frontier for the CA example, which allows us to estimate the needed technologies and costs for achieving a ZC building or microgrid.

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

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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 alternative. 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 [1]. Although thermal distributed generation (DG) units are typically 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 reuse 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 (see Appendix A for a representative microgrid). The first impediment refers to features of utility policy, ranging from poorly defined and enforced interconnection standards to unfavorable 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 electricity purchases and generation, but also recovered heat from DG units in operation or heat from solar thermal systems may be utilized. 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)[7] complicate the picture. Hence, the DER Customer Adoption Model (DER-CAM) a mixed-integer linear program (MILP) that minimizes energy costs or CO_2 emissions has been developed at Berkeley Lab. DER-CAM solves the investment and operational problem of a typical commercial entity when given various market and technological data, and considers 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, how the availability of CHP equipment interacts with a CO_2 tax / price was investigated to determine whether CO_2 emissions may be reduced drastically [2]. More recent work has examined the

[7] We define DSM as set of all efficiency and demand response measures, e.g. more efficient lighting or peak shaving at the site.

impact of storage equipment on cost minimization, energy efficiency, and CO_2 emissions [3, 4, 5]. Thus, even though the perspective of DER-CAM is that of a single commercial entity, it may be used to test how policy changes may affect production and consumption of energy in a deregulated environment. Following on from this approach, in this paper, we examine how zero-net energy buildings (ZNEBs) may be implemented in California. This endeavor is directly relevant now because of the U.S. Department of Energy's commercial building initiative (CBI) that was launched on August 5, 2008 with the objective of developing zero-net energy commercial buildings by 2025, i.e. buildings that produce as much energy as they consume. By directly mentioning the minimization of energy use via innovative technologies and demand response, we feel that the CBI's vision of a ZNEB is something that can be implemented in DER-CAM. Hence, in this paper, we restrict a typical commercial building to comply with the CBI and show that the restriction comes at a high cost given the technologies available. Additionally, since ZNEBs do not necessarily mean zero carbon emissions, we also outline the multi-objective frontier, which allows determination of the costs for zero-carbon (ZC) buildings.

The structure of this paper is as follows:

- Section 2 formulates the optimization problem solved by DER-CAM
- Section 3 introduces the data used in this paper
- Section 4 presents results based on a northern California nursing home as an example site
- Section 5 concludes and offers directions for future research.

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),[8] is amenable to the investigation of various policies over a test year, such as CO_2 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 [2, 6]. Thus, it takes as inputs data describing 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 CO_2 emissions and energy efficiency, are also calculated.

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

[8] GAMS is a commercial mathematical modeling environment that facilitates large-scale optimization by calling a library of solvers (see http://www.gams.com/).

- 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 CO_2 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.

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 CO_2 emissions, i.e.,

$$\min\left\{ \mathrm{w}\frac{Cost}{\mathrm{MaxCost}} + (1-\mathrm{w})\frac{Carbon}{\mathrm{MaxCarbon}} \right\},\ 0 \le \mathrm{w} \le 1 \tag{1}$$

Here, w is a parameter between zero and one that weighs the objective function, e.g., $w = 0$ is a case of pure CO_2 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 CO_2 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 annual CO_2 emissions (in tCO_2/a), respectively. Since we want to find the cheapest possible ZNEB, we always assume $w = 1$ for the optimization runs using the ZNEB constraint in this paper. For the multi-objective frontier, shown in Section 4.2 of this paper, w can vary between 0 and 1.

Another new feature is DSM, which enables the commercial entity to reduce both electricity and heat consumption for a certain number of hours each year. The number of hours and the amount of demand reduction are both capped for each demand type as indicated in the following three constraints for *electricity*:

$$\begin{aligned} &ElectricityConsumed_{m,t,h} = \mathrm{Load}_{\mathrm{'e',m,t,h}} + ElectricityforCooling_{m,t,h} \\ &+ ElectricityforStorage_{m,t,h} + ElectricityforFlowBattery_{m,t,h} - \sum_{d \in D} DemandResponse_{d,m,t,h}\ \forall m,t,h \end{aligned} \tag{2}$$

[9]

[9] 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

$$\sum_{m\in M}\sum_{t\in T}\sum_{h\in H} DemandResponseOnOff_{d,m,t,h}\cdot \mathrm{N}_{\mathrm{m,t}} \leq \mathrm{MaxDRHours}_{\mathrm{d}}\ \forall d \tag{3}$$

$$DemandResponse_{d,m,t,h} \leq DemandResponseOnOff_{d,m,t,h}\cdot \mathrm{MaxDRContribution}_{\mathrm{d}}\cdot \mathrm{Load}_{\text{'e',m,t,h}}\ \forall d,m,t,h \tag{4}$$

where

'e'	electricity
m	month
t	day types, which belong to *T = {weekday, peak, weekend}*
h	hours, which belong to *H = {1,2,…,24}*
d	demand response type, which belong to *D = {low, medium, high}*
$\mathrm{N}_{\mathrm{m,t}}$	Number of days of type *t* in month *m*

Equation 2 modifies the definition of electricity consumed during a typical hour by indicating that it is the total load plus any requirements for cooling and storage (in batteries[10]) less the effect of demand response for that hour. Next, Equation 3 restricts the number of hours in each demand category that DSM can be implemented. In other words, some demand-side measures have a time limit in order to restrict the impact on occupancies in the building. Finally, the third constraint, Equation 4, limits the amount of load in each hour that can be dropped for each implementation of DSM: the load in each time period is scaled by the maximum fraction that can possibly be dropped, $\mathrm{MaxDRContribution}_{\mathrm{d}}$, and multiplied by whether or not load is to be dropped during that time period, $DemandResponseOnOff_{d,m,t,h}$. A modification to the objective function ensures that there is a tradeoff to DSM in the form of a variable cost per hour per load dropped. The equations for heating are similar to Equations 2, 3, and 4.

The ZNEB constraint, which forces the building to offset energy purchases by selling the same amount of energy as it purchases, is also worth highlighting. The following definition is equivalent to a *Net Source Energy Building* [7]:

$$\frac{\left(\sum_{m\in M}\sum_{t\in T}\sum_{h\in H} ElectricityPurchase_{m,t,h}\cdot \mathrm{N}_{\mathrm{m,t}} - \sum_{m\in M}\sum_{t\in T}\sum_{h\in H} ElectricityPVExport_{m,t,h}\cdot \mathrm{N}_{\mathrm{m,t}} - \sum_{i\in I}\sum_{m\in M}\sum_{t\in T}\sum_{h\in H} GenX_{i,m,t,h}\cdot \mathrm{N}_{\mathrm{m,t}}\right)}{\mathrm{MacrogridEfficiency}} \tag{5}$$
$$+ AnnualNGConsumed = 0$$

where

ElelctricityPVExport$_{m,t,h}$ *and*	
GenX$_{i,m,t,h}$	the electric energy produced on-site and sold to the macrogrid. Please note that we distinguish between PV and other DG units.
i	generation technologies, where *I = {the set of technologies selected}*
$\mathrm{N}_{\mathrm{m,t}}$	Number of days of type *t* in month *m*

We assume that the energy-conversion efficiency of the macrogrid (*MacrogridEfficiency*) is given by the average marginal efficiency of the control area in which the commercial entity is

battery stack. Flow batteries can be rapidly "recharged" by replacing the electrolyte liquid stored in an external tank. This difference makes it necessary to separate them from conventional batteries in DER-CAM.

[10] In this work we model lead-acid batteries. See also Table 5.

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 the on-site production of energy. If CO_2 taxes were included, then the savings from having a lower carbon footprint could also be included. The ZNEB constraint (Equation 5) 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 and CHP fuel needs, 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 proves quite demanding.

3. Data

3.1. Test Site

In order to illustrate the implementation of the ZNEB from the perspective of a commercial entity, we perform a case study on a nursing home located in the San Francisco Bay Area of northern California. The site is 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), since this is a site from the California Commercial End-Use Survey (CEUS).

As can be seen in Figure 4, the night heating load is roughly 60% of the peak heating demand. Additionally, during daytime hours, recovered heat from on-site generation may be used to lower the electrical peak via an absorption chiller. When cooling demand increases, this can constitute a stable heat sink if waste heat for absorption chillers is considered. Finally, to the extent that the electricity demand coincides with the total heat demand, this favors the installation of DG units with CHP. Furthermore, the deleterious effects of any desynchronous electricity and heating loads may be mitigated via the use of storage facilities. For example, waste heat from on-site generation that may not be immediately used to offset heating loads via CHP applications may be stored for subsequent use. Similarly, relatively cheap utility-provided electricity during off-peak hours may be stored in batteries to lower the electrical load during peak hours. In this case study, the simultaneous use of heating and cooling is caused by (a) the complexity of nursing facilities where in this moderate climate heating and cooling can appear in different zones at the same time and (b) hot water loads.

3.2. Technologies

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

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 new U-value in case of a new building insulation
- annual time limit for the measure, e.g., in case of behavioral changes in the light usage in an office building the effect is limited to work hours.

For example M3 from Figure 5 can represent an automated shading device that can reduce cooling loads during summer months. During winter months, the shading device has no major impact on cooling loads. Please note that the parameters from Table 1 and 2 are just estimates to show the impact of efficiency and behavioral measures within DER-CAM. The input parameters depend on the building type simulated and will also change with the type of measure considered. For this work, the real efficiency and behavioral measures options linked to those abstract parameters are not that important. 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 or zero-carbon emissions levels. In contrast, the flexible approach of DER-CAM (see also Figure 5) allows picking the optimal operating hours for measures to minimize costs, carbon emissions, or other objective, 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. The parameters used for the electrical and thermal storage are shown in following Table 3 [8, 9]. 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.

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 are 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[11] technology are interpolated from various studies as described in [10], which is based on data collected by the National Renewable Energy Laboratory [11]. 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

[11] Reciprocating engines are the most dominant technologies. Research shows that no fuel cell or micro turbine adoption takes place in our examples due to higher technology costs.

described by the Electricity Storage Association [12]. 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

The California nursing home purchases both electricity and natural gas from Pacific Gas and Electric (PG&E). As is typical for California 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 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 time 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 [4]. Hourly marginal CO_2 emission factors[12] for 2008 along with a macrogrid energy-conversion efficiency of 34% were assumed. For more information on the hourly marginal CO_2 emissions please see the appendix and [13]. This marginal emission factor is used within DER-CAM to determine the carbon emissions from the macrogrid and to be able to estimate the CO_2 reductions of the microgrid in different investment cases.

[12] Older versions of DER-CAM used an average marginal emission factor for the whole year. For this research DER-CAM, version 3.5.1 from July 22nd, 2009 with hourly marginal emission rates was used and this changes the carbon results compared with those from previous DER-CAM versions.

4. Results

4.1. ZNEB Results for the Nursing Home

In order to address how CO_2 emissions and total site energy costs vary when electrical, thermal storage, efficiency measures as well as load reduction measures are present, four 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 *ZNEB invest* case that finds the optimal DER and DSM adoption at current price levels as described in Section 3 considering the ZNEB constraint
4. a *ZNEB low storage and low PV price* run, with low storage prices of \$50/kWh for thermal storage[13], \$60/kWh for electric storage[14], and \$2670/kW for PV[15]; both the ZNEB constraint and DSM are considered.

Since we want to find the lowest cost ZNEB solution for the nursing home, 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 30000 m^2 (roughly the total floorspace of the building) to make the results more realistic.

The annualized results for the nursing home (see Table 7)[16] indicate the type of DER equipment adopted, annual energy costs and consumption, and annual CO_2 emissions. We note that run 2 provides the adoption of 300 kW of on-site generation with a heat exchanger. No absorption chiller, 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 to its energy consumption while considering DSM as described in Section 3.2. We find that, compared to run 1, in which all of the nursing home's energy needs are met via the utility, run 2 has a significant reduction in both costs and CO_2 emissions[17] of approx. 21% and 33%, 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.

If we include the ZNEB constraint in run 3, then we find that at current technology costs, the nursing home would face a near doubling of its energy bill (an increase of 87%) since it would be largely dependent on expensive solar-based equipment and energy storage

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[13] Intercept costs are set to zero.
[14] Intercept costs are set to zero.
[15] Intercept costs are unchanged.
[16] Optimizations were performed with version 3.5.1, July 22nd, 2009. Please note that different versions deliver slightly different results. Since DER-CAM is a MILP problem, an exhaustive search method is used within GAMS and it is influenced by the precision option. In these runs a relative optimality tolerance for MIP models of 3% was used (OPTION optcr = 0.03).
[17] 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.

technologies. Nevertheless, the results indicate that the desired objective of a ZNEB is achieved by reducing natural gas purchases by 62% compared to the do-nothing run 1. The extensive use of renewable energy technologies also provides a drastic reduction in CO_2 emissions, i.e., 61% relative to the do-nothing case. Figure 6 illustrates how the ZNEB constraint and the concomitant reduction in carbon emissions are attained: modest demand (load) reduction (see Figure 6) throughout the day and some cooling offset, but extensive PV generation and sales. The optimal dispatch for meeting the heating load would be similarly reliant on solar thermal heating. As can be seen from Figure 7, the solar thermal system is mostly used to supply the heat storage and absorption chiller with energy. The heat used in the absorption chiller removes electricity load during on- and mid-peak hours (see Figure 6) and reduces electric costs considerably. The heat stored is used during night hours to reduce heating needs. Please note that the example nursing home is located in the San Francisco Bay Area where July nights are mostly foggy and cold. We can infer from this case study that while meeting the ZNEB constraint is feasible via existing technologies, its cost may be prohibitively high to consider implementation currently.

On the other hand, if subsidies on the PV technology and both electric and thermal storage were provided, then the ZNEB constraint would not prohibitively expensive for the nursing home. Table 7 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 CO_2 emissions decrease by 45%. Compared to Figure 6, the optimal dispatch in Figure 8 provides for more load shifting via the battery and more on-site generation via the gas-fired DG system. Please note that DER-CAM does not assume a certain role for storage. DER-CAM finds the optimal operation pattern for all technologies to fulfil the objective of the site, i.e., cost or CO_2 minimization. In our case of cost minimization, it turns out that storage is used in the most economic way when electricity demand from the grid is removed during mid-peak periods, i.e., the battery will be discharged. The charging takes place during morning hours by on-site internal combustion engines and grid electricity and not by PV during the day. From an economic point of view, it is more attractive to sell electricity from PV instead of charging batteries by PV. However, due to the subsidies of \$4005/kW for PV and \$133/kWh for batteries in run 4, the effective cost of CO_2 emissions reduction is \$241/tCO_2[18], which does not compare well with the current price of CO_2 at the EEX in Germany of \$18/tCO_2[19].

4.2. ZC Building Results for the Nursing Home

In the ZC building runs, we vary the weight factor (w) in the objective function, thereby creating a frontier with different annual energy costs and CO_2 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 without DSM (top-right curve in Figure 9) and with DSM (bottom curve in Figure 9) 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, this represents run 2 from Table 7.

[18] This number also considers the carbon offset due to PV electricity sales to the grid.

[19] http://www.eex.com/en/Market%20Data/Trading%20Data/Emission%20Rights/EU%20Emission%20Allowances%20l%20Spot/spot-eua-table/2009-04-29, values are from April 29, 2009.

For the top-right curve, frontier point 2 shows less reduction in both cost and CO_2 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 CO_2 emissions, the annual energy costs increase and the CO_2 emissions go down. However, as can be seen from Figure 9, it is not possible to reach zero carbon without demand reduction measures. The CO_2 emissions level off at 700 tCO_2/a, and the annual energy costs explode to reach levels at 200% above the do-nothing case[20]. Nevertheless, considering the whole set of DSM, the nursing home could reach zero-carbon status at price levels ca. 150% above the actual energy costs (relative to the *do-nothing* case).

To reach zero-carbon status, 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 4 from the bottom frontier with DSM requires 202 kW[21] of absorption chillers, 9840 kWh of electric storage, 16346 kWh of heat storage, 2325 kW of PV, and 4631 kW of solar thermal capacity. The huge amount of storage, necessary to fulfil the ZNEB constraint within DER-CAM, is unrealistic and demonstrates the need for sophisticated DSM within DER-CAM and in reality.

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, it is possible 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 CO_2 taxes and energy efficiency requirements.

In this paper, DER-CAM is used to illustrate how the CBI's ZNEB goal 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 nursing home, results in adoption of PV panels, solar thermal equipment, and storage systems. Consequently, natural gas purchases for heating purposes are driven down, while electricity purchases from the utility are significantly offset by sales back to the grid and DSM for reducing consumption. On the other hand, the nursing home's energy bill soars due to the adoption of costly equipment, although subsidies on these renewable energy and storage technologies would make ZNEB attainable 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

[20] 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.
[21] In terms of electricity displaced. $202kW_e$ translates to 257 refrigeration tons.

cost and CO_2 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 CO_2 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.

List of Symbols

CBI	commercial building initiative
CEC	California Energy Commission
CEUS	California Commercial End-Use Survey
CHP	combined heat and power
DER	distributed energy resources
DER-CAM	Distributed Energy Resources Customer Adoption Model
DG	distributed generation
DSM	demand-side measures
EEX	European Energy Exchange
GAMS	General Algebraic Modeling System
MILP	mixed-integer linear program
NREL	National Renewable Energy Laboratory
O&M	operating and maintenance
PG&E	Pacific Gas and Electric
PQR	power quality and reliability
PV	photovoltaics
TOU	time-of-use
ZC	zero-carbon
ZNEB	zero-net-energy building

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Figures

Figure 1. Sankey diagram of energy flows

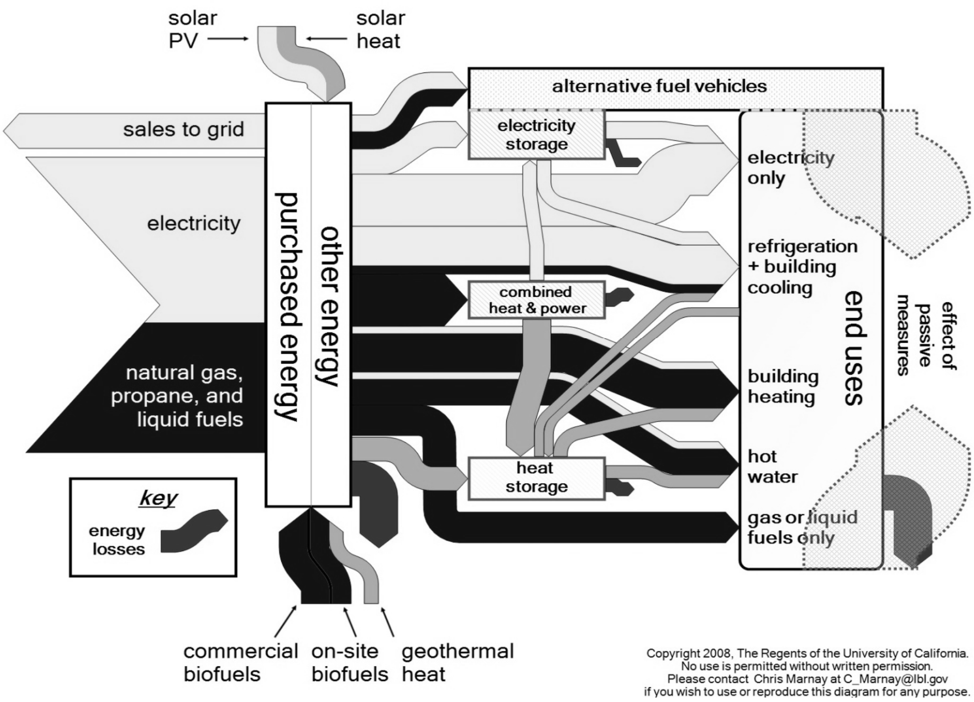


Figure 2. High-level schematic of information flow in DER-CAM

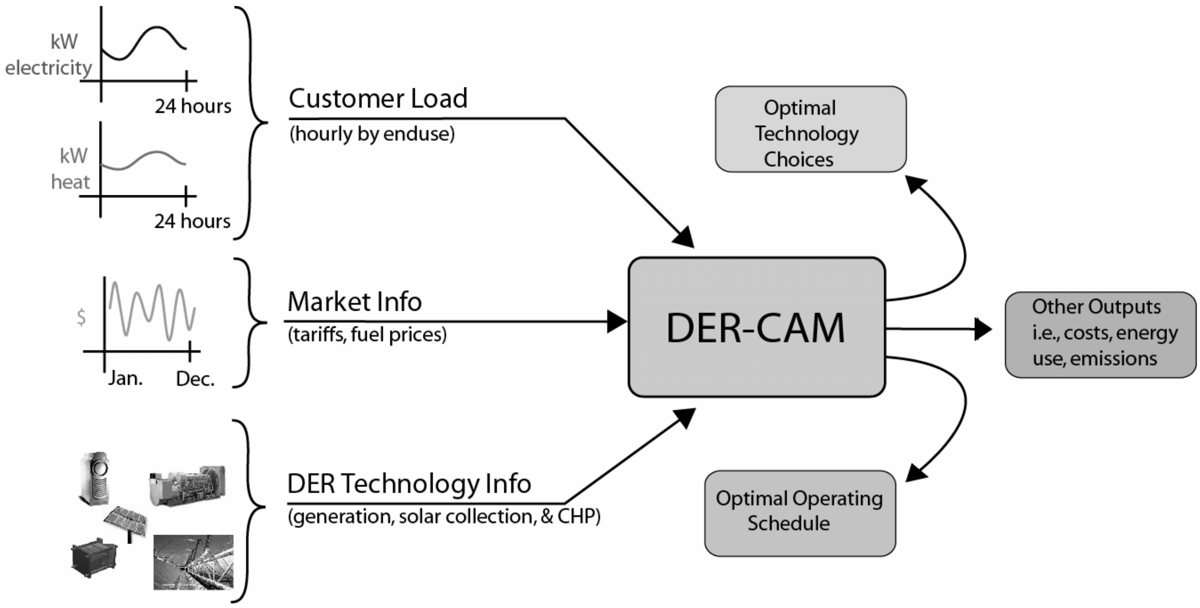
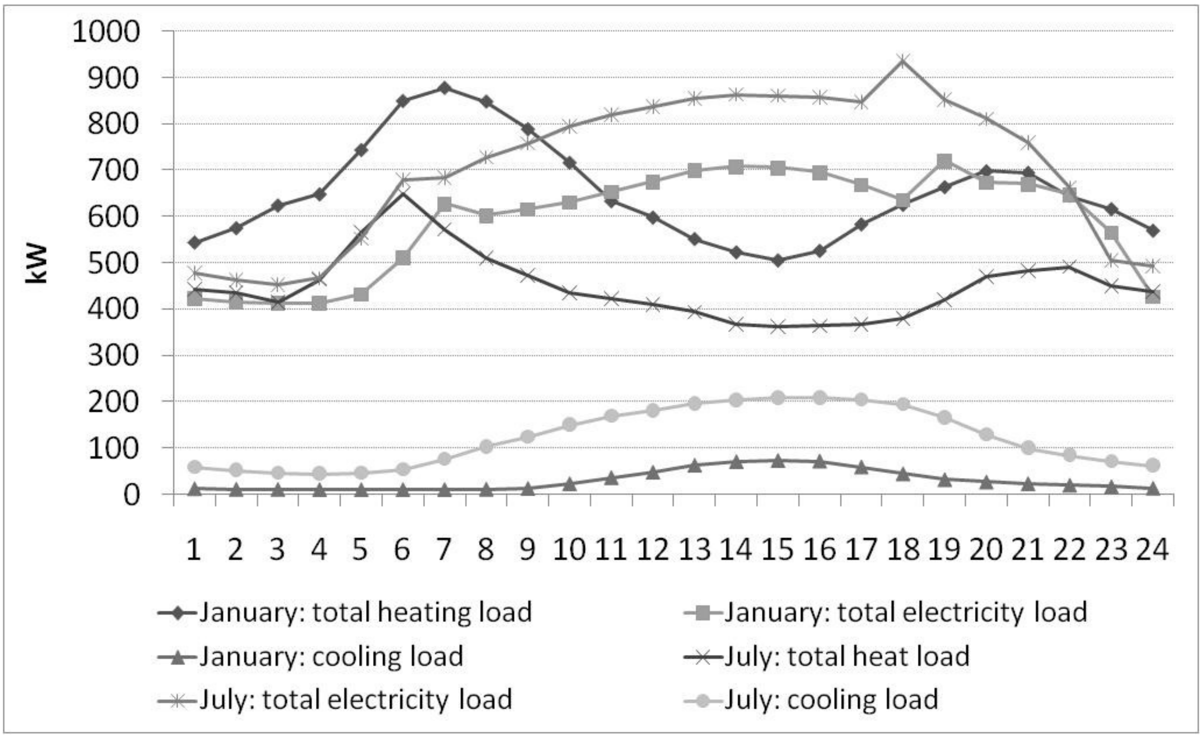


Figure 3. Representative MILP solved by DER-CAM

```
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
```

Figure 4. CA nursing home January and July weekday electricity[22] and total heat (space + water heating)[23] demand



source: [4]

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

[23] 1 kW = 3 412.14 BTU/h

Figure 5. DSM approach within DER-CAM (M1, M2, and M3 are different measures)

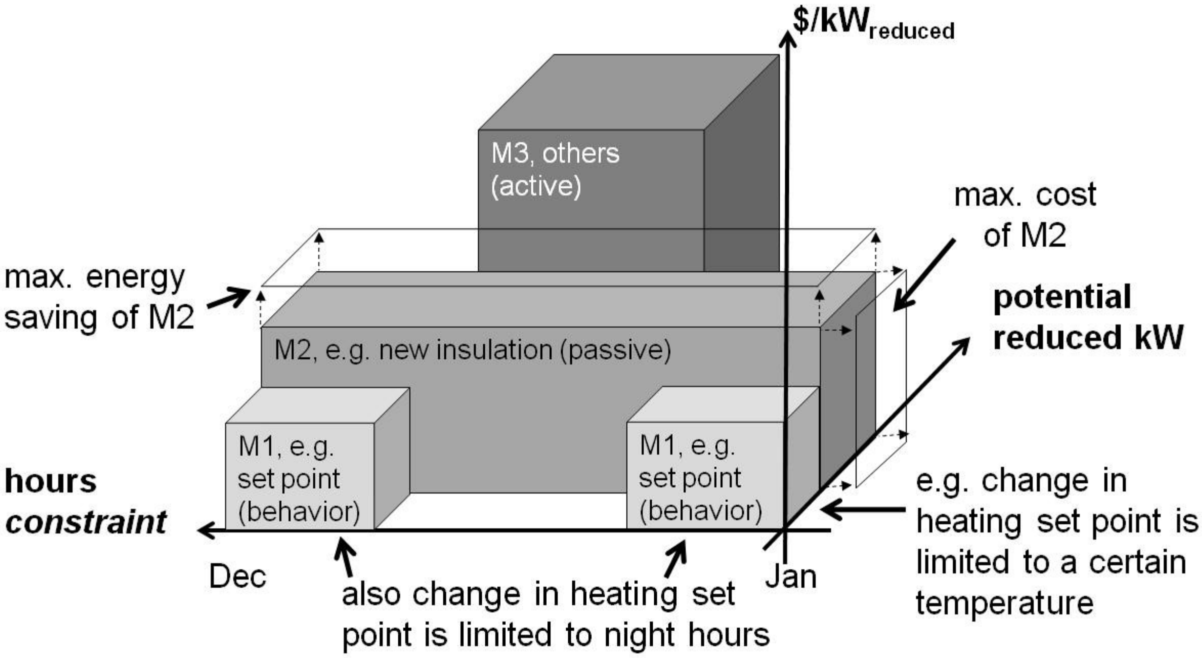


Figure 6. Optimal schedule for meeting the electricity load (run 3) on a July weekday

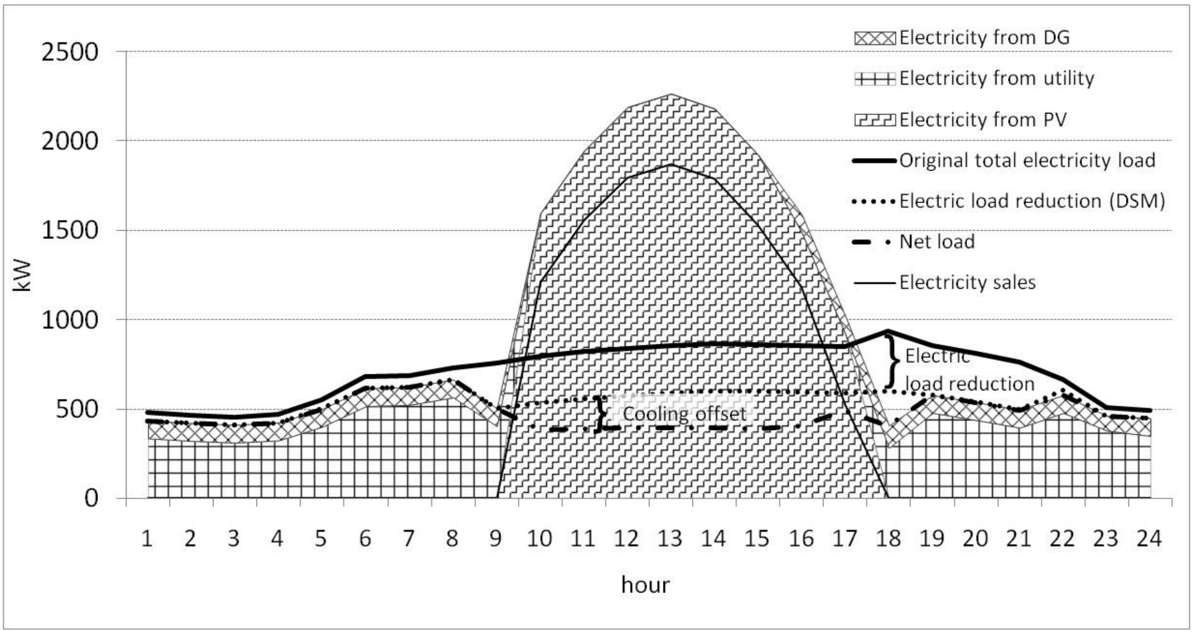


Figure 7. Optimal schedule for meeting the heating load (run 3) on a July weekday

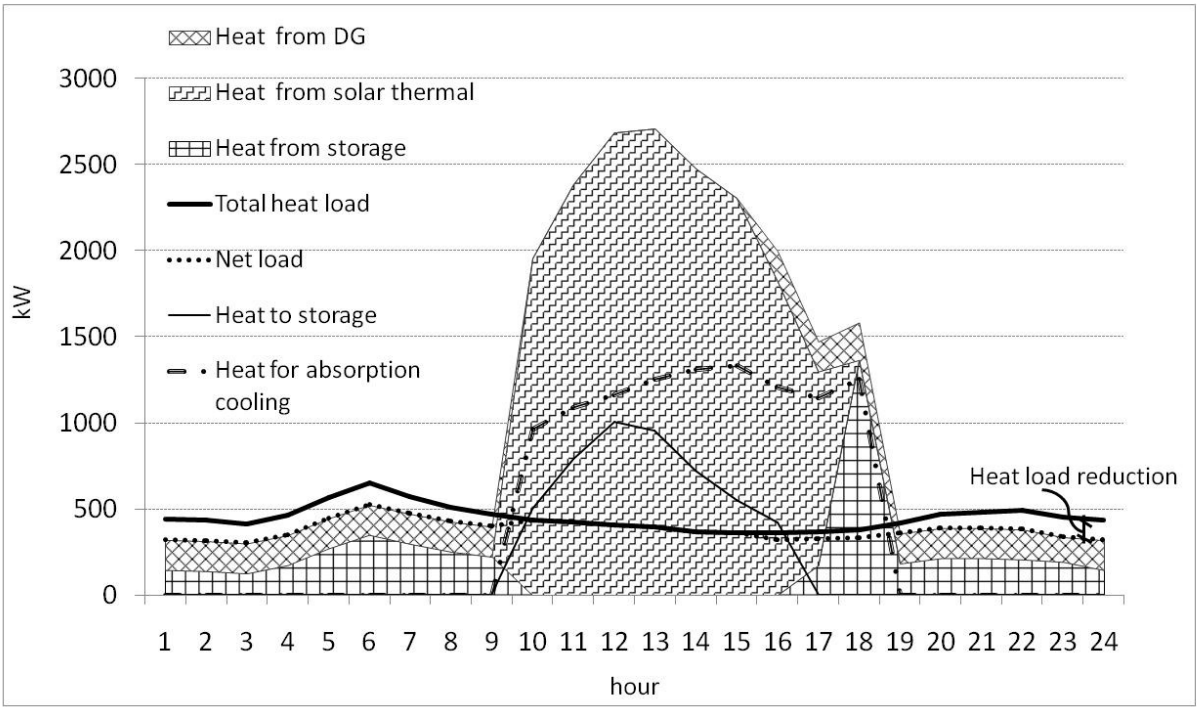


Figure 8. Optimal schedule for meeting the electricity load (run 4) on a July weekday

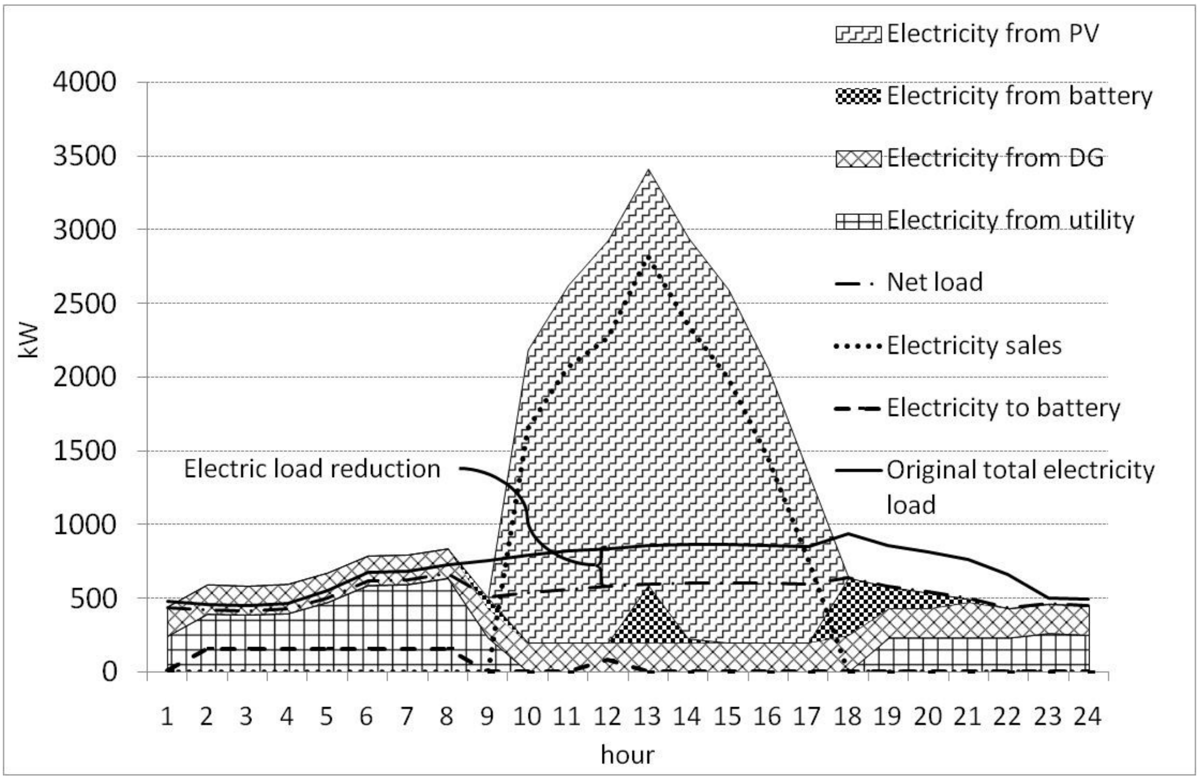
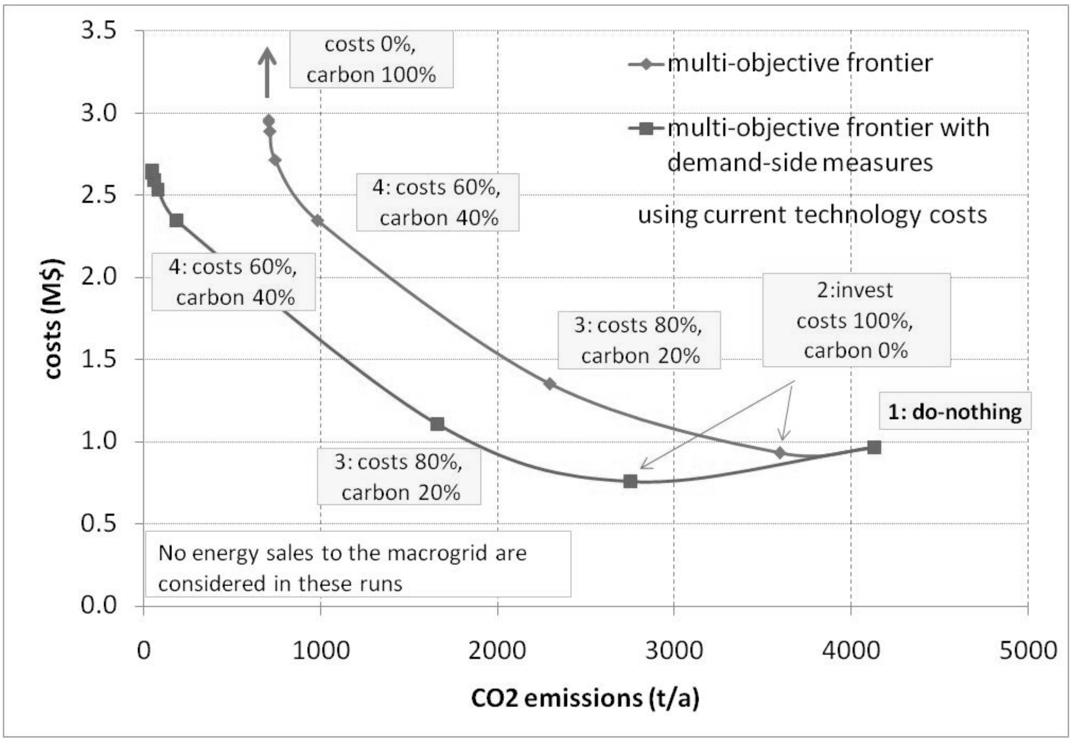


Figure 9. Multi-objective frontier for the northern California nursing home



Tables

Table 1. Example DSM input parameters for electricity

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 estimates[24]

Table 2. Example 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 estimates

[24] At this point, these are very rough estimates and refinement will be considered.

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[25]	0.84	1
decay	portion of state of charge lost per hour	0.001[26]	0.01[27]	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[28]
maximum discharge rate	maximum portion of rated capacity that can be withdrawn from storage in an hour	0.25	n/a	0.25[29]
minimum state of charge	minimum state of charge as apportion of rated capacity	0.3	0.25	0

source: LBNL estimates and [8, 9]

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 ($/kWh)	0.02	0.029
efficiency (%), (HHV)	26	35
lifetime (a)	20	10
operation and maintenance ($/kWh)	0.02	0.029

[25] The impact of different discharge levels is subject to further research.
[26] 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.
[27] Preliminary number; future analysis could address the impact of different decay numbers.
[28] Preliminary number; the impact of different maximum charge rates is subject to further investigations.
[29] Preliminary number; the impact of different maximum discharge rates could be the subject to further investigations.

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

	electrical storage (lead acid)	thermal storage[30]	flow battery	absorption chiller	solar thermal	Photovoltaics
intercept costs ($)	295	10000	0	20000	1000	1000
variable costs ($/kW or $/kWh)	193[31]	100[32]	220$/kWh and 2125$/kW [33]	127[34]	500[35]	6675[36]
lifetime (a)	5	17	10	15	15	20
maintenance costs ($/kW or $/kWh)	~0	~0	0.05	1.88	0.5	0.25

Table 6. 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: [14, 15, 16]

[30] Please note that cold thermal storage is not among the set of available technologies, but could be added.
[31] $\$/kWh_{electricity}$
[32] $\$/kWh_{heat}$
[33] Flow batteries are characterized by both the energy content and power rating.
[34] Abs. chiller capacity is in terms of electricity offset (electric load equivalent).
[35] $\$/kW_{of\ recovered\ heat}$
[36] $\$/kW_{electricity}$

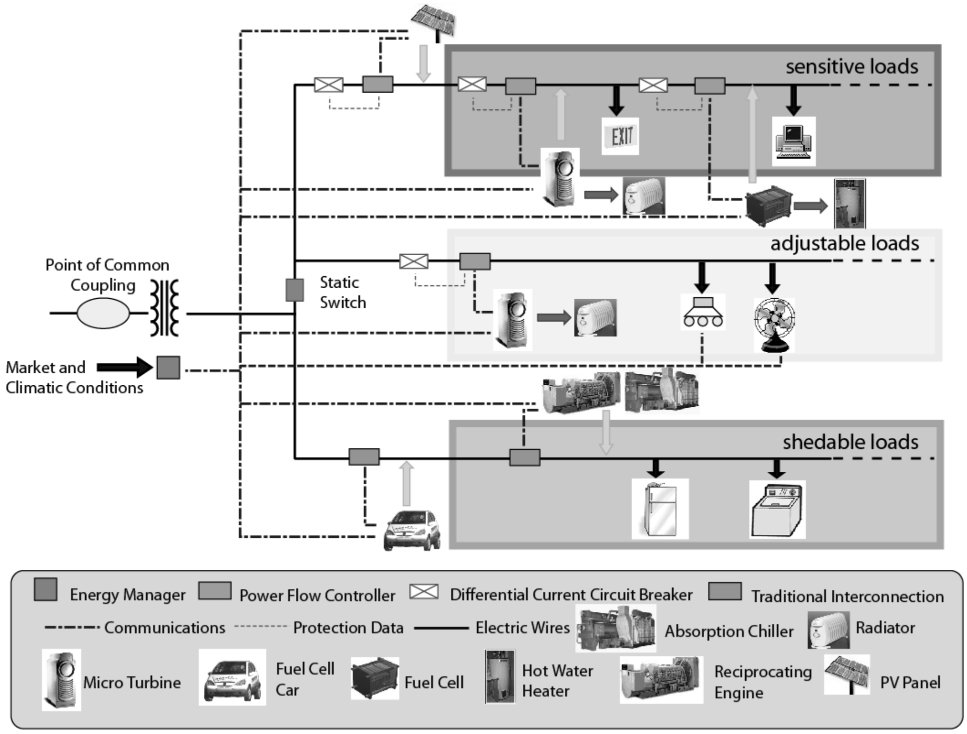
Table 7. Annualized results for the northern California nursing home (*w* = 1), hourly marginal CO_2 emission rates from [13], DER-CAM version 3.5.1

	run 1	run 2	run 3	run 4
	do-nothing	invest in all technologies	ZNEB invest in all technologies	ZNEB low storage and low PV price
equipment				
reciprocating 100 kW engine with heat exchanger (kW)	n/a	300	100	200
abs. chiller (kW in terms of electricity displaced)	n/a	0	220	0
solar thermal collector (kW)	n/a	0	3086	0
PV (kW)	n/a	0	2518	3133
electric storage (kWh)	n/a	0	0	1557
thermal storage (kWh)	n/a	0	6099	0
annual costs (k$)				
Total	963.90	757.18	1802.38	821.98
% savings compared to do-nothing	n/a	21.45	-86.99	14.72
annual energy consumption (GWh)				
electricity	5.76	2.10	2.30	1.70
NG	5.70	9.00	2.17	7.60
annual CO_2 emissions (tCO_2/a)				
emissions	4130.64	2751.73	1604.91	2266.24
% savings compared to do-nothing	n/a	33.38	61.15	45.13

Appendix A: Microgrid Configuration

We represent a typical microgrid in abstract sense in Figure 10. There may be various types of on-site technologies installed to meet diverse end-use loads. The loads may be classified as being either sensitive or sheddable for the purposes of DSM. Allocation of energy production from on-site resources to the end-use loads requires controllers. Furthermore, the interface between the microgrid and the wider macrogrid is such that the former is perceived by the latter as being simply another node in the distribution network with no additional knowledge of the end-use loads and on-site resources embedded within.

Figure 10. Sample microgrid



source: LBNL

Appendix B: Solar Data

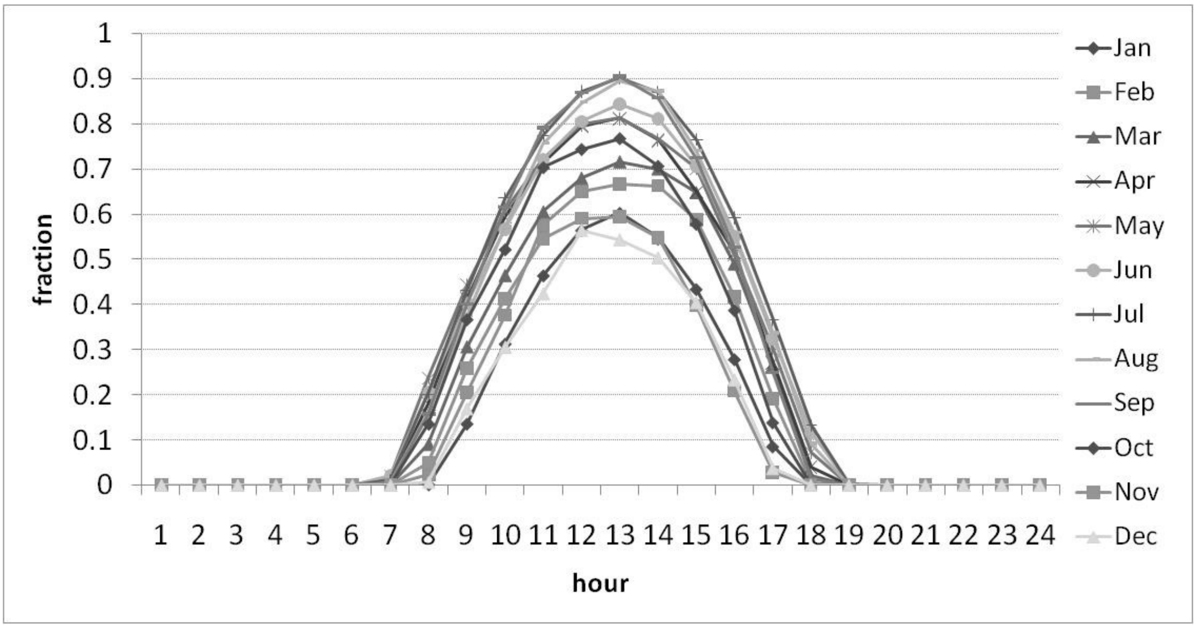
To obtain solar data for DER-CAM, PVWATTS from NREL has been used [17]. Originally designed for gathering information for PV system output for different geographic locations, PVWATTS can be also used to gather solar radiation data for DER-CAM. DER-CAM assumes a maximum solar radiation of 1000W/m^2, which is the same number as used for testing PV panels. Thus, to obtain the fraction of solar insolation of fixed-alignment PV panels in different locations, PVWATTS can be used. Setting the AC Rating to 1 kW, PVWATTS delivers the fraction of solar radiation for a chosen site. In other words, solar radiation is always expressed as a fraction of the test conditions. A fraction of 0.9 at 12.00 means that an average solar radiation of 900W/m^2 arrives at the panel. 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, PVWATTS 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. San Francisco is used as the approximate location for the nursing home in the Bay Area.

Table 8. Settings for PVWATTS to obtain the fraction of solar radiation for San Francisco

PVWATTS: Hourly PV	
City:	SAN_FRA
State:	CA
Lat (deg N):	37.62
Long (deg W):	122.38
Elev (m):	5
Array Type:	“Fixed
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

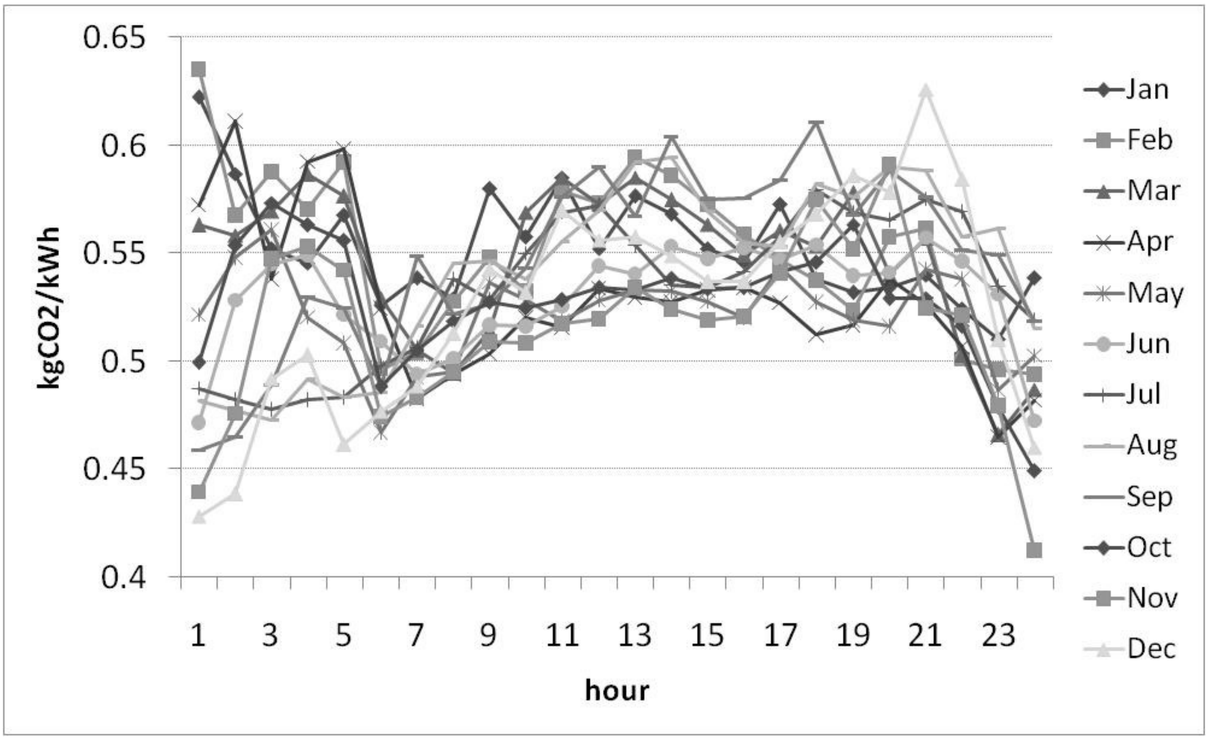
Source: [17]

Figure 11. Solar radiation as fraction of the max. insolation of 1000W/m^2 for San Francisco



Appendix C: Hourly Marginal CO_2 Rates

Figure 12. Average hourly marginal CO_2 rates in 2008



source: [13] and LBNL calculations