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Modeling Electric Vehicle Benefits Connected to Smart Grids

Michael Stadler[1,2], Chris Marnay[1], Ratnesh Sharma[3], Gonçalo Mendes[4,1], Maximillian Kloess[5,1], Gonçalo Cardoso[4,1], Olivier Mégel[6], and Afzal Siddiqui[7]

1 Ernest Orlando Lawrence Berkeley National Laboratory,
2 Center for Energy and Innovative Technologies, Austria
3 NEC Laboratories America Inc., USA
4 Instituto Superior Técnico - MIT Portugal Program, Portugal
5 Vienna University of Technology, Austria
6 Ecole Polytechnique Fédérale de Lausanne, Switzerland
7 University College London, UK

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M. Stadler[1,2,a], C. Marnay[1,b], R. Sharma[3,c], G. Mendes[4,1,d], M. Kloess[5,1,e], G. Cardoso[4,1,f], O. Mégel[6,g], A. Siddiqui[7,h]

[1]*Ernest Orlando Lawrence Berkeley National Laboratory,*
One Cyclotron Road, MS: 90-1121, Berkeley, California 94720, USA
[2]*Center for Energy and Innovative Technologies, Austria*
[3]*NEC Laboratories America Inc., USA*
[4]*Instituto Superior Técnico - MIT Portugal Program, Portugal*
[5]*Vienna University of Technology, Austria*
[6]*Ecole Polytechnique Fédérale de Lausanne, Switzerland*
[7]*University College London, UK*
[a]*MStadler@lbl.gov,* [b]*C_Marnay@lbl.gov,* [c]*ratnesh@sv.nec-labs.com,* [d]*goncalo.p.mendes@ist.utl.pt,* [e]*kloess@eeg.tuwien.ac.at,* [f]*goncalo.cardoso@ist.utl.pt,* [g]*Olivier.Megel@epfl.ch,* [h]*afzal@stats.ucl.ac.uk*

Abstract- **Connecting electric storage technologies to smartgrids will have substantial implications in building energy systems. Local storage will enable demand response. Mobile storage devices in electric vehicles (EVs) are in direct competition with conventional stationary sources at the building. EVs will 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 in 2020, 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. 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. The research shows that considering second life of EV batteries might be very beneficial for commercial buildings.**

INTRODUCTION

This paper focuses on the analysis of the optimal interaction of 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. Definition of a microgrid can be found at [1]. In previous work, the Berkeley Lab has developed the Distributed Energy Resources Customer Adoption Model (DER-CAM) [2], [3]. 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) capacity and storage adoption combination and an hourly operating schedule, as well as the resulting costs, fuel consumption, and CO_2 emissions.

Furthermore, Berkeley Lab has access to the California End-Use Survey (CEUS), which holds roughly 2700 building load profiles for the commercial sector in California [4]. In previous work, 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 [5]. The 139 load profiles are made up of the following building types in different sizes: healthcare facilities, colleges, schools, restaurants, warehouses, retail stores, groceries, offices, and hotels/motels.

NEC Laboratories America Inc. is supporting Berkeley Lab's effort to add electric vehicle capabilities to DER-CAM and to estimate the economic and environmental potential of EVs connected to commercial buildings. Mobile storage can directly contribute to tariff-driven demand response in these buildings. By using EVs connected to them for energy management, the buildings could arbitrage their costs. But since the car battery lifetime is reduced, a model that also reimburses car owners for the degradation is required. In general, the link between a microgrid and an electric vehicle can create a win-win situation, wherein the microgrid can reduce utility costs by load shifting while the electric vehicle owner receives revenue that partially offsets his/her expensive mobile storage investment.

Preliminary work done for certain types of buildings show that the economic impact is limited relative to the costs of mobile storage for the site analyzed, i.e. the economic benefits from electric vehicle connections are modest [6], [7].

To 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).

DER-CAM

The Distributed Energy Resources Customer Adoption Model (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. Combinations of cost and CO_2 minimization are possible and such multi-objective optimization results will be shown in this paper. The DER-CAM approach is fully technology-neutral and can include energy purchases, on-site conversion, both electrical and thermal on-site renewable harvesting, and end-use efficiency investments. Furthermore, this approach considers the simultaneity of results. For example, building cooling technology is chosen such that 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.

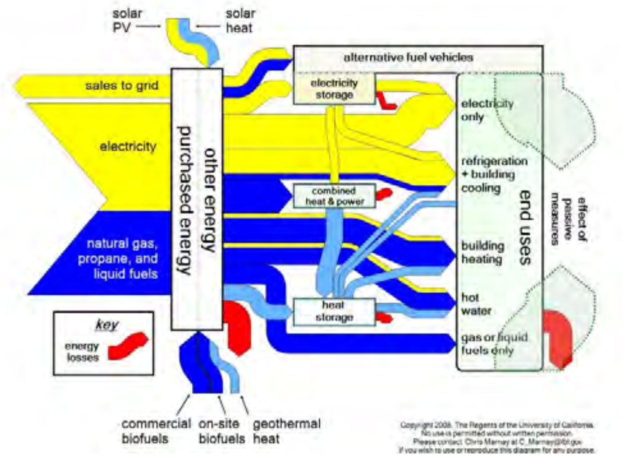

Fig. 1. High level schematic of DER-CAM, including alternative fuel vehicles, e.g. electric cars.

Fig. 1 shows a high-level schematic of the building energy flows modeled in DER-CAM. Available energy inputs to the site are solar radiation, utility electricity, utility natural gas, biofuels, and geothermal heat. For a given site, DER-CAM selects the economically or environmental optimal combination of utility electricity purchase, on-site generation, storage, heating 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 capacity and schedule of technologies to supply the services specified on the right hand side of Fig. 1. All the different arrows in Fig. 1 represent energy flows and DER-CAM optimizes these energy flows to minimize costs or CO_2 emissions. Dark blue arrows represent natural gas or any bio-fuel, yellow represents electricity, and light blue 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 (or shorter time step) operating schedule, as well as the resulting costs, fuel consumption, and CO_2 emissions. Because the solution is analytic, i.e. does not involve simulation through time or iteration other than for numerical solution finding, results can be both detailed over time and include multiple technologies and yet fast enough to find solutions for tens of buildings in a matter of hours on a laptop. The approach does not consider electric vehicles in isolation but rather alongside the rest of the DER equipment. All available technologies compete and collaborate, and ripple effects are therefore embodied in the model. As an example of this, consider the importance of waste heat driven cooling which simultaneously affects the heat and electricity usage pattern. Due to the fact that it is mainly available on peak hours, it has a disproportional effect on site utility bills. Unlike simple analysis that assumes a capacity factor and derives fuel and emissions savings accordingly, the operations are endogenous to DER-CAM. 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.

APPROACH

The starting point for the load profiles used within DER-CAM is the California Commercial End-Use Survey (CEUS) database which contains 2790 premises in total. As can been seen from Fig. 2, not all utilities participated in CEUS, the most notable absence being the Los Angeles Department of Water and Power (LADWP) and climate zones FZ14+15. For this work, the small zones FZ2 and 6 are also excluded, as well as the miscellaneous building types for which there is insufficient information for simulation.

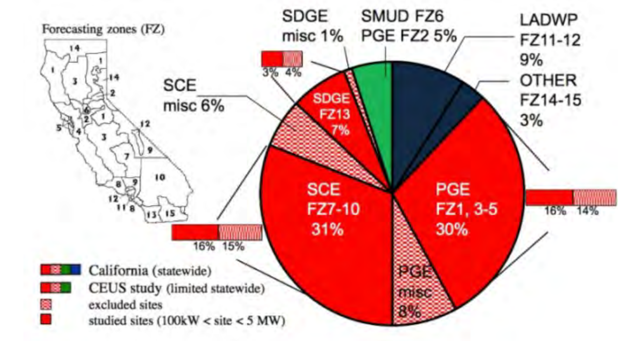

Fig. 2. Commercial electric demand fractions.

The remaining solid red slices of the pie represent 68% of the total commercial electric demand. Because the focus here is on mid-sized buildings[1], between 100 kW and 5 MW electric peak load, almost half of the red slices are also eliminated, leaving 35% of the total commercial electric

[1] Buildings in this size are very attractive for DER adoption and mostly overlooked.

demand in the service territories of PG&E, SCE, and SDG&E[2].

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.

There are five demand types in DER-CAM applicable to demand charges:

- non-coincident: incurred by the maximum consumption in any hour;
- on-peak: incurred only during on-peak hours;
- mid-peak: incurred only during mid-peak hours;
- off-peak: incurred only during off-peak hours; and
- coincident: based only on the hour of peak system-wide consumption.

For example, for buildings with electric peak loads above 500 kW in PG&E service territory, the E-19 TOU tariff is used as 2020 estimate. No Peak Day Pricing (PDP) is used at this point. 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) and 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 [8]. It is assumed that in PG&E and SCE service territory the EVs can be charged at home at night for 6c/kWh [9] and in the SDG&E for 14c/kWh. All used utility tariffs for this paper can be found at [5].

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.

EV batteries can transfer electricity to the commercial building and vice versa provided they are connected to it (equation 7). The building energy management system (EMS) can use this additional battery capacity to lower its energy bill, and/or carbon footprint; and whenever possible, economically attractive energy from a renewable energy source or CHP system at the building can be used to offset EV charging at home. In this work, DER-CAM is used to find the optimal supply solution for commercial buildings while considering possible interactions with EV batteries. This is done by minimizing total costs, including electricity purchases and sales, DER capital costs, fuel costs, demand response measures and EV related costs (equation 2). 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 & 4). On the other hand if the EV is charged by electricity originating from the commercial building the car owner needs to pay the commercial building for the electricity.

[2] Although CEUS contains different building types in different climate zones it is not an objective of this paper to analyze the climate zone impact on the results.

$$C_{bat} = E_{EV} * CL * RC_{bat} * c \tag{1}$$

C_{bat}	*EV battery degradation costs*
E_{EV}	*total electricity exchange through the EV*
CL	*capacity loss due to EMS usage*
RC_{bat}	*replacement cost of the EV battery*
c	*total EV battery capacity*

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 5 & 6). Consider the abstract state of charge (SOC) pattern (red line) for an EV connected to an office building in Fig. 3. It is clear that the commercial building benefits from energy (area A) that has a carbon foot print that is related to a period when the EV is not connected to the commercial building. Therefore, tracking the CO_2 emissions in these different cases is a very important feature within DER-CAM. This becomes even more complicated if the EVs are connected to different buildings during a certain period of time[3]. The marginal carbon emissions of the macrogrid for 2020 are taken from [10].

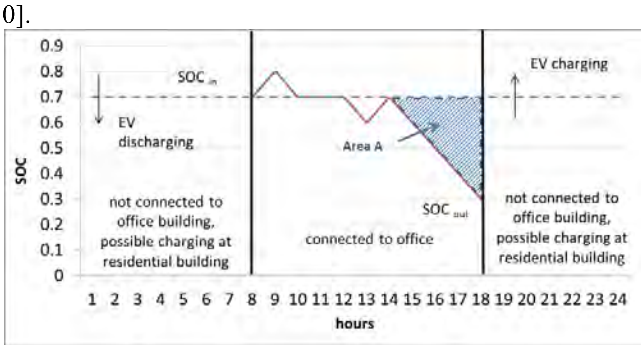

Fig. 3. Hypothetical charging/discharging at a commercial (office) building, SOCin means mobile storage state of charge at the time when the EV connects to the building, SOCout means state of charge at the time when the EV disconnects from the building.

The mathematical formulation used in DER-CAM is briefly explained below.

[3] Which is not considered in this work.

Objective Function[4] – cost minimization:

$$min\ C_{total} = \boldsymbol{C_{elec}} + C_{DER} + C_{fuel} + C_{DR} + \boldsymbol{C_{bat}} - V \quad (2)$$

$$C_{elec} = C_{fix} + C_{var} + \boldsymbol{C_{EV}} \quad (3)$$

$$C_{EV} = p_{EV} * \left(\frac{E^{r\to c}}{\eta_c} + E^{c\to r} * \eta_{dc}\right) \quad (4)$$

C_{total}	*total energy cost of the commercial building*
C_{elec}	*electricity costs*
C_{DER}	*distributed energy resources costs*
C_{fuel}	*fuel costs*
C_{DR}	*demand response costs*
C_{bat}	*EV battery degradation costs*
V	*electricity sales*
C_{fix}	*fixed electricity costs*
C_{var}	*variable electricity costs (energy and demand charges)*
C_{EV}	*EV electricity costs*
p_{EV}	*EV electricity exchange price*
$E^{r\to c}$	*electricity flow from residential building to car*
$E^{c\to r}$	*electricity flow from car to residential building*
η_c	*charging efficiency*
η_{dc}	*discharging efficiency*

Objective Function – CO_2 minimization:

$$\min CO_{2\_total} = CO_{2\_elec} + CO_{2\_fuel} + \boldsymbol{CO_{2\_EV}} \quad (5)$$

$$CO_{2\_EV} = \left(\frac{E^{r\to c}}{\eta_c} + E^{c\to r} * \eta_{dc}\right) * CO_{2_{EV-home}} \quad (6)$$

$CO_{2\ total}$	*total annual CO_2 emissions commercial building*
$CO_{2\ elec}$	*CO_2 emissions from electricity consumption*
$CO_{2\ fuel}$	*CO_2 emissions from fuel burning*
$CO_{2\ EV}$	*CO_2 emissions from EV electricity exchange*
$CO_{2\_EV\text{-}home}$	*marginal grid CO_2 emission during home charging period*

Constraints

$$S_U + S_{DER} + S_{St} + \boldsymbol{S_{EV}} + V = D_B + D_{St} + \boldsymbol{D_{EV}} \quad (7)$$

$$S_{EV} = \sum\nolimits_{m\,h} o_{m\,h} * \eta_{dc} \quad (8)$$

$$D_{EV} = \sum\nolimits_{m\,h} i_{m\,h} * \eta_c \quad (9)$$

$$c * \underline{soc} \le ES_{EV\,m} \le c * \overline{soc} \quad (10)$$

$$ES_{EV\,m\,h} = ES_{EV\,m\,h-1} * (1-\varphi) + i_{m\,h} - o_{m\,h} \quad (11)$$

$$i_{m\,h} \le c * \overline{cr} \quad (12)$$

$$o_{m\,h} \le c * \overline{dr} \quad (13)$$

S_U	*electricity supplied by the utility*
S_{DER}	*electricity supplied by distributed energy resources*
S_{St}	*electricity supplied by local storage*
S_{EV}	*electricity supplied by EVs*
D_B	*electricity demand from the building*
D_{St}	*electricity demand from local storage*
D_{EV}	*electricity demand from EVs*
$\overline{SOC}$	*maximum state of charge*
$\underline{SOC}$	*minimum state of charge*
ES_{EV}	*electricity stored in EVs*
i	*EV storage input*
o	*EV storage output*
φ	*electricity storage losses in the battery*
$\overline{cr}$	*maximum charge rate*
$\overline{dr}$	*maximum discharge rate*
m	*month index*
h	*hour index*

[4] Please note that the shown constraints and functions need to be fulfilled in any hour of the year.

TABLE I
AVAILABLE DISCRETE TECHNOLOGIES[5] IN 2020 [11], [12], [13].

		ICE		GT	MT		FC	
		S	M	n.a.	S	M	S	M
capacity (kW)		60	250	1000	50	150	100	250
installed cost ($/kW)		2721	1482	1883	2116	1723	2382	1909
	w/HX	3580	2180	2580	2377	1936	2770	2220
maintenance cost ($/kWh)		0.02	0.01	0.01	0.02	0.02	0.03	0.03
electrical efficiency[6] (%)		29	30	22	25	26	36	36
HPR (if w/HX)		1.73	1.48	1.96	1.80	1.30	1.00	1.00
lifetime (years)		20	20	20	10	10	10	10

Notes: All technologies running on natural gas; S – small-sized model, M – medium-sized model, HX – heat exchanger (using combined heat and power capabilities), HPR – heat-power ratio, ICE – internal combustion engine, GT – gas Turbine, MT - microturbine, FC – fuel cell.

TABLE II
OTHER AVAILABLE CONTINUOUS DER TECHNOLOGIES IN 2020 [12], [13], [14]. [15], [16], [17], [18]

	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 III
ASSUMED STATIONARY ENERGY STORAGE PARAMETERS [16], [17]

	ES	**TS**
charging efficiency	0.9	0.9
discharging efficiency	1	1
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;

[5] 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.

[6] Higher heating Value.

TABLE IV
EV BATTERY SPECIFICATIONS.

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

RESULTS

Results for cost minimization, CO_2 minimization, and a weighted average of both are shown for two selected buildings of the CEUS building stock: a large school[7] in climate zone FCZ5 (PG&E, San Francisco Bay Area) and a health care facility[8] in San Diego (SDG&E).

These two examples are used to demonstrate how mobile storage capacity is adopted in commercial buildings and how it interacts with buildings' DG generation 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.

As mentioned above, DER-CAM allows optimizing the combination of building energy costs and CO_2 emissions simultaneously (see equation 14). By increasing *w* more focus will be put on CO_2 emission reduction and this approach allows showing the trade-off between costs and CO_2 emissions[9] in a building.

$$\min\ (1-\omega) * \frac{Cost}{RefCost} + \omega * \frac{CO_2Em}{RefCO_2Em} \qquad (14)$$

where:

$Cost$	*total building energy costs including amortized capital costs*[10].
CO_2Em	*total building CO_2 emissions.*
ω	*weight factor [0..1]*
$RefCO2Em$	*parameter to make equation unit less*
$RefCost$	*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 in PG&E service territory and the healthcare facility in SDG&E service territory. It is assumed that the EVs connect to the commercial buildings at 8am and disconnect at 6pm. During that time the building EMS can manage the mobile storage in combination with other DER technologies and different optimization strategies can apply (ω can vary from 0 to 1). From 6pm to 8am the EVs are disconnected from the commercial buildings and are subject to driving and charging / discharging at the residential building.

[7] 3 300m² floorspace, 550kW electric peak load.
[8] 3 200 m² floorspace, 400kW electric peak load.
[9] Please note that DER-CAM tracks the CO_2 emissions transferred to the commercial building by mobile storage.
[10] In this analysis we use a 12 year payback period.

Please note that both scenarios are subject to very different EV charging tariffs at the residential buildings. In PG&E service territory EVs can be charged for 6c/kWh compared to 14c/kWh in SDG&E. This difference in price will influence the overall level of EV adoption, but still, general results can be derived from these two cases.

Fig. 4 and 5 show that costs can be reduced by using EVs in the building (see do nothing vs. min cost in Fig. 4 and 5), but more focus on CO_2 emission reduction results in less EVs connected to the building (see red curve in the Figures below). Despite the major difference in residential EV charging rates both cases show a very similar pattern and show increasing stationary storage capacities combined with decreasing numbers of EV connected to buildings. However, due to the very low EV charging rates at homes in PG&E regions, the utilized number of EVs is very high and very unrealistic[11]. The major strategy derived from the DER-CAM optimization is to charge EVs for cheap electricity at home and provide that energy during connection times to the commercial building. The higher residential EV charging rates in SDG&E, therefore, reduce the connected numbers of EV in Fig. 5.

Another finding from the optimization runs also shown in Fig. 4 and 5 is the importance of natural gas fired fuel cell systems with CHP. Due to the heat requirement and constraint budget ($\omega < 1$) efficient fuel cell systems, which allow total efficiencies up to 80%, will be used during times when solar thermal is not available or heat storage is too expensive. Furthermore, in urban areas the available space for PV and solar thermal might be limited and then efficient CHP becomes even more important. However, in the runs shown here an area constraint of 16 000m^2 was used and does not limit the solar thermal and PV adoption.

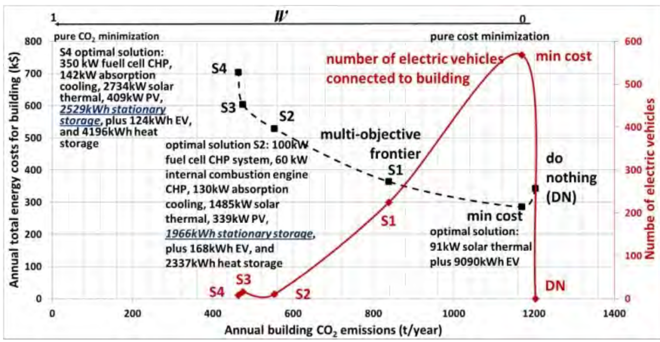

Fig. 4. Multi-objective frontier for the large school building in FCZ5 (PG&E) and connected EVs.

Fig. 6 to Fig. 8 show the optimal diurnal electric pattern for different optimization cases for the large school building in PG&E service territory. Fig. 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 hours mid- and on-peak hours (9 am to 6pm). No other DER technologies will be adopted at the school in this case.

[11] Future research needs to consider an area constraint for parking space and number of cars that can connect to the building.

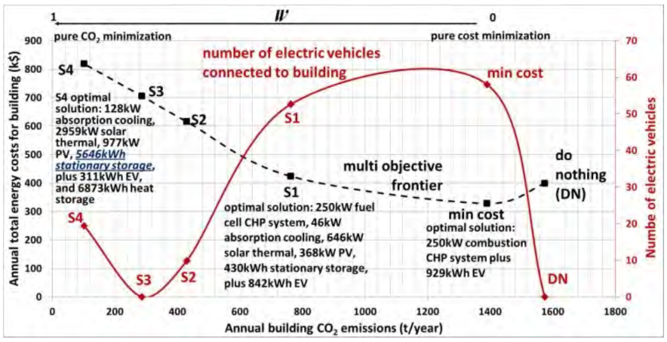

Fig. 5. Multi-objective frontier for the healthcare facility in FCZ13 (SDG&E) and connected EVs.

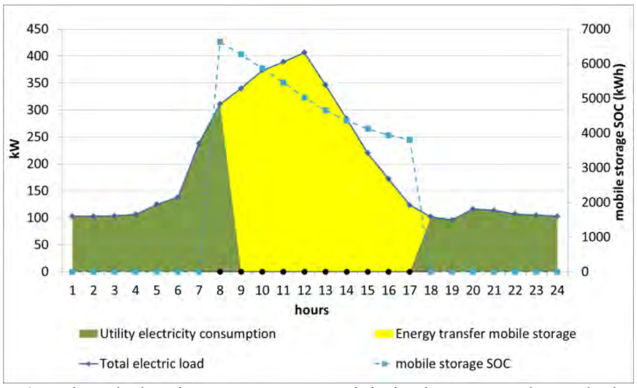

Fig. 6. Diurnal electric pattern at cost-minimization on a July work day, large school in climate zone FCZ5 - PG&E, San Francisco Bay Area.

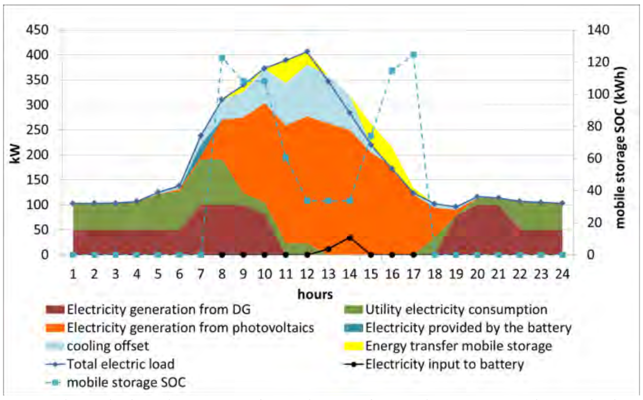

Fig. 7. Diurnal electric pattern for point S2 from Fig. 4 on a July work day, large school in climate zone FCZ5 - PG&E, San Francisco Bay Area.

Fig. 7 illustrates the electric pattern for the same building with a multi-objective function for point S2 from Fig. 4. In this case considerable PV-power (roughly 340 kW) and stationary storage capacities (roughly 2000 kW) is installed. The connected mobile storage is reduced by a factor 50 compared to the pure cost minimization case (ω=0) and transfer from mobile storage is much lower in this case since the major part of the load is covered by PV during the expensive hours. Energy taken out from the mobile storage is put back in the afternoon with excessive PV capacity. During the noon hours the PV system, in combination with the absorption cooling system, reduces the utility demand and costs. Stationary batteries are charged with excessive PV in the afternoon. The stationary storage is used in the morning hours. The stationary storage is only marginally used in July, but extensively in January as shown in Fig. 8. The mobile storage is not used in winter months and the stationary storage is charged by the CHP system. The waste heat from the CHP system will be used to supply heat loads.

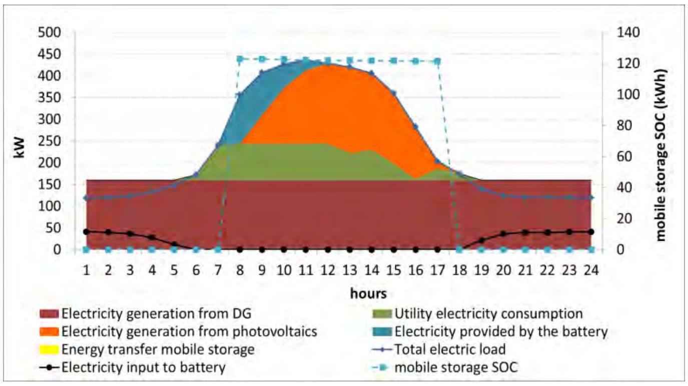

Fig. 8. Diurnal electric pattern for point S2 from Fig. 4 on a January work day, large school in climate zone FCZ5 - PG&E, San Francisco Bay Area.

Fig. 9 shows the electric pattern for the San Diego health care facility on a summer day with cost minimization point (min cost, ω=0 in Fig. 5). In this case the electricity supply of the building is mainly supplied by the electricity generation from DG and from the utility. During peak hours energy transfer from mobile storage is used to cover demand. In the cost minimization case there is no PV installed and no stationary battery capacity. One reason for this is how the 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 are 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.

Fig. 10 depicts the S1 case from Fig. 5. In this cases PV is used to cover major parts of the total demand during day hours, replacing DG generation and consumption from the utility. During peak hours energy from EVs is used to cover demand. The energy transferred from EVs is similar like in the cost minimization case. However the discharge pattern is slightly different. They main energy transfer happens in the morning between 9 and 10 to compensate for DG/CHP generation which is shutting down due to inefficiencies in part load. A similar pattern can be observed from noon to 3pm before DG/CHP restarts. Between 3am and 4am after DG/CHP has been restarted there is an access of power since PV production is still high. During this time stationary battery capacity is used to shift some of this energy to the early evening hours (blue area in Fig. 10).

With increasing priority to CO_2 reduction, as assumed in S3 and S4 (Fig. 11 and Fig. 12), the full PV potential of the building is achieved and stationary storage is used to shift PV energy to night hours. In the S3 case there are no EVs at all since they are not able to shift supply from day to night hours at the health care facility. This can only be done by using stationary batteries. When CO_2 emission reduction is further prioritized in the S4 case some EVs are charged at the building in the afternoon by excessive PV, but the effect is marginal and most of the renewable energy is stored in stationary storage eliminating DG/CHP technologies (Fig. 12).

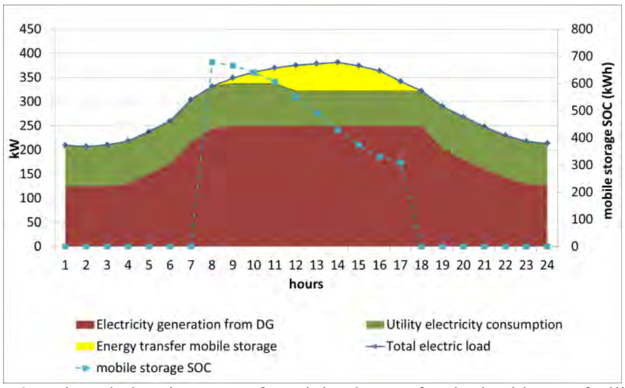

Fig. 9. Diurnal electric pattern for minimal costs for the health care facility in SDG&E at summer days (July).

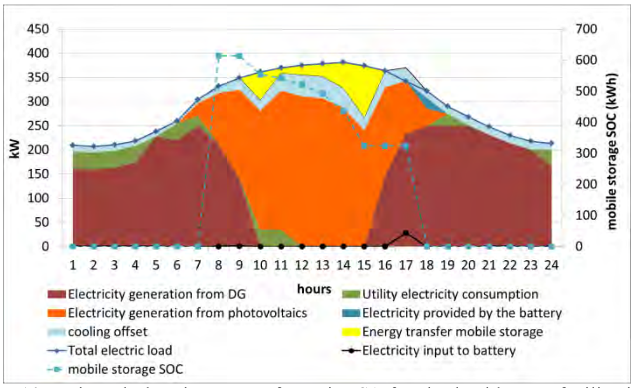

Fig. 10. Diurnal electric pattern for point S1 for the health care facility in SDG&E at summer days.

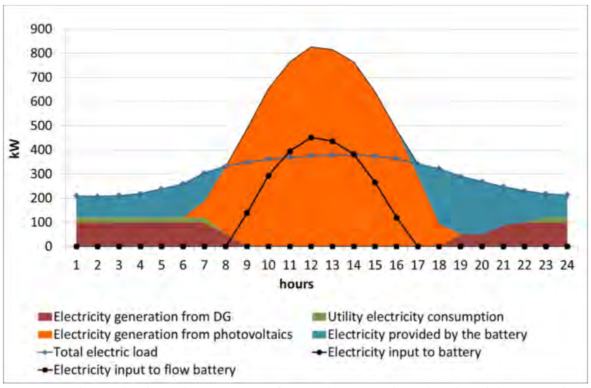

Fig. 11. Diurnal electric pattern for point S3 for the health care facility in SDG&E at summer days (July).

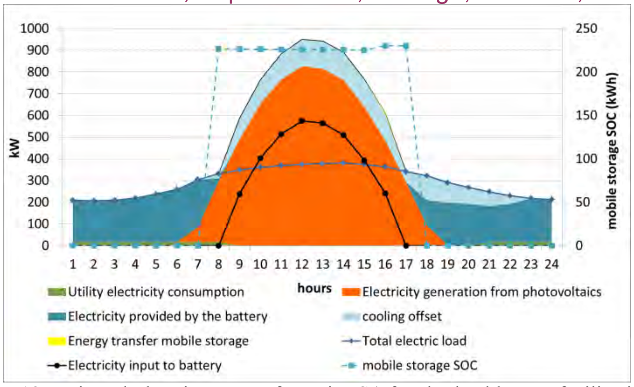

Fig. 12. Diurnal electric pattern for point S4 for the health care facility in SDG&E at summer days (July).

Summing up the results for the two buildings, analyzed in detail with respect to EVs, it was demonstrated that the use of mobile storage capacity from EVs is rather driven by the objective of cost minimization than efficiency improvement (Fig. 6 and Fig. 9) The availability of EV storage capacity to the building is also strongly dependent on the charging rate for home charging of EVs. The lower the charging rate at residential buildings, the more EV users are willing to provide energy to the commercial building during the day. This effect is clearly shown in Fig. 6 and Fig. 9. For Fig. 6 a home charging rate of 6c/kWh and for Fig. 9 14c/kWh is assumed and this reduces the mobile storage capacity considerable.

In most cases EVs are charged at the residential building and only one case shows 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.

Finally, 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 second life of mobile storage.

Finally, the aggregated results for California are shown. Table V gives the results of the entire CEUS building stock assuming a CO_2 minimization strategy of the commercial buildings. When assuming a full CO_2 minimization strategy (ω=1) a maximum cost increase boundary needs to be imposed .Without such a cost constraint the optimization algorithm could adopt any size of equipment and this would create very unrealistic adoption patterns as well high investment costs. For the aggregated results shown in Table V 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 48%. To achieve this reduction roughly 26 GWh of stationary storage needs to be adopted. The utilized mobile storage is roughly only half of the stationary storage (11 GWh) and this shows the importance to consider second life of mobile storage in form of stationary storage. The 7 GW of adopted PV are mostly used to charge the stationary storage and not to charge the mobile storage (see also the diurnal electric patterns above). Finally, Table V also shows that combined heat and power plays a role in CO_2 minimization strategies and 1.8 GW of CHP systems will be adopted.

TABLE V
RESULTS FOR CO_2 MINIMIZATION

result	unit	value
energy cost savings by buildings compared to do-nothing*	[%]	-30.00
CO_2 emission reduction of buildings compared to do-nothing	[%]	47.50
number of cars energy management system (EMS) would like to utilize	[million cars]	0.72
mobile storage capacity	[GWh]	11.44
PV in commercial buildings	[GW]	7.00
stationary storage	[GWh]	25.50
combined heat and power (CHP) and other distributed generation (DG)	[GW]	1.83

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

CONCLUSIONS

The following major conclusions can be drawn from this analysis:

- Use of mobile energy storage provided by EVs in commercial buildings is rather driven by cost reduction objectives than by CO_2-reduction/efficiency improvement objectives.
- At 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.
- Also 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 is not fully available, because of the cost increase constraints.
- For CO_2 minimization strategies the use of stationary storage is more attractive since, unlike EV storage, it is available at the commercial building for 24 hours a day, which makes it more effective for energy management.
- Being available all day stationary storage can shift PV supply during the day to off-peak hours, where the building would otherwise be supplied by more carbon intense electricity from the utility. Since this is impossible with mobile storage there is only marginal charging of EVs using PV power.
- The number of connected EVs varies widely depending on the residential charging rate and possibility of arbitrage.

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