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Optimal Planning and Operation of Smart Grids with Electric Vehicle Interconnection

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Abstract
Connection of electric storage technologies to smartgrids will have substantial implications for building energy systems. Local storage will enable demand response. When connected to buildings, mobile storage devices such as electric vehicles (EVs) are in competition with conventional stationary sources at the building. EVs can change the financial as well as environmental attractiveness of on-site generation (e.g. PV or fuel cells). In order to examine the impact of EVs on building energy costs and CO_2 emissions, a distributed-energy-resources adoption problem is formulated as a mixed-integer linear program with minimization of annual building energy costs or CO_2 emissions and solved for 2020 technology assumptions. The mixed-integer linear program is applied to a set of 139 different commercial buildings in California and example results as well as the aggregated economic and environmental benefits are reported. Special constraints for the available PV, solar thermal, and EV parking lots at the commercial buildings are considered. The research shows that EV batteries can be used to reduce utility-related energy costs at the smart grid or commercial building due to arbitrage of energy between buildings with different tariffs. However, putting more emphasis on CO_2 emissions makes stationary storage more attractive and stationary storage capacities increase while the attractiveness of EVs decreases. The limited availability of EVs at the commercial building decreases the attractiveness of EVs and if PV is chosen by the optimization, then it is mostly used to charge the stationary storage at the commercial building and not the EVs connected to the building.

Keywords
carbon emissions, combined heat and power, commercial buildings, distributed energy resources, distributed generation, electric vehicle, load shifting, microgrid, optimization, smart grid, storage technologies

1. Introduction

Several papers analyze the impact of renewable energy sources and EVs on the power grid and electricity prices. For example, Sioshansi and Denholm, 2009 look into the possibility of providing ancillary services and storage capabilities to the power grid by utilizing plug-in hybrid electric vehicles (PHEVs). Wang et al., 2010 model the impact on electricity prices due to additional power grid loads from EVs. Since buildings are the link between the power system and the EVs, this work uses a building centric approach and looks into the cost and CO_2 benefits for buildings adopting distributed energy resources (DER). Furthermore, there are many DERs in a building which will be influenced by EV batteries. Also, stationary storage in buildings attracts more research attention and this can create competition between mobile storage and stationary storage. On the other hand, when mobile storage is not suitable for EV usage anymore it can be recycled and used as stationary storage in buildings, where the battery specifications can be relaxed. This 2nd life of EV batteries attracts the attention of researchers and this might also create opportunities for EV batteries (see also TSRC). All these options and interactions of DER in buildings require an integrated approach for analyzing the benefits of EVs connected to buildings.

This paper focuses on the analysis of the optimal interaction of electric vehicles (EVs) with commercial smartgrids/microgrids, which may include photovoltaic (PV), solar thermal, stationary batteries, thermal storage, and combined heat and power (CHP) systems with and without absorption chillers. A microgrid is a group of interconnected loads and DER within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid. A microgrid can connect and disconnect

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from the grid to enable it to operate in both grid-connected or island mode. An overview of microgrids can be found in Hatziargyriou et al., 2007.
In previous work, Berkeley Lab has developed the Distributed Energy Resources Customer Adoption Model (DER-CAM) with its mathematical formulation documented in Siddiqui et al., 2005 and Stadler et al., 2008. Its optimization techniques find both the combination of equipment and its operation over a typical year that minimizes the site's total energy bill or carbon dioxide (CO_2) emissions, typically for electricity plus natural gas purchases, as well as amortized equipment purchases. It outputs the optimal distributed generation (DG) and storage adoption combination and an hourly operating schedule, as well as the resulting costs, fuel consumption, and CO_2 emissions. DER-CAM always takes the perspective of the building owner or operator since it is a customer adoption model and does not optimize the benefits of utilities or the society directly. However, the results can be aggregated to a state level as shown below, which allows estimating changes in the state's or the commercial sector's CO_2 emissions.

Berkeley Lab has access to the California End-Use Survey (CEUS), which holds roughly 2700 building load profiles for the commercial sector in California (see CEUS). These hourly load profiles are needed to make optimal decisions on the operation of the DG equipment, which influences the optimal DG investment capacities since DER-CAM considers amortized investment and operation costs. Berkeley Lab compiled a database of 139 representative building load profiles for buildings with peak loads between 100 kW and 5 MW, and buildings in this size range account for roughly 35% of total statewide commercial sector electric sales (Stadler et al., 2009). The 139 load profiles are made up of the following building types in different sizes: hospitals, colleges, schools, restaurants, warehouses, retail stores, groceries, offices, and hotels/motels.

Mobile storage can directly contribute to tariff-driven demand response in these commercial buildings. By using EVs connected to the buildings for energy management, the buildings could arbitrage their costs. However, since the car battery lifetime is reduced due to the increased energy transfer, a model that also reimburses car owners for the degradation is required. In general, the link between a microgrid and an EV can create a win-win situation, wherein the microgrid can reduce utility costs by load shifting, while the EV owner receives revenue that partially offsets his/her expensive mobile storage investment. Previous work done for certain types of buildings shows that the economic impact for the car owner is limited relative to the costs of mobile storage for the site analyzed, i.e., the economic benefits from EV connections are modest (Momber et al., 2010 and Mendes et al., 2011). However, that work does not consider all possible DER technologies in buildings nor does it track the CO_2 savings from mobile storage connected to buildings.

This paper will specifically focus on the new EV equations in DER-CAM, e.g. EV specific electric balance equation or CO_2 emissions from EV electricity exchange, and assess the impact of EVs connected to different types of commercial buildings in 2020. The 139 buildings are grouped in different climate zones in California and within the three major utility service territories of Pacific Gas & Electric (PG&E), Southern California Edison (SCE), and San Diego and Gas Electric (SDG&E). Please note that this paper does not model the impact on electricity prices due to additional power grid loads from EVs and the assumed tariffs for the three used service territories are assumed to be static. For impacts on marginal energy prices please refer to (Wang et al., 2010). Furthermore, this work uses an area constraint for the maximum possible PV and solar thermal adoption as well as for the available EV parking space. This constraint has a significant impact on the DER adoption and operation and can drive up building energy costs.

The structure of this paper is as follows:

- Section 2 describes the Distributed Energy Resources Customer Adoption Model (DER-CAM)
- Section 3 discusses how EVs are modeled in DER-CAM
- Section 4 presents the data used for the analyses performed here
- Section 5 provides the results and discusses the impact on mobile and stationary storage adoption
- Section 6 summarizes the paper, discusses its limitations, and provides directions for future research in this area.

2. DER-CAM

DER-CAM is a mixed-integer linear program (MILP) written and executed in the General Algebraic Modeling System (GAMS). Its objective is typically to minimize the annual costs or CO_2 emissions for providing energy services to the modeled site, including utility electricity and natural gas purchases, plus amortized capital and maintenance costs for any DG investments. Other objectives, such as carbon or energy minimization, or a combination are also possible. The approach is fully technology-neutral and can include energy purchases, on-site conversion, both electrical and thermal on-site renewable harvesting. Furthermore, this approach considers the simultaneity of results. For example, building cooling technologies are chosen such that the results reflect the benefit of electricity demand displacement by heat-activated cooling, which lowers building peak load and, therefore, the on-site generation requirement, and also has a disproportionate benefit on bills because of demand charges and time-of-use (TOU) energy charges. Site-specific inputs to the model are end-use energy loads, detailed electricity and natural gas tariffs, and DG investment options. In general these load profiles can be simulated and gathered from building simulation tools (EnergyPlus) or taken from building information systems in the case of existing buildings.

Figure 1 shows a high-level schematic of the possible building energy flows modeled in DER-CAM. For this we use Sankey diagrams, which show in a graphical way how loads can be met by different resources at given efficiencies (Schmidt, 2006). Thus, a Sankey diagram provides a full view of possible resources that can be considered within the optimization.

Available energy inputs to the site are solar radiation, utility electricity, and utility natural gas. The location-specific solar radiation will impact the adoption of PV and solar thermal technologies. Previous work has shown that the utility electricity prices and utility natural gas prices are a main driver for natural gas fired distributed technologies. The gross margin of a gas-fired power plant from selling a unit of electricity (spark spread) determines the attractiveness of the plant. In case of TOU tariffs, the spark spread increases dramatically during the expensive (normally noon) hours, which increases the attractiveness of gas-fired technologies.

DER-CAM solves the mixed integer linear problem over a given time horizon, e.g., a year, and selects the economically or environmental optimal combination of utility electricity purchase, on-site generation, storage and cooling equipment required to meet the site's end-use loads at each time step. In other words, DER-CAM looks into the optimal combination/adoption and operation of technologies to supply the services specified on the right hand side of Figure 1. All the different arrows in Figure 1 represent energy flows, and DER-CAM optimizes these energy flows to minimize costs or CO_2 emissions. Black arrows represent natural gas or any bio-fuel, light grey represents electricity, and darker grey heat and waste heat, which can be stored and/or used to supply the heat loads or cooling loads via absorption cooling.

The outputs of DER-CAM include the optimal DG/storage adoption and an hourly operating schedule, as well as the resulting costs, fuel consumption, and CO_2 emissions. The approach does not consider EVs in isolation but rather alongside the rest of the DER equipment. All available technologies compete and collaborate, and simultaneous results are derived. In this way, it can be shown that PV and stationary electric storage can compete in certain situations. If the focus of the optimization is on cost minimization and a TOU rate with high costs during noon hours is used, then it can be demonstrated that stationary electric storage will be discharged at the same time when the PV system is operational (Stadler et al., 2009b). The on-site fuel use and carbon savings are, therefore, quite accurately estimated and can deviate significantly from simple estimates. Also, the optimal pattern of utility electricity purchase is accurately delivered. Finding likely solutions to this complex problem for multiple buildings would be impossible using simple analysis, e.g. using assumed equipment operating schedules and capacity factors. Because CEUS buildings each represent a certain segment of the commercial building sector, results from typical buildings can readily be scaled up to the state level in order to provide policymaking insights.

3. EV Approach

Once EVs are connected to commercial buildings, electricity from their batteries can be transferred to and from the sites. The building energy management system (EMS) can use this additional battery capacity to lower its energy bill and/or carbon footprint. Whenever possible, economically attractive energy from a renewable energy source or CHP system at the building could be used to offset EV charging at home. In this paper, DER-CAM is used to find the optimal charging and discharging schedule for the EV batteries. Decision variables are, therefore, the activity levels of all available energy sources so that energy loads are met, as well as the optimal installed capacity, making it a three-level assignment problem: energy loads, supply scheduling, and installed capacity. Included in these variables are utility energy purchases, local energy production, and EV interactions, which are the focus of this paper. It is assumed that the EV owner will receive compensation for battery degradation caused by the commercial building EMS and is reimbursed for the amount of electricity charged at home and later fed into the commercial building (see equations 1 & 5). On the other hand, if the EV is charged by electricity originating from the commercial building, then the car owner needs to pay the commercial building for the electricity.

$$C_{bat} = E_{EV} * CL * RC_{bat} \quad (1)$$

C_{bat}	EV battery degradation annual costs caused by the commercial building, $
E_{EV}	total annual electricity exchange through the EV battery, caused by the commercial building, kWh
CL	capacity loss factor, dimensionless
RC_{bat}	replacement cost of the EV battery, $/kWh

The monetary losses attributable to charging and discharging as well as the decay will be covered by the commercial building. However, since this work also reports on the environmental impact of EVs connected to commercial buildings, the modeling of the marginal CO_2 emissions is important. The marginal CO_2 emissions when the EVs are plugged in at residential buildings for charging are tracked as this is necessary to be able to calculate the proper CO_2 changes in the commercial buildings (see equations 6 & 7). Consider the abstract state of charge (SOC) pattern (solid black line) for an EV connected to an office building in Figure 2, and it is obvious that the commercial building benefits from energy (area A) that has a carbon foot print that is related to times when the EV is not connected to the commercial building. Since the state of charge at disconnection (SOC_{out}) is less than at connection (SOC_{in}), a net energy transfer to the commercial building takes place and that energy might have a different carbon content since it originates from other sources at different times. Therefore, tracking the CO_2 emissions and different cases is an important feature within DER-CAM. This becomes even more complicated if the EVs are connected to different buildings during a certain period of time[10].

The high-level formulation used in DER-CAM follows the standard linear programming approach:

$$\begin{aligned} &\mathrm{Min}\ f = c^{T}x \qquad (2)\\ &\mathrm{s.t.}\\ &Ax \leq b\\ &L \leq x \leq U \end{aligned}$$

where:

c	cost coefficient vector
x	decision variable vector
A	constraint coefficient matrix
b	constraint coefficient vector
L	decision variable lower boundary vector
U	decision variable upper boundary vector

This translates to DER-CAM in the simplified[11] mathematical formulation explained below, where an emphasis is given to EV specific formulation. Please refer to Figure 3 for the representative MILP solved by DER-CAM

3.1 Input Parameters

a. Indices

m	month index (1,2,… 12)
h	hour index (1,2,… 24)

b. Market data

$C_{fix\ m}$	fixed electricity costs, $
$CO_{2\ EV\text{-}home\ m,h}$	macrogrid CO_2 emission during home charging period, $kgCO_2/kWh$. These are the CO_2 emissions of energy transferred to the commercial building. $CO_{2EV\text{-}home\ m,h}$ is calculated based on the emissions when the EV is connected to the residential building.

c. EV parameters

c	EV battery capacity, kWh
$\overline{cr}$	EV battery maximum charge rate, dimensionless
$\overline{dr}$	EV battery maximum discharge rate, dimensionless
p_{EV}	EV electricity exchange price, $/kWh. Set to residential charging rate for EVs
$\overline{SOC}$	EV battery maximum state of charge, dimensionless
$\underline{SOC}$	EV battery minimum state of charge, dimensionless
η_c	EV battery charging efficiency, dimensionless
η_{dc}	EV battery discharging efficiency, dimensionless
φ	electricity storage loss factor for the EV battery, dimensionless

[10] Multiple building connections are not considered in this work.

[11] The full DER-CAM code consists of roughly 5600 lines of code for equations, parameters, and data sets. Please note that the full detailed mathematical formulation of DER-CAM is roughly 17 pages.

d. Customer loads

$D_{B\,m,h}$ electricity demand from the building, kWh

3.2 Decision Variables

a. Costs

C_{total} total annual energy cost of the commercial building, $

C_{elec} electricity costs, $

C_{DER} distributed energy resources costs (amortized capital costs of investments), $.

C_{fuel} fuel costs, $

C_{DR} demand response costs for other non-storage technologies, $

C_{bat} EV battery degradation costs, $

$C_{var\,m,h}$ variable electricity costs (energy and demand charges), $

$C_{EV\,m,h}$ EV electricity costs, $

b. CO_2 emissions

CO_{2_total} total annual CO_2 emissions, $kgCO_2$

CO_{2_elec} CO_2 emissions from electricity consumption, $kgCO_2$

CO_{2_fuel} CO_2 emissions from DG fuel burning, $kgCO_2$

CO_{2_EV} CO_2 emissions from EV electricity exchange, $kgCO_2$

c. Electricity exchange with the micorgrid/building

$S_{U\,m,h}$ electricity supplied by the utility, kWh

$S_{DER\,m,h}$ electricity supplied by distributed energy resources, kWh

$S_{St\,m,h}$ electricity supplied by local/stationary storage, kWh

$V_{m,h}$ electricity sales, $

d. Electricity exchange with EVs

$D_{EV\,m,h}$ electricity demand from EVs, kWh

$D_{St\,m,h}$ electricity demand from local/stationary storage, kWh

$E^{c\rightarrow r}{}_{m,h}$ electricity flow from car to residential building, $E^{c\rightarrow r} \leq 0$, kWh

$E^{r\rightarrow c}{}_{m,h}$ electricity flow from residential building to car, kWh

$ES_{EV\,m,h}$ electricity stored in EVs, kWh

$i_{\,m,h}$ EV storage input, kWh

$o_{\,m,h}$ EV storage output, kWh

$S_{EV\,m,h}$ electricity supplied by EVs, kWh

3.3 Objective Function – cost minimization

The most commonly used goal function in DER-CAM is total energy cost minimization. This includes electricity related costs, amortized capital costs of DER equipment, fuel costs, demand response measure costs, EV battery degradation costs, and sales.

$$\min \mathrm{C_{total}} = \mathrm{C_{elec}} + \mathrm{C_{DER}} + \mathrm{C_{fuel}} + \mathrm{C_{DR}} + \mathrm{C_{bat}} - \sum_m \sum_h V_{m,h} \qquad (3)^{12}$$

$$\mathrm{C_{elec}} = \sum_m \sum_\mathrm{h} \left(\mathrm{C}_{\mathrm{fix}\,m} + \mathrm{C}_{\mathrm{var}\,m,h} + \mathrm{C}_{\mathrm{EV}\,m,h}\right) \qquad (4)$$

$$\mathrm{C}_{\mathrm{EV}\,m,h} = \mathrm{p_{EV}} * \left(\frac{\mathrm{E^{r\rightarrow c}}_{m,h}}{\eta_\mathrm{c}} + \mathrm{E^{c\rightarrow r}}_{m,h} * \eta_{\mathrm{dc}}\right) \qquad (5)$$

3.4 Objective Function – CO_2 minimization

As mentioned previously, a second objective function is also available to DER-CAM. In this case, the objective becomes minimizing total CO_2 emissions, which includes emissions linked to utility electricity and fuel usage, but also to the CO_2 emissions associated with the use of electricity from EVs and their charging at different time periods.

$$\min \mathrm{CO_{2\,total}} = \mathrm{CO_{2\,elec}} + \mathrm{CO_{2\,fuel}} + \mathrm{CO_{2\,EV}} \qquad (6)^{13}$$

[12] Please note that only the EV relevant variables of equation 3 are shown in more detail. For C_{bat} please refer to equation 1.

[13] Please note that only the EV relevant variables of equation 6 are shown in more detail.

$$CO_{2\,EV} = \sum_m \sum_h \left(\left(\frac{E^{r \to c}{}_{m,h}}{\eta_c} + E^{c \to r}{}_{m,h} * \eta_{dc} \right) * CO_{2_{EV-home_{m,h}}} \right) \quad (7)$$

3.5 *Constraints*

a. Balance equations

This includes electric, heating and cooling balance equations, but we focus on the electric balance (equation 8), as this relates to the EV interactions. Another relevant example is the EV battery specific electric balance equation (equation 9).

$$S_{U\,m,h} + S_{DER\,m,h} + S_{St\,m,h} + S_{EV\,m,h} + V_{m,h} = D_{B\,m,h} + D_{St\,m,h} + D_{EV\,m,h} \quad (8)$$

$$ES_{EV\,m,h} = ES_{EV\,m,h-1} * (1 - \varphi) + i_{m,h} - o_{m,h} \quad (9)$$

b. Operational constraints

Operational constraints are applied to all technologies involved in DER-CAM, and are used, for instance to model technology behavior. Highlighted here are the net input and output electric flows from EVs (equations 10 &11), as well as capacity related constraints (equations 12, 13 &14).

$$S_{EV\,m,h} = o_{m,h} * \eta_{dc} \quad (10)$$

$$D_{EV\,m,h} = \frac{i_{m,h}}{\eta_c} \quad (11)$$

$$c * \underline{soc} \leq ES_{EV\,m,h} \leq c * \overline{soc} \quad (12)$$

$$i_{m,h} \leq c * \overline{cr} \quad (13)$$

$$o_{m,h} \leq c * \overline{dr} \quad (14)$$

4. Input Data, Technology Specification, and Parameters

The starting point for the hourly load profiles used within DER-CAM is the CEUS database, which contains 2790 premises in total. DER are very common at industrial buildings with electric peak loads above 5 MW, but mostly overlooked for commercial buildings with loads below 5 MW. Thus, the focus here is on mid-sized buildings, between 100 kW and 5 MW electric peak load, and the assumption that DER will not be attractive for <100 kW buildings. This assumption results in the consideration of 35% of the total commercial electric demand in the service territories of PG&E, SCE, and SDG&E.

As is typical for Californian utilities, the electricity tariff has a fixed charge plus TOU pricing for both energy and power (demand) charges. The latter are proportional to the maximum rate of consumption (kW), regardless of the duration or frequency of such consumption over the billing period. Demand charges are assessed monthly and may be for all hours of the month or assessed only during certain periods, e.g. on-, mid-, or off-peak, or be assessed at the highest monthly hour of peak system-wide consumption. For example, for buildings with electric peak loads above 500 kW in PG&E's service territory, the E-19 TOU tariff is used as the 2020 estimate. This tariff is used for the PG&E school example in the next section. The E-19 consists of a seasonal demand charge between $13.51/kW (summer) and $1.04/kW (winter), the TOU tariff varies between $0.16/kWh (on-peak) and $0.09/kWh (off-peak) in the summer months (May-Oct). Winter months show only $0.01/kWh difference between mid-peak and off-peak hours. Summer on-peak is defined from 12:00-18:00 on weekdays. All details of E-19 can be found at (PG&E E-19 tariff). It is assumed that in PG&E and SCE service territory the EVs can be charged at home at night for 6c/kWh (PG&E E-9 tariff) and in the SDG&E for 14c/kWh. All used commercial utility tariffs for this paper can be found at (Stadler et al., 2009). The demand charge in $/kW/month as well as the on-peak energy costs are a significant determinant of technology choice and sizing of DG and electric storage system installations as can be seen in the next section.

As described in previous sections, DER-CAM finds the optimal combination of technologies in order to reach the objective, defined in the specific runs. The available investment options comprise of technologies for distributed generation of electricity, heating and cooling energy, as well as storage technologies. DER-CAM distinguishes between discrete and continuous technologies to improve the optimization speed of DER-CAM: the former can only be picked in discrete sizes, whereas the latter may be selected in any size. However, discrete technologies allow modeling of economies of scale in a better way than continuous ones, and therefore, some important technologies, e.g. CHP are considered as discrete ones. For discrete technologies please refer to Table 1 and for continuous ones to Table 2.

In DER-CAM, there are two types of internal combustion engines (ICE) and fuel cells (FC) available – with and without heat exchangers (HX) (see Table 1). HX can enable waste heat utilization for hot water usage and absorption cooling, thereby allowing total energy conversion efficiencies of up to 80%. Their technical specifications and costs are based on historic data and our own estimates (Goldstein et al., 2004, Firestone, 2004, and SGIP, 2008). The continuous technologies available in DER-CAM at this point are PV, solar thermal collectors, absorption chiller systems as well as thermal and electric storage, and EV batteries. Costs of continuous technologies available in 2020 are derived from various sources and are displayed in Table 2. For storage technologies, the economic performance and, hence, the adoption by the building EMS is also affected by some key technical parameters (see Table 3). First, there is the charging and discharging efficiency of the storage. For both electric and thermal storage, a charging and discharging efficiency of 90% is assumed, thus representing a technology status likely to become standard in 2020. Another important parameter is the decay of the storage systems, which defines their degradation due to usage. Finally, there is the maximum charging and discharging rate, which is a key input for the building energy management system, since it determines the maximum energy flow that the storage can provide to the building at every time step.

For the mobile storage systems, it is assumed that Li-Ion batteries with a capacity of 16 kWh are used. This is roughly the size of current EVs or plug-in hybrid vehicles and is used as a proxy for vehicle batteries connected to the commercial building (GreenCarCongress). For mobile storage systems, a charging/discharging efficiency of 95% is assumed, a value likely to be the standard in 2020, given the dynamic progress in this field. Battery decay is an important parameter for mobile storage as well, since it defines the degradation cost that has to be covered by the commercial building when using mobile storage capacities (see section "EV Approach"). Table 5 shows the assumed times when vehicles are connected to the different building types and can be used by the EMS in principle. This, of course, neglects the stochastic nature of the driving patterns. However, sensitivity results show that the main results for the charging and discharging strategies for mobile storage, derived from this deterministic work will basically hold under consideration of uncertain driving patterns. Driving patterns just changes the connection periods to the buildings, but not the main drivers for the charging cycles - the electricity prices. Finally, Table 6 shows the area constraint used for PV, solar thermal, and EV parking space. Based on the CEUS database, the average floor space was taken as an estimate for the maximum area available for these technologies. Since no detailed building information can be collected from CEUS, no other information is available.

The marginal carbon emissions of the macrogrid for 2020 are taken from Mahone et al. 2008.

5. DER-CAM Results

Results for cost minimization, CO_2 minimization, and multi-objective optimization for two selected buildings of the CEUS building stock are shown in this section. A large school in the San Francisco Bay Area with 3340 m^2 floorspace and 550kW electric peak load as well as a healthcare facility in San Diego with 3260 m^2 floorspace and 400kW electric peak load are selected. These two examples are used to demonstrate how mobile storage capacity is adopted in commercial buildings considering an area constraint for PV, solar thermal, and EV adoption, and how it interacts with buildings' DG output and stationary storage. At the end of this section, we show the aggregated results on CO_2 savings, number of EVs used, and capacity of PV, as well as other DG for the state of California, considering the building types and climate zones from CEUS.

DER-CAM allows optimization of the weighted building energy costs and CO_2 emissions at the same time by using a multi-objective approach (see equation 15). By increasing *w,* more focus on CO_2 emission reduction is placed, and this approach allows showing the trade-off between costs and CO_2 emissions[14] in a building.

$$\min\ (1-\omega) * \frac{\mathrm{C_{total}}}{\mathrm{RefCost}} + \omega * \frac{\mathrm{CO_{2\,total}}}{\mathrm{RefCO_2Em}} \qquad (15)$$

where:

ω	weight factor [0..1]
$\mathrm{RefCO_2Em}$	parameter to make equation unit less
$\mathrm{RefCost}$	parameter to make equation unit less

By analyzing the cases of minimal costs (ω=0) and four further cases with increasing ω (S1 to S4), we approximated the multi-objective frontier of the school building and the healthcare facility in two different parts of California. The principal connection periods of EVs to the commercial buildings differ for each building type and are shown in Table 5. In both the school and healthcare buildings, it is assumed that the EVs connect to the commercial buildings at 8 AM and disconnect at 6 PM. During that time, the building EMS can manage the mobile storage in combination with other DER technologies, and

[14] Please note that DER-CAM tracks the CO_2 emissions transferred to the commercial building by mobile storage.

different optimization strategies can apply. From 6 PM to 8 AM, the EVs are disconnected from the commercial buildings and are subject to driving and charging/discharging at the residential building. Both scenarios are subject to very different EV charging tariffs at the residential buildings. In the San Francisco Bay Area, EVs can be charged for 6cents/kWh compared to 14cents/kWh in San Diego. This difference in price will influence the overall level of EV adoption, but still, general insights can be derived from these two cases.

Figure 4 and 5 show that total energy costs can be reduced by using EVs in the building (see do-nothing vs. min cost in Figure 4 and 5), but more focus on CO_2 emission reduction results in fewer EVs connected to the building (mobile storage curve in Figure 4 and 5). Despite the major difference in electricity tariff rates, both cases show a similar pattern and show increasing stationary storage capacities combined with decreasing numbers of EVs connected to buildings. The space constraints impact the results dramatically as evidenced by the nearly vertical multi-objective frontier from S2 and S1 in Figures 4 and 5, respectively. The maximum area available for PV and solar thermal is 3340 m^2 for the large school building and 3260 m^2 for the healthcare facility. Also, the parking space for EVs is constrained by 3340m^2 and 3260 m^2 respectively. Another finding from the optimization runs shown in Table 7 and 8 is the importance of natural gas fired fuel cell systems with CHP. Due to the heat requirement and as well as the area constraint, efficient fuel cell systems, which allow total efficiencies up to 80%, will be used during times when solar thermal or PV cannot be selected. For more detailed results for all optimization cases, please refer to Tables 7 and 8.

The major *cost reduction* strategy derived from the DER-CAM optimization is to charge EVs with cheap electricity at home and provide that energy during connection times to the commercial building (Figure 6 and 9). The higher residential EV charging rates in San Diego, however, reduce the connected numbers of EV in Figure 5. Figures 6 to 8 show the optimal diurnal electric pattern for different optimization cases for the large school building in the San Francisco Bay Area. Figure 6 clearly shows that EVs will be used to minimize utility related energy and demand charges, since the mobile storage will be discharged during expensive mid- and on-peak hours (9 AM to 6 PM). No other DER technologies will be adopted at the school.

Figure 7 illustrates the electric pattern for the school building with a multi-objective function for point S2. In this case, considerable PV of 352 kW and stationary storage capacity of 2068 kWh is installed. The connected mobile storage is practically negligible (14 kWh, or one vehicle) and so is the transferred electricity. There is a significant difference between summer and winter days in the way how stationary batteries are used. In summer, they are charged in the afternoon with excessive PV power and discharged at the beginning of the evening before CHP is activated (see Figure 7). In winter, they are charged during night hours with excessive CHP capacity and discharged in the morning hours before sufficient PV power is available (see Figure 8). In this case, stationary storage plays an important role for the electricity supply of the building especially in winter days.

Figure 9 shows the electric pattern for the San Diego healthcare facility on a summer day with cost minimization (corresponding to the point min. cost, w=0 in Figure 5). In this case, the electricity for the building is mainly supplied by DG and by the utility. During peak hours, energy transfer from mobile storage is used to cover marginal demand. In the cost minimization case, there is no PV installed and no stationary battery capacity. One reason for this is the way capital costs of storage systems are considered within DER-CAM. Stationary storage is owned by the building, and therefore, the annualized capital costs for stationary storage will be considered in the optimization. In contrast, mobile storage is owned by the car owner, and therefore, no major capital cost reimbursements are assumed – the cars are simply around and utilized. However, this also means that stationary storage has considerable disadvantages in a pure cost minimization strategy.

Figure 10 depicts the S1 case from Figure 5. In this case, PV is used to cover large parts of the total demand during day hours, thereby replacing CHP generation and consumption from the utility. During peak hours, energy from EVs is used to cover some demand. In the afternoon, EVs are used to balance supply and demand when DG/CHP is activated, and they absorb excessive electricity. Later, when demand decreases and CHP is shut down again due to a must take from PV and a 50% minimum capacity[15] constraint on CHP, they feed electricity back to the building. Stationary batteries are charged in the morning and are discharged in late afternoon where they compensate the reduction in supply when EVs are leaving the building. Figure 10 also shows that waste heat utilization and absorption cooling reduces the electricity demand during expensive day hours and contributes to cost reductions (see cooling offset at the top of Figure 10).

[15] To limit non-linear effects, the adopted discrete technologies need to be shut down at a minimum capacity of 50% of the nameplate capacity.

With increasing priority to CO_2 reduction, as assumed in S2 (Figures 11 and 12), the full PV potential of the building is exploited. In summer, PV can cover almost the entire demand between 10 AM and 2 PM. Electricity from EVs is transferred to the building during shoulder hours (9-10 AM and 2-4 PM). In winter days, the total load of the building is considerably lower mainly because of lower cooling demand. This is why excessive supply from PV can be used to transfer electricity to the stationary storage around midday to be used in afternoon and evening hours. In the afternoon, PV is used to charge EVs (see Figure 12).

Summing up the results for the two buildings, analyzed in detail with respect to EVs, we have seen that the use of mobile storage capacity from EVs is driven by the objective of cost minimization rather than efficiency improvement (Figures 6 and 9). The availability of EV storage capacity to the building is also strongly dependent on the tariff for home charging of EVs. The lower the residential charging rate, the more EV users to provide energy to the commercial building during the day. This effect is clearly shown in Figures 6 and 9. For Figure 6, a home charging rate of 6 cents/kWh and for Figure 9 14 cents/kWh is assumed, and this reduces the mobile storage SOC considerably in Figure 9 compared to Figure 6.

In most cases, EVs are charged at the residential building, and only some cases show that renewable energy is transferred from the commercial building to the residential building. EVs are always used to reduce the demand charges and energy-related costs at peak or shoulder hours when PV or other DG/CHP is not fully available. Also, we have seen that all cases with increasing focus on CO_2 emission show increasing capacities for stationary storage, and this makes the case for considering the 2nd life of mobile storage, meaning to re-use EV batteries in buildings after they have decommissioned from EV usage due to tighter performance requirements in EVs.

Finally, we show the aggregated results for California. Table 9 shows the results for CEUS building stock with electric peak loads between 100 kW and 5 MW assuming a CO_2 minimization strategy. When assuming a full CO_2 minimization strategy (w=1), a maximum cost increase boundary needs to be imposed. Without such a cost constraint, the optimization algorithm could adopt any size of equipment, which would create very unrealistic adoption patterns as well high investment costs. For the aggregated results shown in Table 9, a cost increase constraint of 30 % was used, which is considered as realistic increase that customers can accept by 2020.

The considered commercial buildings can reduce their CO_2 emissions by adopting DER by roughly 37%. To achieve this reduction, roughly 15 GWh of stationary storage needs to be adopted. The utilized mobile storage is roughly 12.5 GWh, and this shows the importance to consider second life of mobile storage in form of stationary storage. The 4.55 GW of adopted PV are used to charge the stationary storage and not to charge the mobile storage (see also the diurnal electric patterns above). Finally, Table 9 also shows that CHP plays an important role in CO_2 minimization strategies and 3.5 GW of CHP systems will be adopted.

6. Conclusions

The emergence of smart grids and EVs provides opportunities for transitioning towards a more energy efficient, less costly, and greener energy system. However, deployment of these resources by commercial microgrids requires decision support that simultaneously treats investment and operations. Furthermore, there is likely to be a tradeoff between costs and CO_2 emissions barring more substantial policy reforms. In order to illustrate the benefits and challenges of the incorporation of EVs into a microgrid, we model the decisions of various types of California users in different geographical regions for the year 2020.

Via a MILP, we find that the use of mobile energy storage provided by EVs in commercial buildings is driven more by cost reduction objectives than by CO_2-reduction/efficiency improvement objectives. Under pure cost minimization, EVs are mainly used to transfer low-cost electricity from the residential building to the commercial building to avoid high demand and energy charges during expensive day hours. By contrast, with CO_2 minimization strategies, EVs are used to reduce the utility demand charges and energy-related costs at peak or shoulder hours when PV or CHP is not fully available. Here, the use of stationary storage is more attractive compared to EV storage, because stationary storage is available at the commercial building for 24 hours a day and readily accessible for energy management. In particular, stationary storage can shift PV supply during the day to off-peak hours, when the building would otherwise be supplied by more carbon-intensive electricity from the utility. To benefit from the stationary storage and PV CO_2 reduction potential, stationary storage should get a major focus in R&D funding and policy making. To be able to use mobile storage in 2nd life, special focus needs to be put on the process of recycling mobile storage in buildings since this creates larger CO_2 savings. Finally, we find that the number of connected EVs varies widely depending on the residential charging rate and possibility of arbitrage.

Although the analysis presented here attempts to model a cost- or CO_2-minimizing decision maker, it is limited by several assumptions and simplifications. First, it assumes a given pattern of EV arrival and departure, which is only a rough approximation of reality. Second, electricity prices are subject to uncertainty, but here they are assumed to be deterministic. In general, a stochastic model of the investment and operational decisions would better capture the risks and tradeoffs faced by a typical decision maker. Third, the model does not consider investment timing or subsequent upgrades to installed technology based on changing market conditions. Again, these features could be incorporated into a real options or stochastic programming framework. Fourth, the model assumes that in spite of the arbitrage, the energy tariffs remain unchanged. In reality, the utility is likely to respond in the long run to such forces, which would necessitate a game-theoretic model and change the incentives of the decision maker.

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Acronyms

CHP	combined heat and power
CEUS	California End-Use Survey
DER	distributed energy resources
DER-CAM	Distributed Energy Resources Customer Adoption Model
DG	distributed generation
EMS	energy management system
EV	electric vehicle
FC	fuel cells
HX	heat exchanger
ICE	internal combustion engines
MILP	mixed-integer linear program
PHEV	plug-in hybrid electric vehicles
PG&E	Pacific Gas & Electric
PV	Photovoltaics
SCE	Southern California Edison
SDG&E	San Diego and Gas Electric
TOU	time-of-use

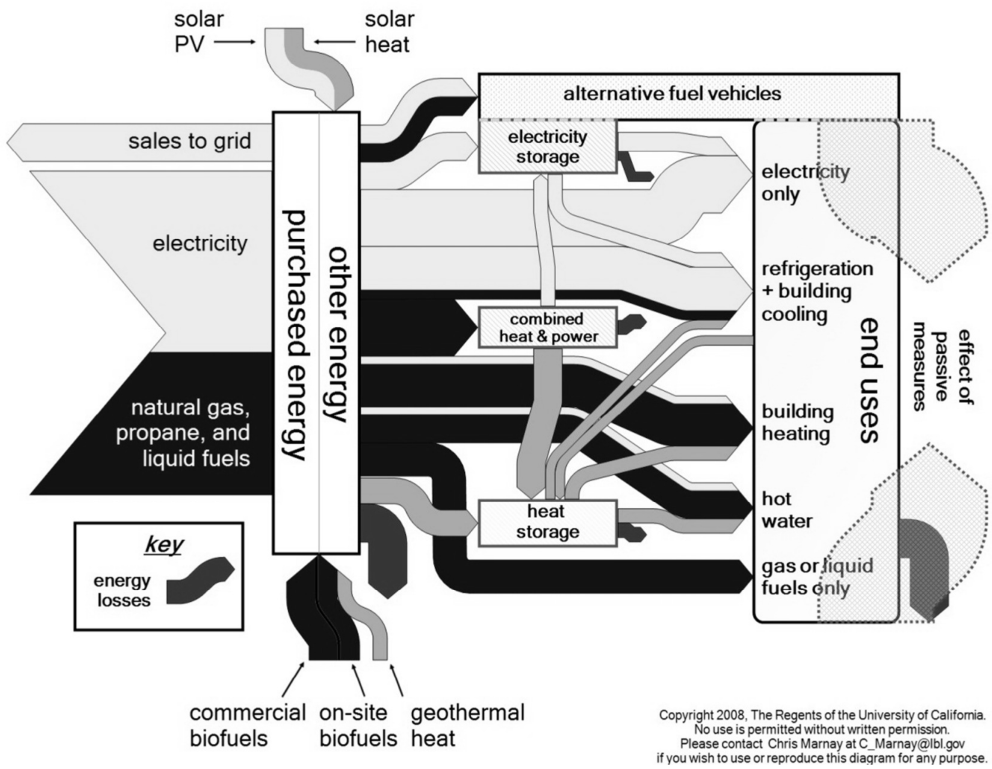

Figure 1. High level schematic of DER-CAM (Stadler et al., 2009)

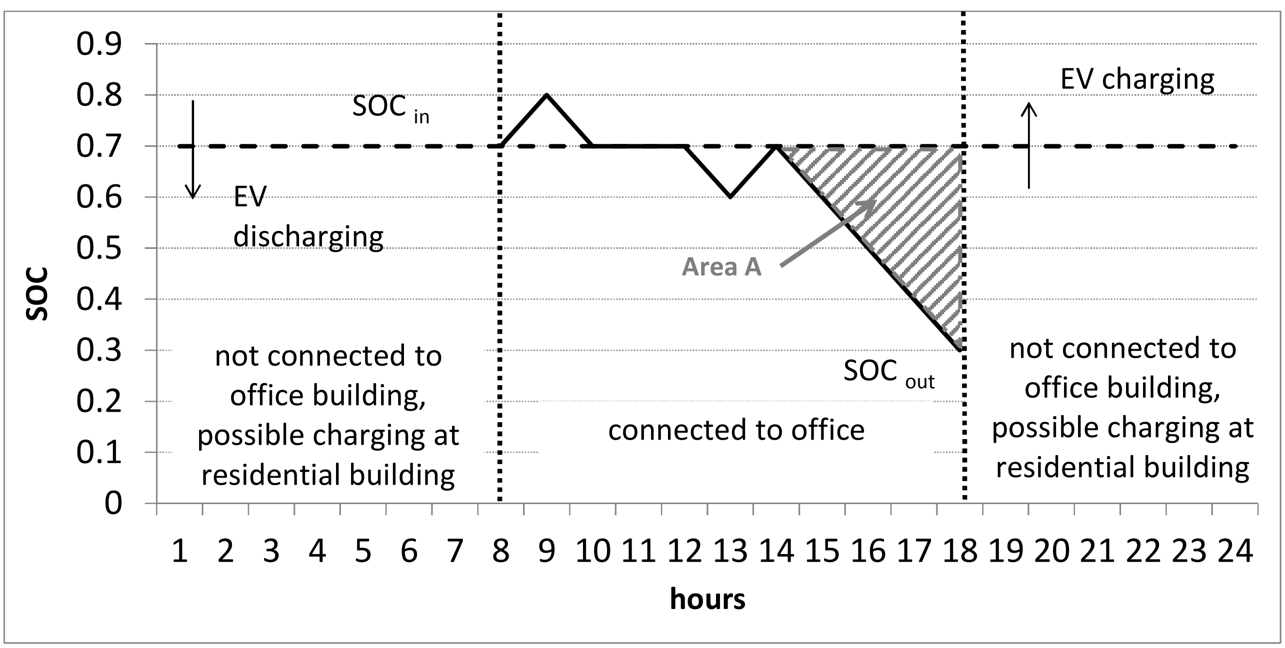

Figure 2. Hypothetical charging/discharging at a commercial (office) building, SOC_{in} means mobile storage state of charge at the time when the EV connects to the building, SOC_{out} means state of charge at the time when the EV disconnects from the building.

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

Figure 3. Representative MILP solved by DER-CAM

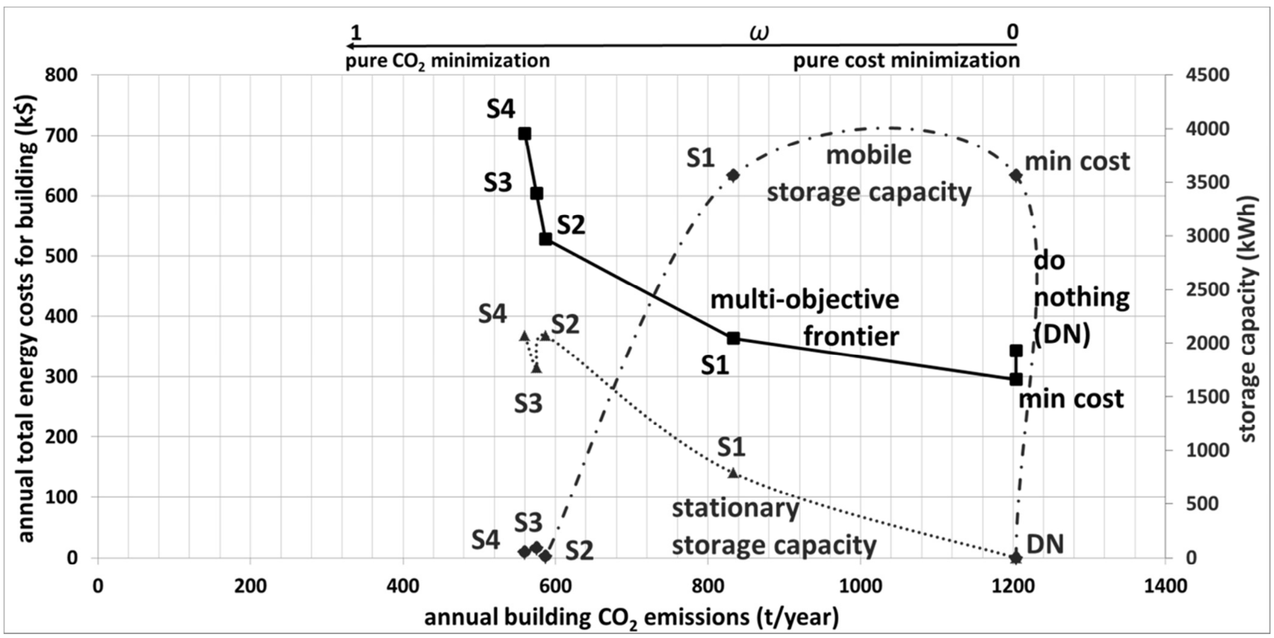

Figure 4. Results, multi-objective frontier for the large school building in the San Francisco Bay Area (PG&E service territory) and storage capacity

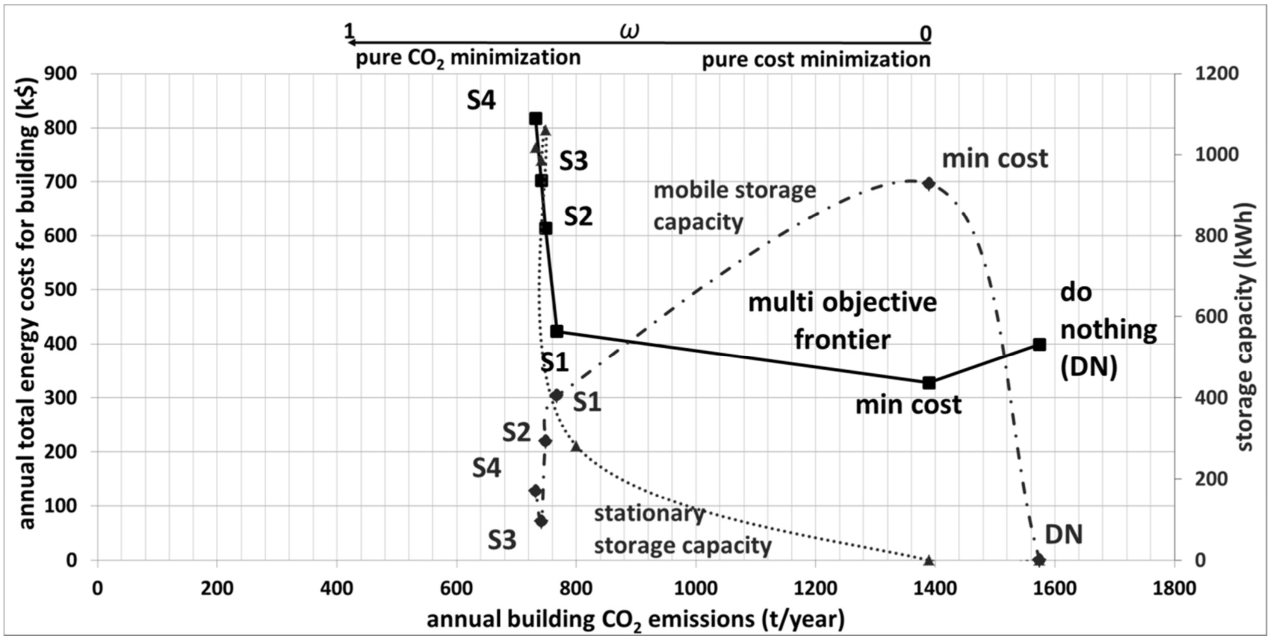

Figure 5. Results, multi-objective frontier for the healthcare facility in San Diego (SDG&E service territory) and storage capacity

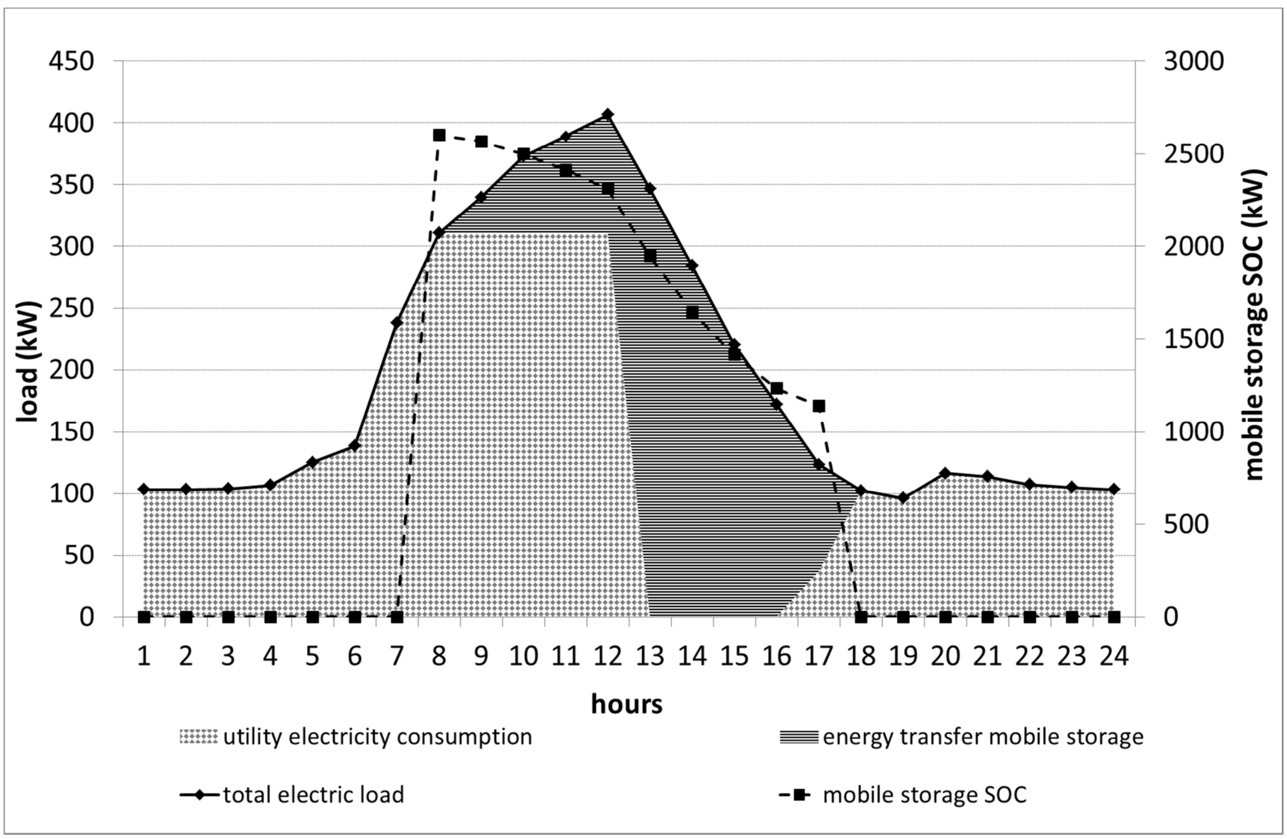

Figure 6. Diurnal electric pattern at cost-minimization on a July work day, large school in the San Francisco Bay Area (PG&E service territory)

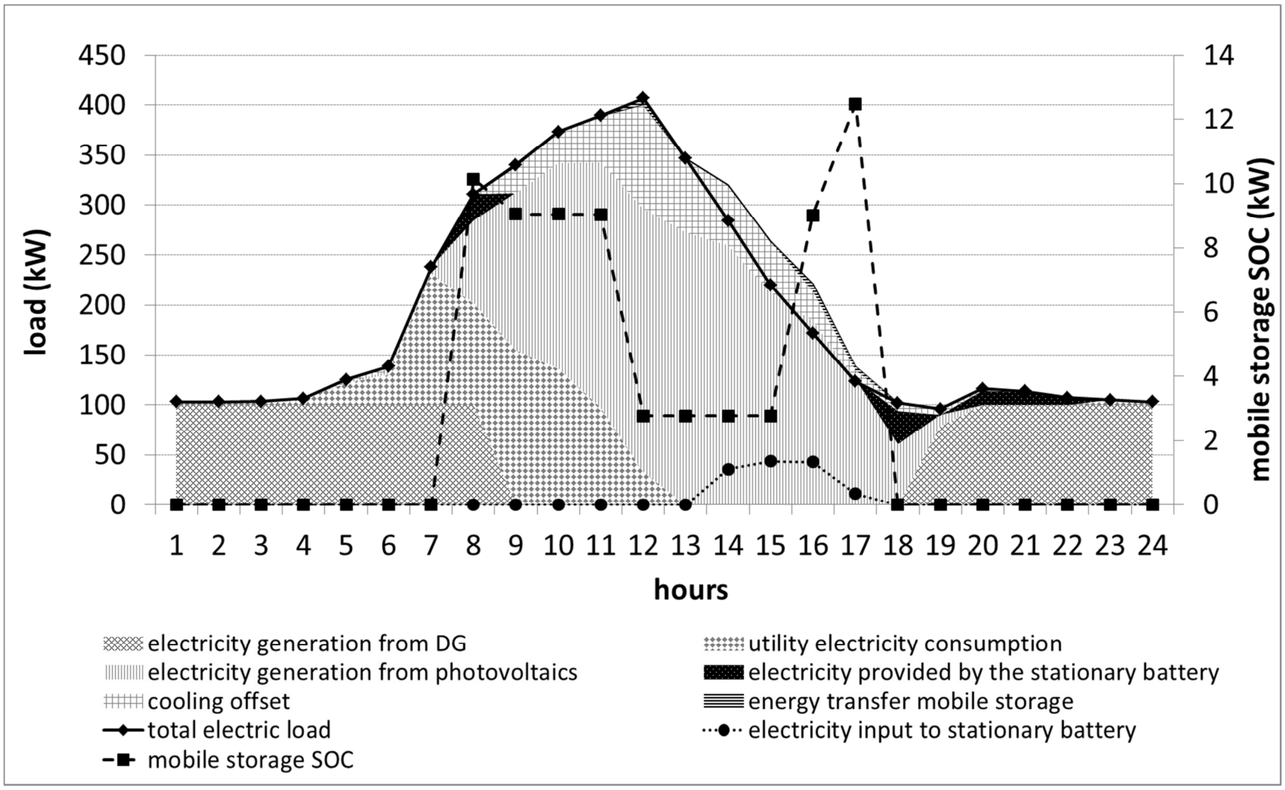

Figure 7. Diurnal electric pattern for point S2 on a July work day, large school in the San Francisco Bay Area (PG&E service territory)

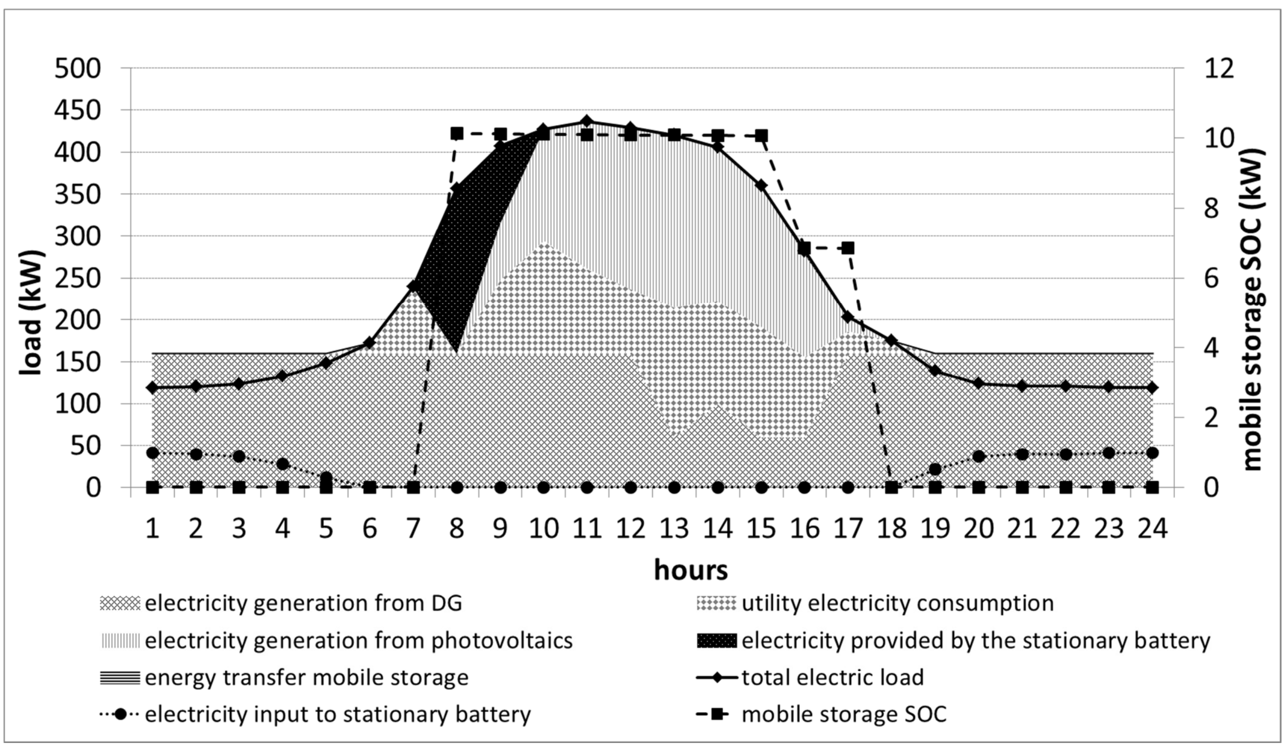

Figure 8. Diurnal electric pattern for point S2 on a January work day, large school in the San Francisco Bay Area (PG&E service territory)

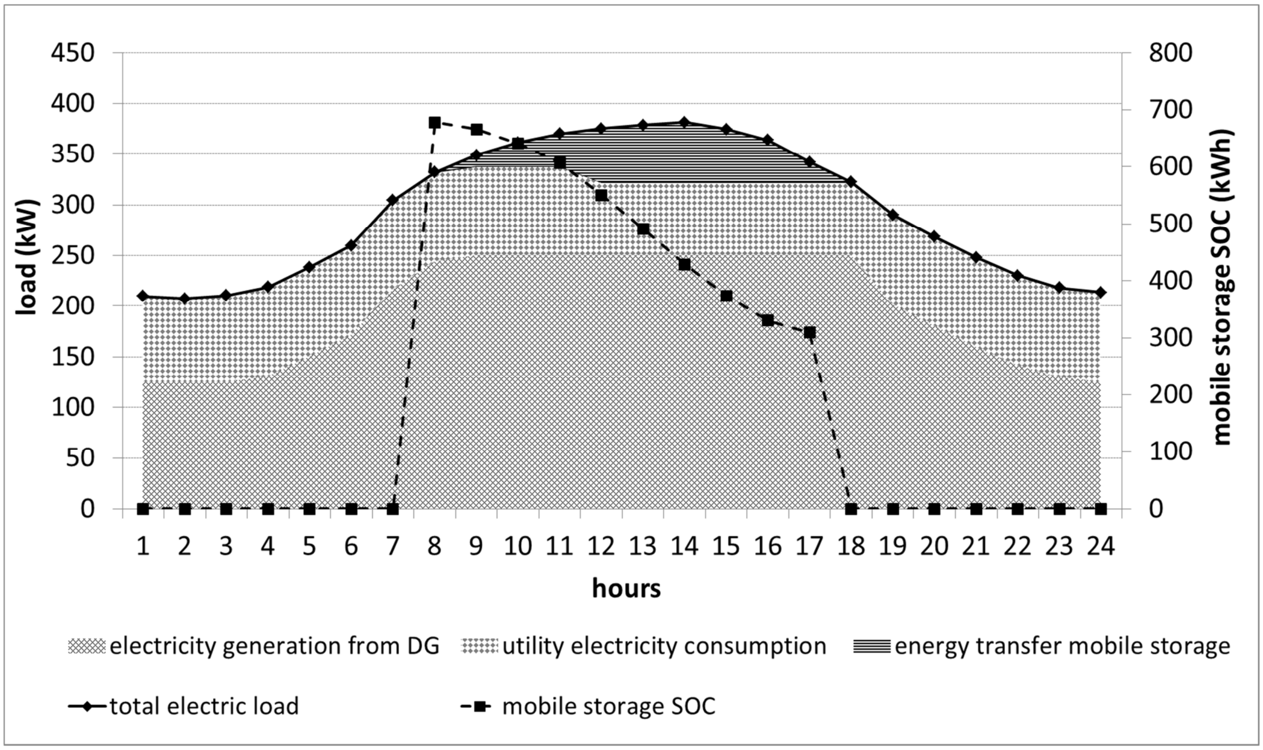

Figure 9. Diurnal electric pattern on a July work day for minimal costs for the healthcare facility in San Diego (SDG&E service territory)

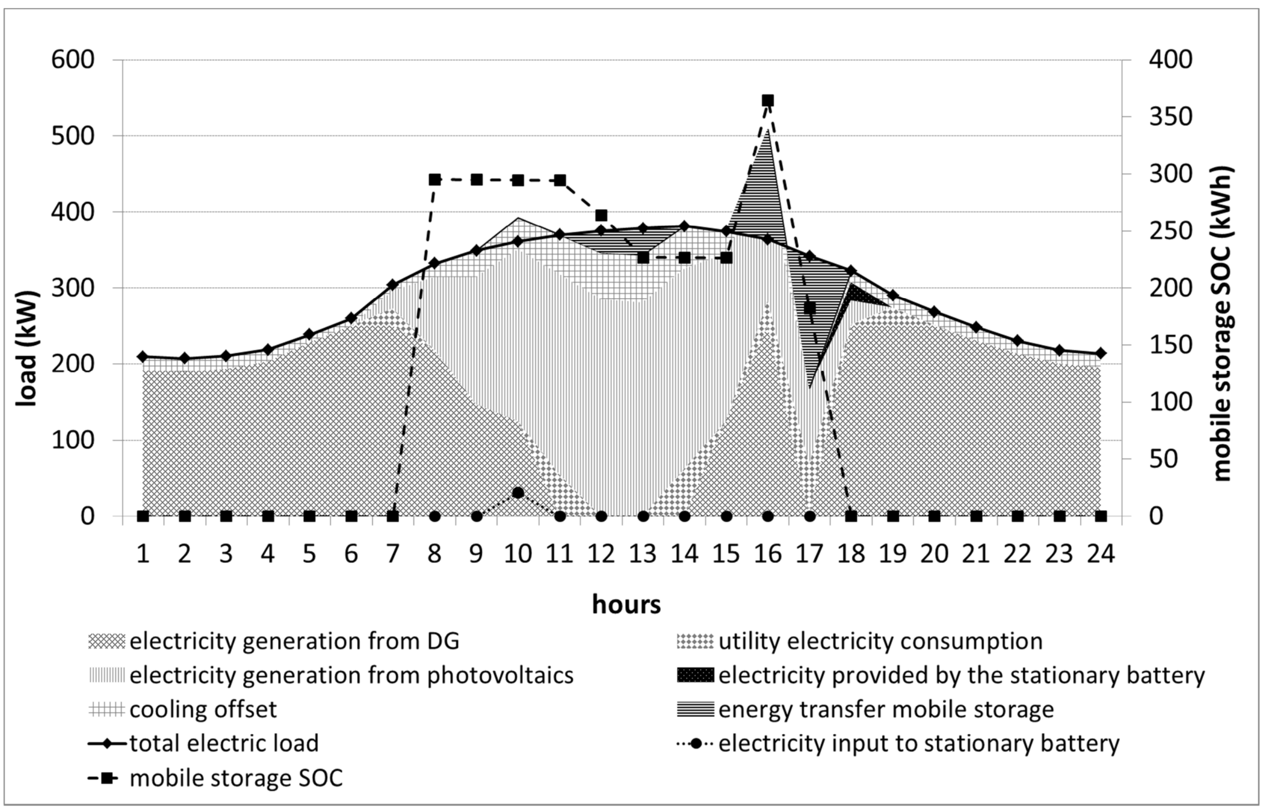

Figure 10. Diurnal electric pattern for point S1 on a July work day for the healthcare facility in San Diego (SDG&E service territory)

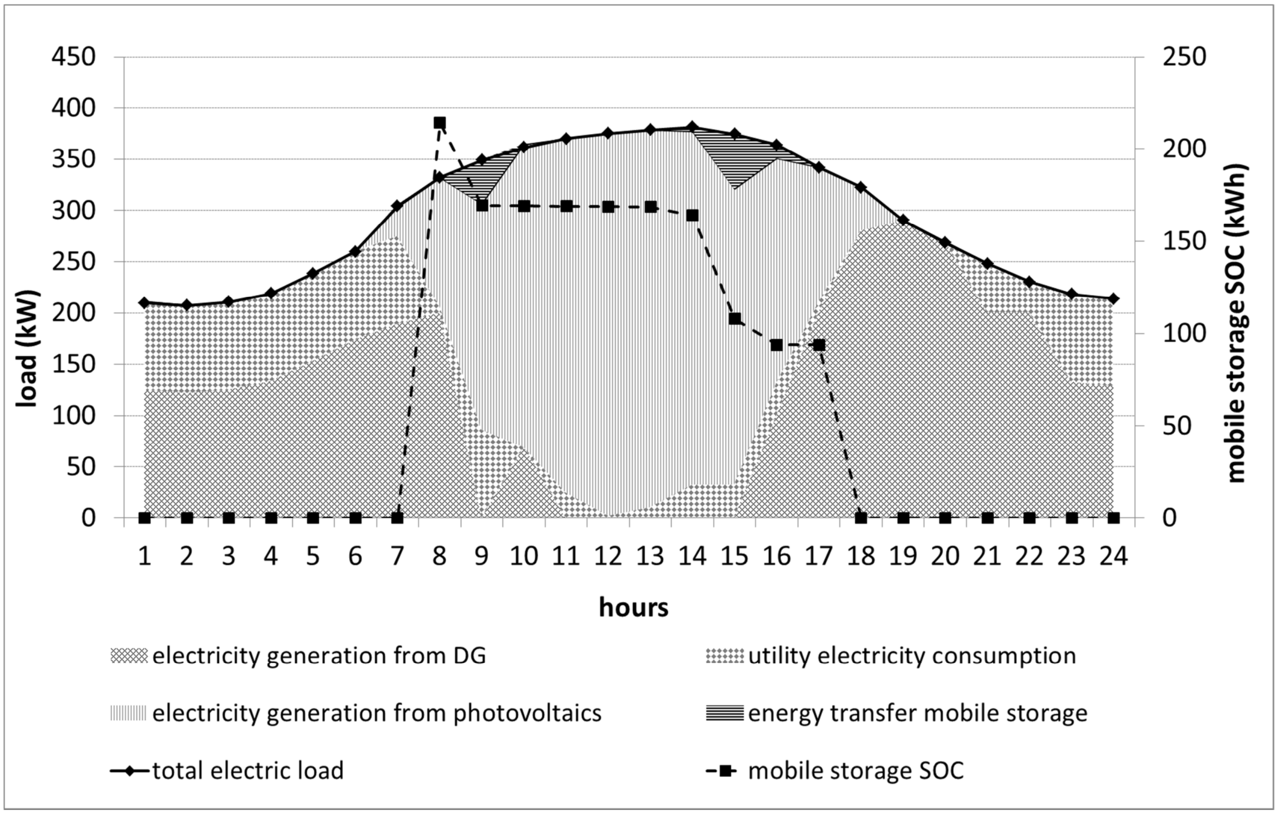

Figure 11. Diurnal electric pattern for point S2 on a July work day for the healthcare facility in San Diego (SDG&E service territory)

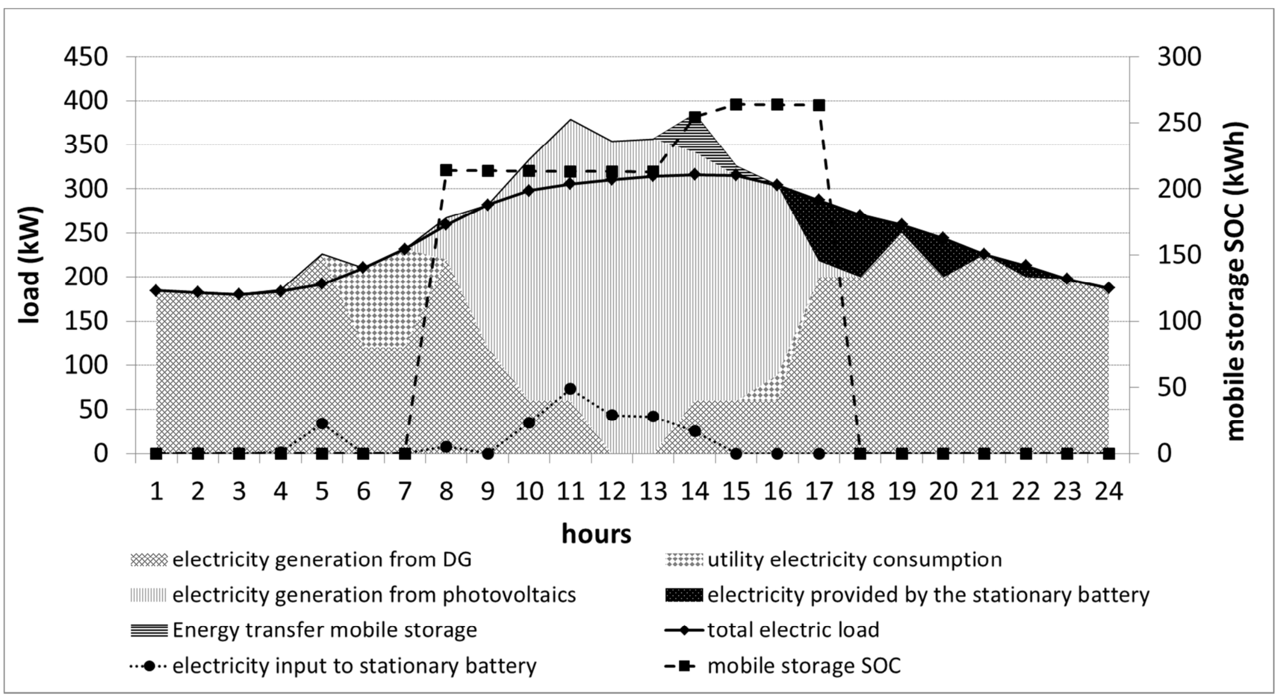

Figure 12. Diurnal electric pattern for point S2 on a January work day for the healthcare facility in San Diego (SDG&E service territory)

Table1. Available discrete technologies[16] in 2020 (Goldstein et al., 2003), (Firestone, 2004), (SGIP, 2008)

		ICE		FC	
		S	M	S	M
capacity (kW)		60	250	100	250
installed cost ($/kW)		2721	1482	2382	1909
	w/HX	3580	2180	2770	2220
maintenance cost ($/kWh)		0.02	0.01	0.03	0.03
electrical efficiency[17] (%)		29	30	36	36
heat to power ratio (if w/HX)		1.73	1.48	1.00	1.00
lifetime (years)		20	20	10	10

Table 2. Available continuous DER technologies in 2020 (Firestone, 2004), (SGIP, 2008), (EPRI-DOE, 2003), (Mechanical Cost Data 31st Annual Edition, 2008), (Stevens and Corey, 1996), (Symons and Butler, 2001), (Electricity Storage Association)

	ES	TS	AC	ST	PV
capital cost ($)	295	10000	93911	0	3851
variable cost ($/kW or $/kWh when referring to storage)	193	100	685	500	3237
maintenance cost ($/kWh)	0	0	1.88	0.50	0.25
lifetime (years)	5	17	20	15	20

ES – stationary electrical storage, TS – thermal storage, AC - absorption cooling, ST-solar thermal, PV-Photovoltaics

Table 3. Assumed stationary energy storage parameters (Stevens and Corey, 1996), (Symons and Butler, 2001)

	ES	TS
charging efficiency	0.9	0.9
discharging efficiency	0.9	0.9
decay	0.001	0.01
maximum charge rate	0.1	0.25
maximum discharge rate	0.25	0.25
minimum state of charge	0.3	0

Notes: all parameters are dimensionless; ES – stationary electrical storage, TS – thermal storage;

Table 4. EV battery specifications

charging efficiency	0.95
discharging efficiency	0.95
battery hourly decay (related to stored electricity)	0.001
capacity	16 kWh

Table 5. Principle EV connection periods for different building types[18]

building type	building connection period	EV owners
Hotel	19h-8h	guests
Office	9h-18h	employees
School/College	8h-18h	employees
Retail	9h-18h	employees/customers
Restaurant	18h-21h	employees/customers
Warehouse	8h-18h	employees
Grocery	9h-18h	employees/customers
Healthcare	8h-18h	employees

[16] DER-CAM distinguishes between discrete and continues technologies. Discrete technologies can only be picked in discrete sizes and continues ones in any size. The usage of continues technologies increases the optimization performance and reduces the run time. Also gas turbines and micro turbines are available, but they were never selected in the optimization, and therefore, not shown here.
[17] Higher heating Value.
[18] For clarity, some of the formal building types were aggregated (i.e large and small offices).

Table 6. Area constraints for PV, solar thermal, and EVs (CEUS and own calculations)

building type	area constraint A (m^2)
Hotel	3600
Small Office	175
Warehouse	1390
School	3340
Retail	800
Restaurant	300
Refrigerated Warehouse	5560
Large Office	16200
Healthcare	3260
Grocery	540
College	5600

Table 7. Detailed optimization results for large school building

	do-nothing (DN)	min cost	S1	S2	S3	S4
equipment						
inernal combustion CHP (kW)			250	60	120	420
fuell cell CHP (kW)				100	350	350
abs. Chiller (kW in terms of electricity)				106	142	113
solar thermal collector (kW)		91	308	779	961	779
PV (kW)			193	352	315	352
stationary electric storage (kWh)			790	2068	1769	2068
mobile electric storage (kWh)		3563	3563	14	91	53
thermal storage (kWh)			767	2932	3063	2932
annual building costs (k$)						
electricity	269.24	212.38	90.21	65.98	36.07	40.81
NG	73.74	67.88	94.36	94.33	115.90	109.77
onsite DG technologies (amortized costs)		15.02	179.02	367.91	451.71	552.57
total	342.97	295.28	363.58	528.22	603.68	703.15
% savings compared to do-nothing		13.90	-6.01	-54.01	-76.02	-105.02
annual utility consumption (GWh)						
electricity	1.74	1.39	0.58	0.36	0.15	0.17
NG	1.74	1.60	2.23	2.24	2.76	2.62
annual building carbon emissions (t/a)						
emissions	1203.92	1203.79	833.18	586.99	575.33	559.94
% savings compared to do-nothing		0.01	30.79	51.24	52.21	53.49

Table 8. Detailed optimization results for healthcare facility

	do-nothing (DN)	min cost	S1	S2	S3	S4
equipment						
inernal combustion CHP (kW)		250		180	180	180
fuell cell CHP (kW)			250	550	300	500
abs. Chiller (kW in terms of electricity)			67		64	43
solar thermal collector (kW)			792	280	323	305
PV (kW)			337	441	433	436
stationary electric storage (kWh)			281	1061	986	1017
mobile electric storage (kWh)		929	405	293	95	170
thermal storage (kWh)			0	440	15582	23353
annual building costs (k$)						
electricity	336.07	83.70	19.37	33.48	42.41	39.97
NG	62.74	173.57	118.77	106.00	105.90	110.37
onsite DG technologies (amortized costs)		70.70	284.62	474.72	553.64	667.26
total	398.81	327.97	422.76	614.20	701.94	817.60
% savings compared to do-nothing		17.76	-6.01	-54.01	-76.01	-105.01
annual utility consumption (GWh)						
electricity	2.33	0.58	0.06	0.19	0.18	0.10
NG	2.13	5.91	4.04	3.61	3.60	3.76
annual building carbon emissions (t/a)						
emissions	1574.39	1389.53	767.38	748.68	741.65	732.06
% savings compared to do- nothing		11.74	51.26	52.45	52.89	53.50

Table 9. Aggregated results for CO_2 minimization

energy cost savings buildings compared to do-nothing*	[%]	-30.00
CO_2 emission reduction of buildings compared to do-nothing	[%]	37.13
number of cars energy management system (EMS) would like to utilize	[million cars]	0.78
mobile storage capacity	[GWh]	12.45
PV in buildings	[GW]	4.55
stationary storage	[GWh]	14.71
combined heat and power (CHP) and other distributen generation (DG)	[GW]	3.50

*) the average max cost increase due to CO_2 minimization was set to 30% and is constrained within DER-CAM