Energy Policy 103 (2017) 47–61

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Evaluating business models for microgrids: Interactions of technology and policy

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ARTICLE INFO

Keywords:
Decarbonization
Decentralization
Distributed energy resource
Modeling
Natural gas
Renewable energy

ABSTRACT

Policy makers are increasingly focused on strategies to decentralize the electricity grid. We analyze the business model for one mode of decentralization—microgrids—and quantify the economics for self-supply of electricity and thermal energy and explicitly resolve technological as well as policy variables. We offer a tool, based on the Distributed Energy Resources Customer Adoption Model (DER-CAM) modeling framework, that determines the cost-minimal capacity and operation of distributed energy resources in a microgrid, and apply it in southern California to three "iconic" microgrid types which represent typical commercial adopters: a large commercial building, critical infrastructure, and campus. We find that optimal investment leads to some deployment of renewables but that natural gas technologies underpin the most robust business cases—due in part to relatively cheap gas and high electricity rates. This finding contrasts sharply with most policy advocacy, which has focused on the potentials for decentralization of the grid to encourage deployment of renewables. Decentralization could radically reduce customer energy costs, but without the right policy framework it could create large numbers of small decentralized sources of gas-based carbon emissions that will be difficult to control if policy makers want to achieve deep cuts in greenhouse gas emissions.

1. Introduction

The electric power grid may be in the midst of a transformation. Following decades of deregulatory efforts (Wilson, 2002), it may now be heading toward a more decentralized system of supply and response. We focus on grid-connected microgrids, which are widely thought to be one of the most attractive options for decentralized power networks. Indeed, forecasted growth is substantial. When compared with 2014 levels of investment, all major segments of the microgrid market are expected to grow by 2020, for example small microgrids at commercial buildings (94%), medium sized microgrids such as those in communities (199%) or in public institutions (228%) that have special requirements for reliability, and large microgrids at military installations (142%) and universities (115%). All told, one credible study forecasts the total US microgrid capacity to reach 2854 MW in 2020 (142% percent growth over the 2014 installed capacity of 1181 MW) (Saadeh, 2015).

Three factors are primarily driving this shift from the traditional centralized grid structure to one with perhaps a larger role for microgrids. Through technological innovation, the cost of solar photovoltaics (PV) (Kann et al., 2016) and electric storage (Nykvist and Nilsson, 2015) have fallen precipitously. A second factor is rising rates for grid-service electricity—for decades US retail rates have risen at near the general rate of inflation, typically at 2–3% annually (Short-Term Energy Outlook (STEO), 2016). Third, and perhaps most decisively, are concerted policy efforts to reduce global greenhouse gas emissions while also promoting decentralization of the grid through more autonomous production from distributed energy resources (DERs). These policy interventions have taken many forms, such as renewable energy mandates (some designed to favor distributed renewables), deployment quotas for distributed generation (in California nearly 2000 MW of distributed solar through the California

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http://dx.doi.org/10.1016/j.enpol.2017.01.010
Received 16 August 2016; Received in revised form 5 January 2017; Accepted 9 January 2017
Available online 16 January 2017
0301-4215/

Solar Initiative program, 4000 MW of combined heat and power (CHP) per AB-32, and 1325 MW of storage through AB-2514), and an array of subsidy schemes such as California's Self-Generation Incentive Program (SGIP). In addition, some jurisdictions have adopted whole visions for a more decentralized and reliable electric power system—notably New York's Reforming the Energy Vision (REV).

While there is support for microgrid deployment in some jurisdictions, in many settings the situation is quite different. Large interconnection fees, lengthy wait times, and outright bans on self-generated networks prevail in many places. Where the policy environment is attractive, the logic for support points to the many potential *public* benefits microgrids can provide, such as improved power quality through voltage and frequency support, improved macro grid reliability, deferred costs for grid capacity expansions, improved blackstart capability after macro grid failure, and possibly lower emissions from the energy system overall. Whether those public benefits are realized, however, will hinge on whether potential investors see *private* benefits from building microgrids—what we call the "business model" or "business case" through which real investors can save money by shifting from standard grid service to microgrids. Within industry and policy circles there is intense discussion about business models but relatively little systematic quantification (Reitenbach, 2016). We aim to show ways to add quantitative methods to that important commercial and policy debate.

In the real world, business models for microgrids depend on many factors, including the potential for energy cost savings, improved reliability, and perhaps other factors such as the amenity value of self-supply. Here we focus on economic costs and benefits of self-supply as they lie at the core of any commercial proposition, and point to subsequent work that can be done to add reliability to the analysis. We model the business case for *local energy provision*—which we define as the case in which a utility customer adopts a microgrid to self-generate (partially or fully) electricity and possibly thermal energy (i.e., heating and cooling) loads. This business case, in our analysis, stems solely from the ability to supply these loads with the microgrid at a total cost lower than standard utility service. We adopt the definition of the US Department of Energy (DOE), which defines a microgrid as "a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid and that connects and disconnects from such grid to enable it to operate in both grid-connected or'island' mode."

The present work makes two new contributions to the modeling literature. First, we build internally consistent load data sets for three "iconic" types of microgrids based on real world electric and thermal loads—large systems sized for campuses or military bases; medium-sized systems for critical assets such as hospitals; and smaller systems for commercial buildings such as box stores, hotels, and office buildings. We build these three iconic microgrid types to align with forecasted market growth per (Saadeh, 2015) and suggest that a consistent, reality-based set of iconic microgrids can help introduce some consistency and comparability in published academic work in this field, as well as promote more systematic microgrid analysis.

Second, we calibrate these systems using real market and policy conditions in southern California—one of the most promising locations for microgrids—and perform several types of analysis to examine how the interplay between energy prices, technology and policy affect investment decision-making for specific technology types in microgrids—what we call the "investment case" underpinning microgrid adoption. Through sensitivity analysis we identify four variables—the price of natural gas, cost of emitting carbon dioxide (CO_2), the cost of electricity and demand in the electric tariff, and the cost of energy storage—that are most important for the future of microgrid deployment, and quantify their impacts on investment and business cases. Analyses such as these are crucial, as these systems may face highly volatile electricity, gas, and technology prices. Other work on DERs has addressed this type of uncertainty directly; for example, (Karl Magnus Maribu, 2008) and (Maurovich-Horvat et al., 2016) explore electricity and gas prices while (Rocha et al., 2016) looks at energy and technology costs. While we have configured our analysis for conditions in southern California, we publish our parameters and assumptions (see the Supplementary information to this work) to allow ready modification for other jurisdictions. In addition to our focus on the business case for investment, we give attention to important policy-relevant outcomes from that investment, such as emissions of CO_2 from small gas generators that may prove very difficult to control as policy makers aim to achieve deep decarbonization of the whole energy system.

The remainder of the paper is as follows. In Section 2 we present our model formulation and data sets for the three iconic microgrids; in Section 3 we report results for baseline and sensitivity analyses; and Section 4 addresses policy implications and concludes.

2. Methodology: building a tool for assessing business models

We provide an overview of the DER-CAM model (Distributed Energy Resources Customer Adoption Model) in Section 2.1 and present the formulation for our configured version of the model in Section 2.2, with explicit modifications noted in Section 2.2.2. The basis for our formulation is the source code for DER-CAM version 4-4.1.1, which we term the *standard model formulation*. We then present end-use load profiles for three iconic microgrids in Section 2.3.1 and policy-relevant model calibrations for present-day market settings in Section 2.3.2.

2.1. The DER-CAM optimization model

DER-CAM is an investment support tool for DER and microgrid systems. It computes DER investment and operation to supply load over the first year of operation, and with operating and maintenance (O & M) costs and standard amortization of capital costs allows for analysis of the net present cost and benefit of microgrid configurations. DER-CAM can be configured to minimize either an economic (total cost) or environmental (CO_2 emissions) objective, or a weighted combination of these two (i.e. Pareto optimization). For our purposes, the adaptability along with extensive published record[1] and open-source[2] nature of the source code are attractive features of the DER-CAM platform for academic research.

DER-CAM selects, sizes, and schedules DERs via several decision variables. Selection is binary (technologies are either selected or not), sizing decisions are made by individual technology and may be discrete (available in select sizes only) or continuous (available in all sizes) depending on the technology, and scheduling is determined for dispatchable DERs and for purchases of electricity and natural gas from the utility. The model outputs DER capacities and operating schedules for the first year of adoption, capital and operating costs, energy flows from source to end-use, fuel consumption, and CO_2

[1] Development of DER-CAM by the Lawrence Berkeley National Laboratory (LBNL) is well documented. Publications include initial development in (Marnay et al., 2000; Siddiqui et al., 2003) as well as later enhancements, including the addition of a carbon tax (Siddiqui et al., 2005), heat recovery (Siddiqui et al., 2007), electric and thermal storage (Marnay et al., 2008), power quality and reliability considerations (Stadler et al., 2009a), CO_2 emission minimization (Stadler et al., 2009b), zero-net-energy building constraints (Stadler et al., 2011), electric vehicles (Stadler et al., 2013), and building retrofits (Stadler et al., 2014). Other groups have used DER-CAM to systematically analyze model parameters that affect microgrid economics, for example tariff structures (Firestone et al., 2006), energy storage (Stadler et al., 2013), and climate zones (Maribu et al., 2007). More recently, it has been adapted to study electric vehicle integration in microgrids (Momber et al., 2010), ancillary service provision using electric storage in microgrids (Beer et al., 2012), and reactive power provision (von Appen et al., 2011).

[2] The source code is in certain cases made available by LBNL for non-commercial collaboration after signing a collaboration license agreement.

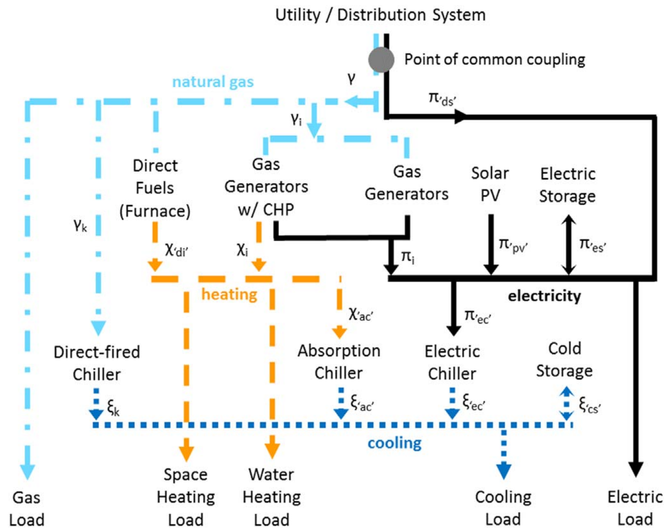

Fig. 1. The microgrid network topology shows sources of energy demand and supply, as well as points of energy conversion, in the model. Energy balances for electricity, cooling, and heating are given by Eqs. (2)–(4). The gas load is supplied trivially so the gas balance equation is omitted.

emissions from purchased and self-generated electric and thermal energy. See (Siddiqui et al., 2007) for a more detailed discussion of inputs and outputs.

For the purpose of policy oriented analysis later in this work, we classify four sets of DER technologies in DER-CAM:

1. *Fossil fuel generators*. Micro turbines, gas turbines, reciprocating engines, fuel cells—all units have discrete capacity, may or may not have heat recovery, and combust natural gas in our models.
2. *Renewable generators*. Solar PV.
3. *Thermal energy generators*. Natural gas direct-fired chillers, absorption chillers, electric central chiller, solar thermal heating, heat pumps—all units supply heating or cooling loads directly.
4. *Flexible technologies*. Electric energy storage, heat storage, cold storage, EVs, demand response, schedulable load (i.e., load that must be met at some time during each 24-h period).

Databases in DER-CAM are highly detailed and thus can be unwieldy to configure, but they are particularly useful in studies such as reported here because they can be adjusted to many real world conditions that are often changing quickly.

Though DER-CAM does have a simplistic demand response module, we do not consider it. It is unclear at present how to connect the real-world demand response characteristics of buildings to the generic building data modeled in this work. While including demand response may shift baseline results, we focus first on the core economic logic for microgrids considering generation and storage assets, before looking at demand-side flexibilities (which our team is planning for future work).

2.2. Problem formulation

Mathematically, DER-CAM is formulated as a mixed integer linear program and is coded in GAMS. (Siddiqui et al., 2005) and (Stadler et al., 2009a) provide a complete mathematical formulation. Though here we provide key highlights—decision variables, objectives, constraints, inputs and outputs, and model databases—to provide context for our modeling and analysis, and present only those elements (loads, DERs, costs, energy flows, emissions) present in our models, we give sufficient information to formulate the model and run our analyses.

Following the topology in Fig. 1, the microgrid is interconnected to the utility distribution system, which we call the "macro grid". In line with common regulatory rules for electric utilities, the DERs that comprise the microgrid are installed behind a single billing meter at the point of common coupling, lie within the boundaries of a single customer, and serve only the load of that customer.[3]

2.2.1. Standard model formulation and assumptions

The modeling approach is described by Eqs. (1)–(4), with nomenclature summarized in Table 1, which we adapt from (Ghatikar et al., 2016) and (Stadler et al., 2008). The annual modeling period is defined across three time periods: month $m\varepsilon M$, day-type $t\varepsilon T$ and hour $h\varepsilon H$, where a chosen number $N_{m,t}$ of two day-types (week-days and week-end-days) define each month. Load, supply, costs, etc. are defined or determined over these time periods. Tariff periods $p\varepsilon P$ and demand types $d\varepsilon D$ are further defined across M, T, and H.

We configure DER-CAM to select, size, and schedule DERs to minimize the year-one total cost of microgrid adoption. Selection and sizing is made for three technology sets—gas generators $i\varepsilon I$, direct-fired gas chillers $k\varepsilon K$, and DERs $q\varepsilon Q$, in addition to switchgear.[4] DERs in I and K are discrete (i.e. they have a set nameplate capacity that must be purchased), whereas those in Q are continuous (i.e. any capacity may be purchased). To enable islanding, switchgear is always selected (with $Binary_s$ and $PurchCap_s$). Scheduling is determined by month m and hour h for electricity provision $\pi_{e,m,t,h}$, cooling provision $\xi_{c,m,t,h}$, and heating provision $\chi_{g,m,t,h}$, where $e\varepsilon E$, $c\varepsilon C$, and $g\varepsilon G$ are the sources of electricity, cooling, and heating provision, respectively.

DER-CAM computes the year-one total cost c, Eq. (1). The total cost includes the full year-one operating cost, which includes electricity and natural gas purchases, DER fuel and maintenance, and the cost of emissions, as well as the year-one annualized capital cost for investment. Energy flows are subject to common constraints such as supply-demand balance in Eqs. (2)–(4), which we show here because they depend on technology selection in our models, as well as energy storage balance, energy conversion efficiencies, and heat recovery, which we do not show because they are unmodified from the standard model formulation.

$$\min c := c_{tariff} + c_{fuel} + c_{der} + c_{carbon} \tag{1}$$

subject to

$$L_{'el',m,t,d} + \pi_{'ec',m,t,d} = \sum_{e\in E} \pi_{e,m,t,d}\ \forall\, m,\ t,\ h \tag{2}$$

$$L_{'cl',m,t,d} = \sum_{c\in C} \xi_{c,m,t,d}\ \forall\, m,\ t,\ h \tag{3}$$

$$L_{'sh',m,t,d} + L_{'wh',m,t,d} + \chi_{'ac',m,t,h} = \sum_{g\in G} \chi_{g,m,t,d}\ \forall\, m,\ t,\ h \tag{4}$$

We decompose c into four components: tariff costs c_{tariff} in Eq. (5) include a volumetric, demand, service fee, and standby component; natural gas fuel costs c_{fuel} in Eq. (6) include a volumetric and service fee component; DER costs c_{der} in Eq. (7) include capital costs as well as fixed and variable operating and maintenance costs; and carbon costs c_{carbon} in Eq. (8) are taxes on CO_2 emissions from on-site natural gas combustion.

[3] While some regulators envision futures in which unrelated customers are interconnected, we focus here on single customers because regulatory rules that constrain adoption to this framework are common to many jurisdictions (New York State Energy Research and Development Authority, 2014), and in some settings the constraints on microgrids are even more severe—for example, through public franchise laws that make it illegal for a developer to lay wires that cross public roadways.

[4] Note that the technology sets I, K, and Q do not align with the four technology sets in Section 2.1. The distinction between I, K, and Q is a mathematical one—discrete and continuous variables are fundamentally different in the optimization formulation—while the distinction made previously is done to facilitate discussion of policy implications.

Table 1
Nomenclature.

Sets and indices	
m	Month, M = {1,2,...,12}
t	Day-type, T = {week, weekend}
h	Hour, H = {1,2,...,24}
p	Electric tariff period, P = {on-peak, mid-peak, off-peak}
d	Electric tariff demand type, D = {non-coincident, on-peak, mid-peak, off-peak}
u	End-use load, U = {electricity 'el', cooling 'cl', space heating 'sh', water heating 'wh', natural gas 'ng'}
s	Index for switchgear
i	Discrete gas generator, I = {ICE, MT, ICE-HX, MT-HX}[a]
k	Direct-fired gas chiller, K = {DFChiller-HX}
q	Continuous DER, Q = {solar PV ‘pv’, electric storage ‘es’, absorption chiller ‘ac’, cold storage ‘cs’}[b]
v	All microgrid technologies, V = {I, K, Q, switchgear}
e	Source of electricity provision, E = {I, ‘pv’, 'es', distribution system 'ds'}
c	Source of cooling provision, C = {K, absorption chiller 'ac', electric chiller 'ec', cold storage 'cs'}
g	Source of heating provision, G = {I, direct fuel 'di'}
Customer load	
$N_{m,t}$	Number of days of day-type t in month m
$L_{u,m,t,h}$	Load profile for end-use load u, month m, day-type t and hour h, kW
Tariff parameters	
$ElecFee$	Fee for electric service, \$/mo
$VChg_{m,p}$	Volumetric charge for month m and tariff period p, \$/kWh
$DChg_{m,d}$	Demand charge for month m and demand type d, \$/kW
$SChg$	DER standby charge, \$/kW/mo
$NGFee$	Fee for natural gas service, \$/mo
$NGPrice_m$	Natural gas price in month m, \$/kWh
Technology data	
R_v	Nameplate capacity of technology v, kW
$Cfcap_v$	Fixed capital cost of technology v, \$
$Cvcap_v$	Variable capital cost for technology v, \$/kW or \$/kWh
$Cfom_v$	Fixed O & M cost for technology v, \$/kW/yr for I, K and \$/kW/mo or \$/kWh/mo for Q
$Cvom_v$	Variable O & M cost for technology v, \$/kWh
A_v	Annuity factor for technology v[c]
CO_2 parameters	
EF	Natural gas CO_2 emission factor, tCO_2/kWh
$CTax$	Tax on CO_2 emissions, \$/tCO_2
Selection and sizing decision variables	
$PurchNum_i$, $PurchNum_k$	Number of purchased gas generators i, direct-fired chillers k
$Binary_q$, $Binary_s$	Binary decision variable to invest in DER q, switchgear
$PurchCap_q$, $PurchCap_s$	Capacity of installed DER q, switchgear, kW
Scheduling decision variables[d]	
$\pi_{e,m,t,h}$	Electricity provision from source e, kW
$\xi_{c,m,t,h}$	Cooling provision from source c, kW
$\chi_{g,m,t,h}$	Heating provision from source g, kW
Secondary variables[e]	
$\pi_{e,m,t,h}$	Electricity supplied by solar PV, kW
$\pi_{'ec',m,t,h}$	Electricity input to the central electric chiller, kW
$\chi_{'ac',m,t,h}$	Heat consumed by the absorption chiller, kW
$\gamma_{m,t,h}$	Total natural gas purchased, kW
$\gamma_{i,m,t,h}$, $\gamma_{k,m,t,h}$	Natural gas purchased for gas generator i, direct-fired chiller k, kW

[a] Notation: ICE – internal combustion engine, MT – microturbine, -HX – with heat recovery.
[b] Q does not include the electric central chiller (which consumes electricity to supply the cooling load) because it is installed in every model run and hence does not affect comparison of results.
[c] Equations for annuity factors are given in the Supplementary information.
[d] Subscript “m,t,h” denotes in month m, day-type t and hour h.
[e] Secondary variables are derived from decision variables and not decision variables themselves. For example, electricity supplied by solar PV $\pi_{'pv',m,t,h}$ is a function of sizing $PurchCap_{'pv'}$ and solar irradiance. The same principle applies for the other secondary variables.

$$c_{tariff} := \sum_{m\in M}\sum_{p\in P}\sum_{t\in T}\sum_{h\in H}\pi_{'ds',m,t,h}\cdot N_{m,t}\cdot VChg_{m,p} + \sum_{m\in M}\sum_{d\in D} DChg_{m,d}\cdot\max_{t\in T,h\in d}\{\pi_{'ds',m,t,h}\} + \sum_{m\in M} ElecFee + \sum_{m\in M}\left[\sum_{i\in I} PurchNum_i\cdot R_i + PurchCap_{'pv'}\right]\cdot SChg \tag{5}$$

$$c_{fuel} := \sum_{m\in M} NGFee + \sum_{m\in M}\sum_{t\in T}\sum_{h\in H}\gamma_{m,t,h}\cdot N_{m,t}\cdot NGPrice_m \tag{6}$$

$$\begin{aligned} c_{der} :=\ & Binary_s\cdot(Cfcap_s + Cvcap_s\cdot PurchCap_s)\cdot A_s + \sum_{i\in I} PurchNum_i\cdot R_i\cdot Cvcap_i\cdot A_i \\ & + \sum_{i\in I}\sum_{m\in M} PurchNum_i\cdot R_i\cdot\frac{Cfom_i}{12} + \sum_{i\in I}\sum_{m\in M}\sum_{t\in T}\sum_{h\in H}\pi_{i,m,t,h}\cdot N_{m,t}\cdot Cvom_i \\ & + \sum_{k\in K} PurchNum_k\cdot R_k\cdot Cvcap_k\cdot A_k + \sum_{k\in K}\sum_{m\in M} PurchNum_k\cdot R_k\cdot\frac{Cfom_k}{12} \\ & + \sum_{k\in K}\sum_{m\in M}\sum_{t\in T}\sum_{h\in H}\xi_{k,m,t,h}\cdot N_{m,t}\cdot Cvom_k \\ & + \sum_{q\in Q}\left(Binary_q\cdot Cfcap_q + PurchCap_q\cdot Cvcap_q\right)\cdot A_q \\ & + \sum_{q\in Q}\sum_{m\in M} PurchCap_q\cdot Cfom_q \end{aligned} \tag{7}$$

$$c_{carbon} := \sum_{m\in M}\sum_{t\in T}\sum_{h\in H}\left(\sum_{i\in I}\gamma_{i,m,t,h} + \sum_{k\in K}\gamma_{k,m,t,h}\right)\cdot N_{m,t}\cdot EF\cdot CTax \tag{8}$$

Two constraints in particular affect DER investment in our work. The first limits the area available for solar PV installations, which we term the *solar PV space constraint*. This constraint is often the factor that caps investment in solar PV. We include it nevertheless, and for comparison quantify the effect of removing it in Section 3. This is an important variable to consider for urban microgrids in compact areas, such as office buildings and urban campuses and where other siting constraints (e.g., aesthetic considerations, shadows, or building codes) limit potential utilization of low power density renewables options.

The second, which we term the *resource adequacy constraint*, concerns the supply-demand balance of electric energy during islanded operation. This constraint requires that the model invest in sufficient generator capacity to operate in islanded mode indefinitely (assuming unaffected fuel supply), where “sufficient capacity” supplies at a minimum the maximum critical electric load, assuming one battery charge/discharge cycle per day and an average annual solar irradiance received each day. This constraint does not guarantee perfect adequacy, nor does it guarantee the ability to island during all hours of the day or days of the year. Rather, it approximates the investment required to island generally—an outcome designed to approximate the estimated microgrid configuration with reasonable DER capacities but with full appreciation that further analysis and modeling refinement would be needed when designing any particular system. Though we require resource adequacy, we do *not* monetize improvement to reliability—such as from reduced interruption costs.[5]

Our model runs are built on several notable assumptions. We explicitly neglect other potential revenue streams by considering only the economic benefit derived from local energy provision (i.e., avoided utility costs). We further neglect potentially important demand-side flexibilities, such as demand response and load scheduling, which could improve microgrid economics substantially. These limitations add conservatism to our results that report the viability of business cases.

There are, conversely, two model features that likely overestimate the benefit of microgrid adoption. One, the model is deterministic. All parameters (e.g., those that are in reality stochastic such as load, solar irradiance, and DER availability) are prescribed and known. In effect this implies that operating forecasts are perfectly accurate—an advantage that likely lessens the need for and value of electric storage. Operation with real forecasts—which are imperfect—would likely require more investment in storage capacity to match results with perfect forecasts. Alternatively the same storage capacity would likely achieve less savings through reduction in demand charges—charges paid by most utility customers for their maximum power draw, which we explain in Section 2.3.2.

Two, irradiance profiles, as is typical in planning models, are based on clear weather days—that is, they do not include diminished and/or variable solar PV output. The model captures seasonal variability across months but not day-to-day or hourly variability due to clouds. The model has a 1 h timestep and thus cannot capture sub-hourly variability either, which can be important as demand charges are based on 15 min intervals and some are calling for finer-resolution market-based tariffs. As with the deterministic assumption, this lack of variability likely overestimates demand charge savings or decreases the need for storage (depending on one's perspective), and hence the value of storage to the microgrid as well as investment cost.

We make these assumptions, which are standard in such modeling, highly transparent to help aid interpretation of results and to identify areas where future work can refine such models.

2.2.2. Modifications to the standard model formulation

We modify the standard model formulation in three ways to make it particularly suited for evaluating business cases. One, we remove the carbon cost *CTax* associated with electricity purchases $\pi_{'ds',m,t,h}$—a \$/tCO$_2$ (metric ton carbon dioxide) measure based on the marketplace generation CO_2 emission factor. Instead, we imbed *CTax* in volumetric rates $VChg_{m,p}$—noting that, ceteris paribus, wholesale electricity rates increase when the carbon cost increases. We also remove the carbon cost associated with natural gas purchases $\gamma_{m,t,h}$ and instead tax only the CO_2 emitted by gas-fired DERs (the sum of $\gamma_{i,m,t,h}$ and $\gamma_{k,m,t,h}$).

Second, to enable a more robust policy analysis, we remove financial parameters that cap the payback period for capital costs—as might exist, for example, for those with difficulty accessing capital—which can restrict investment in capital intensive microgrids.

Third, we neglect all revenue streams beyond those derived from local energy provision. Other revenue could come from participation in electricity markets, utility service agreements, improving reliability via islanding (i.e., reducing interruption costs), and incentives (investment incentives such as tax credits, production credits such as net energy metering and feed-in tariffs, and those with elements of both like the California SGIP). Incentives are applicable to select settings and technologies; we neglect them to build a more widely applicable analysis. Lastly, we neglect several modules within the code (e.g., zero net energy constraints, building retrofits for energy efficiency, and electric vehicles) that are not directly relevant to evaluating the business case and the particular policy aspects of interest. Our interest in neglecting these other revenue streams is to focus on one core business case for microgrids—beyond systems that might be built under special conditions such as with large subsidy or other explicit policy support.

2.2.3. Solution algorithm

The optimization is solved using the IBM ILOG CPLEX Optimization Studio. We vary the relative optimality gap (the gap between the best known solution and optimal solution) depending on the iconic microgrid being modeled—from 0.01 (1%) for the large commercial microgrid to 0.00001 (0.001%) for the campus microgrid. Model runtimes vary depending on this criterion—baseline and green-field sensitivity analyses (Sections 3.1, 3.4) require selection, sizing and scheduling and range from 10 min to 10 h, while simple sensitivity analyses (Section 3.3) require only scheduling and terminate in a few minutes. All model runs used a 3.40 GHz Intel Core i7-2600 processor and 16 GB of installed RAM.

2.3. Data

2.3.1. Load data for three iconic microgrids

We create data sets for three iconic microgrids—which we term the *large commercial*, *critical asset*, and *campus*. We construct data sets to align with forecasted market growth for the largest grid-tied microgrid segments (see Section 1).[6]

In our view commercial systems supply a single building (or a small cluster of perhaps 2-3), for example large box stores such as Walmart and Costco or office buildings. Critical assets are those facilities with a particularly great need for reliability (a large portion of the load is critical and must be maintained during outages) and may include hospital complexes, community centers, critical public infrastructure, and data centers. Lastly, campus systems may include military bases, university and government campuses, and corporate parks. These are geographically large systems covering many buildings (residential, commercial, and/or industrial) but within a single ownership boundary that does not cross public rights of way.

We generate annual data sets at a 1-h timestep for five types of load—electricity $L_{'el'}$, cooling $L_{'cl'}$, space heating $L_{'sh'}$, water heating $L_{'wh'}$, and natural gas $L_{'ng'}$—using the US DOE data set of commercial reference buildings (Deru et al., 2011; Office of Energy Efficiency and Renewable Energy, 2015)—a set of 1-h resolution annual profiles for 16 building types representative of approximately 70% of all US commercial buildings, such as offices, schools, restaurants, hotels, and a hospital, among others. Thermal loads ($L_{'cl'}$, $L_{'sh'}$, and $L_{'wh'}$) are available for 16 climate zones. We use climate zone 3B-coast for southern California. Fig. 2 shows representative daily profiles for a weekday along with annual energy consumption; full profiles are reported in the Supplementary information. By combining the DOE data into three types of building clusters—each served by a microgrid—we hope to promote more systematic microgrid analysis.[7]

We model the three iconic microgrids as an office building, hospital complex (a hospital with ancillary facilities) and university campus, and map them to the DOE commercial reference buildings as follows:

[5] We report in the Supplementary information baseline results with the resource adequacy constraint removed. In short, for the critical asset, which has high demand for reliability, including the constraint pushes investment toward gas generators and away from solar PV and electric storage, but does not change the total cost. Results for the large commercial and campus microgrids are essentially affected because they have less demand for reliability.

[6] (Saadeh, 2015) distinguishes between five microgrid segments: military, university, city/community, public institution, and commercial. Each of those finer resolution categories falls into 1-2 of the three main segments in the present study: in our view, our "large commercial" category covers the commercial segment; "critical asset" includes city/community and public institution segments; and "campus" includes the military and university segments.

[7] The Grid Integration Group at LBNL has used DER-CAM with the DOE reference building data set, which has been available since 2011, to study varying tariff structures and climate conditions (Mendes et al., 2014, 2013; DeForest et al., 2014). Systematic studies such as these are valuable because they provide insight into adoption trends for specific DERs across a range of important parameters.

the large commercial as the medium office; the critical asset as the sum of the hospital, quick-serve restaurant, and outpatient facility; and the campus as the sum of the small office, medium office, two large offices, three stand-alone retail centers, three supermarkets, four midrise apartments, two primary schools, two secondary schools, one strip mall, and one quick- and one full-serve restaurant.

Several features distinguish the three load profiles:

- *Large commercial*. Consists primarily of electric load, but also includes variable demand for heating and cooling (i.e., it has a large ratio of maximum to minimum thermal load), so CHP investments are not optimal. This class consumes the least energy of the three.
- *Critical asset*. Distinct from the other microgrids, the heating and cooling loads are relatively constant throughout the day. It has the highest electric load factor (the ratio of average to maximum load), which, with thermal loads, favors CHP investment. The peak critical electric load is large relative to the base electric load, so higher capital costs for generators are needed to reliably supply peak critical load.
- *Campus*. Of the three it has the largest demand and volumetric consumption, and in particular has large thermal demand.

2.3.2. Important parameters for policy analysis

We provide in Table 2 our parameterizations relevant to policy and that most affect investment outcomes, and leave full detail on the empirical calibration (i.e., the larger set of model parameterizations) for the supplementary information.

The business case for local energy provision rests on avoiding utility service costs. To quantify those costs we consider the costs of interconnection to the San Diego Gas & Electric (SDG & E) distribution system. Applicable electric tariffs are from 2015 and include the SDG & E commercial Schedule AL-TOU and Schedule S.[8]

Three other parameters (the discount rate, gas price, and carbon cost), as we will show, are also of particular importance. We assume that the cost of capital is 7%—based on the lower medium grade corporate bond rate—and use the same rate for discounting calculations. The gas price varies by region and time of year, among other factors. We use a single price of 8 $/mmbtu based on retail sales to commercial customers in California (US Energy Information Administration, 2015). We use the California Carbon Allowance futures carbon price of 12 $/tCO$_2$e (metric ton carbon dioxide equivalent), which is essentially the floor price in the carbon market ("California Carbon Dashboard," 2015). To explore the potential for future low-carbon microgrids based around solar PV and electric storage we use current costs for non-residential rooftop PV systems (Kann et al., 2016) and a *projected* cost estimate for electric storage that aligns with estimates of current and projected costs (Bronski et al., 2015; Christiansen and Murray, 2015; Nykvist and Nilsson, 2015). This projected electric storage cost is the only calibration based outside of the "present day."

[8] Schedule AL-TOU imposes volumetric charges ($/kWh) and demand charges ($/kW) that vary by season and tariff period—the former are based on energy consumption and the latter on monthly maximum power draw. Schedule S codifies a standby charge, a $/kW charge on the installed generator capacity that is designed to reflect the increased load the microgrid might draw from the utility if microgrid generators were to fail. The charge can be substantial and has been debated (Darrow and Hampson, 2013) but, as we will show, is not a driving parameter of optimal configurations. In addition to these two, another schedule, Schedule E-DEPART, codifies a departing load charge—a charge on the portion of load no longer supplied by utility service (and instead supplied via self-generation). Because it is very small (approximately 0.005–0.015$/kWh) relative to other tariff charges, and moreover specific to the three investor-owned utilities in California (Darrow and Hampson, 2013), we neglect it.

3. Results and discussion

3.1. Definitions and scenarios

We term the optimal selection and sizing of DERs the *optimal configuration* and year-one operation of DERs the *optimal dispatch*. Together they comprise the *optimal system*. We model two types of customers for each iconic microgrid, as is typical with DER-CAM—(1) a *microgrid customer*, who adopts a microgrid to supply load with some combination of self-generated electric and thermal energy and/or purchased electricity and natural gas; and (2) a *macro grid customer*, who supplies the same set of loads by purchasing electricity and natural gas services from the utility. We term the cost savings derived from microgrid adoption (i.e., the difference in total cost between the two customers) the *economic benefit* (which can be negative).

We perform three sets of analyses for each iconic microgrid and customer type (Fig. 3). First is a baseline analysis (Section 3.2). Second is a simple sensitivity analysis (Section 3.3), in which we hold constant the optimal configuration from the baseline analysis while varying individual parameters and then re-optimize the dispatch of generation technologies. These analyses explore the robustness of business cases for microgrids that might be "locked in" economically due to investment in a configuration of technologies. They also help to identify areas where more in-depth (and computationally difficult) sensitivity analysis would be needed. Third, for the four factors identified in the simple sensitivity as most important we perform a greenfield sensitivity analysis (Section 3.4), in which we vary individual parameters before re-optimizing configuration as well as dispatch. This latter type of sensitivity analysis is most useful for unbuilt microgrid systems that might be in the planning phase.

3.2. Baseline analysis

In the baseline optimal configurations (Table 3) we distinguish between investments in the four technology sets noted in Section 2.1—conventional gas generators, renewables, thermal energy generators, and flexible technologies. We further distinguish generators with CHP—which supply both power and thermal energy within the microgrid—because they can greatly improve energy efficiency and thus can prove pivotal to establishing the business case. Detailed investment by individual unit and technology is provided in the Supplementary information.

Operationally, the DERs that comprise the microgrids supply peak and base electric load (Fig. 4), and hence target reduction in both demand and volumetric charges—the largest costs to the macro grid customer. The optimal configurations are sized to supply peak electric load for three reasons: to facilitate islanding per the resource adequacy constraint, to shave on-peak load (which has the highest demand charges), and to supplant electricity and fuel purchases with less costly self-generated electricity. Purchases do supply a small amount of base load in some configurations and months.

The key difference across the optimal configurations for the three iconic microgrids is not DER capacity relative to peak load, but rather the combination of DER types (gas generators, gas generators with CHP, solar PV, and electric storage) that comprise the configuration. Those combinations we observe—and especially the variation in them when compared across sensitivity in policy variables—has the biggest implications for policy, as we will discuss in Sections 3.4 and 4.

While the details of each optimal system are complex, the broad patterns are as follows:

- *Large commercial*. Gas generators supply base load and solar PV supplies peak load. Electric storage complements solar PV by supplying peak load when solar output is unavailable, as observed during winter evenings. Cold storage (i.e. chilled water) is produced during off-peak hours. The thermal demand is relatively small so the

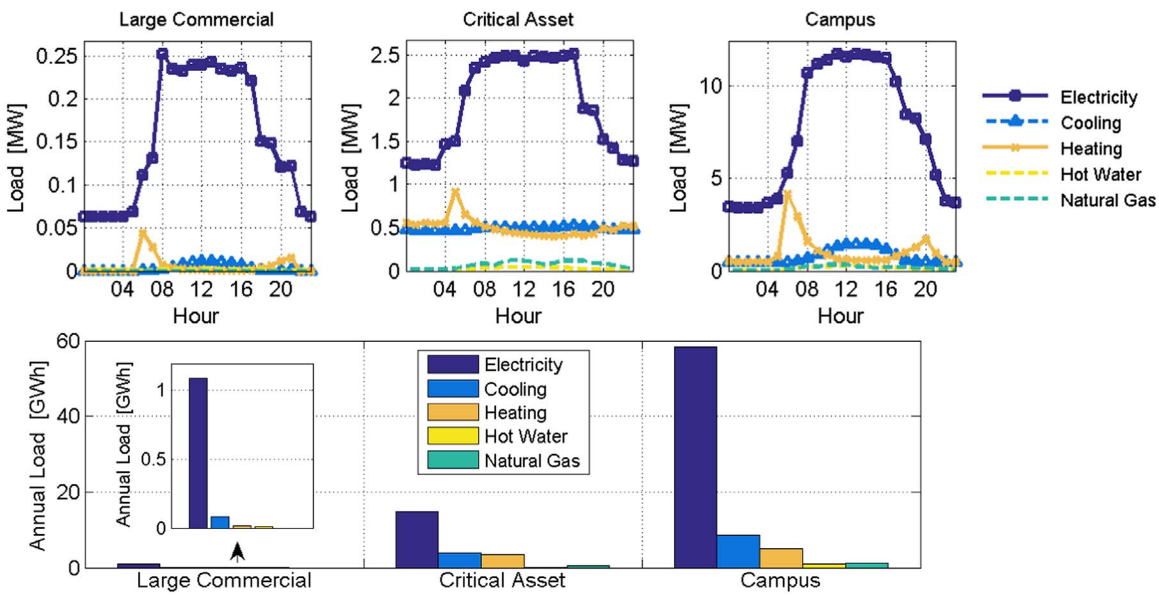

Fig. 2. (top) Load profiles presented for a February weekday are representative of the load shape on weekdays throughout the year. (Weekend-days have a similar base load but do not peak so significantly during the day.) (bottom) Annual energy consumption for all end-use loads shows the disparity in size between the three. Note variable y-axis scaling at top and constant y-axis scaling at bottom.

Table 2
Model calibrations important for policy analysis—costs of electricity, gas, carbon, and DERs.

Parameter	Value	Units
Tariff parameters		
Volumetric charges		$/kWh
Summer on-peak	0.12331	
Summer mid-peak	0.11362	
Summer off-peak	0.08287	
Winter on-peak	0.11157	
Winter mid-peak	0.09602	
Winter off-peak	0.07460	
Demand charges		$/kW
Non-coincident	23.83	
Summer on-peak	20.93	
Winter on-peak	7.62	
Standby charge	13.76	$/kW
Exogenous Parameters		
Interest rate	7	%
Natural gas price	8	$/mmbtu
Carbon cost	12	$/tCO$_2$
DER Parameters		
Solar PV capital cost	2390	$/kWac
Electric storage capital cost	350	$/kWh

model foregoes CHP.

- *Critical asset*. Gas generators supply base load, two-thirds of which have CHP to meet the relatively large thermal load. An absorption chiller further supplies cooling. Solar PV supplies peak load and electric storage supplies an indistinguishable amount of shoulder load (i.e., load between the on- and off-peak periods, 1600–1700 LST in winter).
- *Campus*. Gas generators supply the base load, 60% of which have CHP to meet thermal demand. An absorption chiller further supplies cooling and cold storage is produced during off-peak hours. Solar PV supplies peak load and electric storage again complements when solar output is small or unavailable.

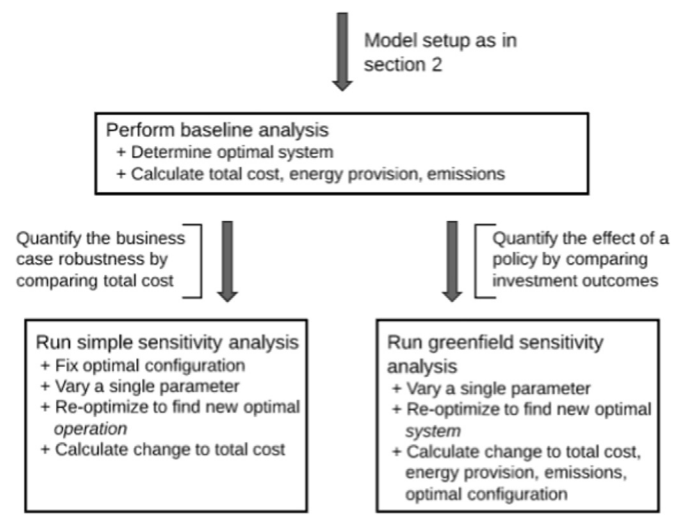

Fig. 3. We run two types of sensitivity analysis after the baseline analysis: simple and greenfield sensitivities.

Table 3
Optimal microgrid configuration for the baseline model runs.

	Large commercial	Critical asset	Campus
Gas generators			
without CHP	150 kW	750 kW	4000 kW
with CHP	–	1650 kW	6250 kW
Renewable generators			
Solar PV	200 kW	1240 kW	3100 kW
Thermal energy generators			
Direct-fired chiller with CHP	–	200 kW	200 kW
Absorption chiller	–	340 kW	1420 kW
Flexible technologies			
Electric storage	230 kWh	20 kWh	1479 kWh
Cold storage	220 kWh	–	3340 kWh

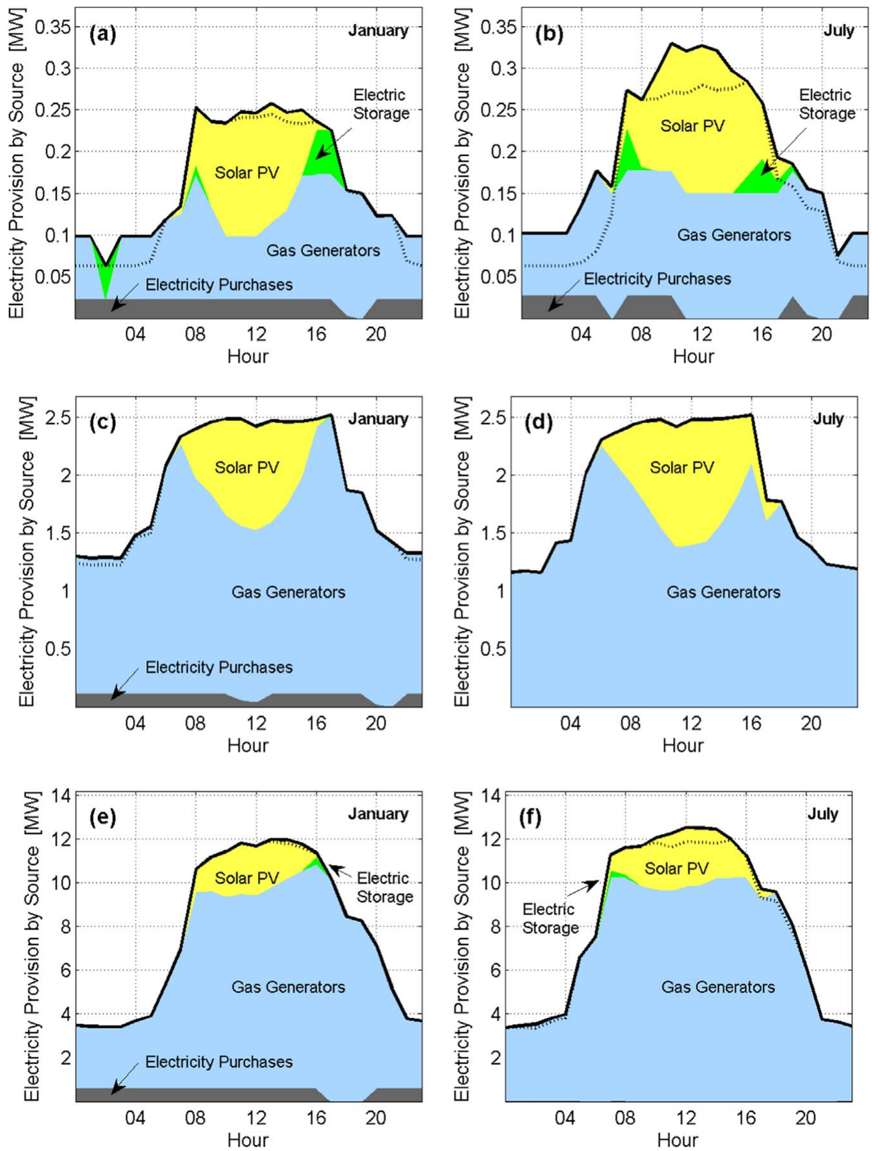

Fig. 4. The optimal dispatch for a representative weekday in winter (left) and summer (right) for the large commercial (a, b), critical asset (c, d) and campus (e, f) microgrids shows how the microgrid supplies electric load with a combination of purchased and self-generated electricity. The microgrid electric load is denoted in solid black; for reference, the electric load for utility service is shown in dashed black. The two are different because some DERs consume electricity—see for example (a) and (b). Electric storage is shown as energy provision when discharging (green) and added to the load curve when charging. Dispatch for all 12 months of the year is in the Supplementary information. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The primary driver of these investment trends is the potential to utilize natural gas to supply electricity and thermal loads at high efficiency and low cost. The models largely supplant electricity purchases with self-generated electricity, using gas generators to supply a huge fraction of the base load. The model is driven to this result because gas prices are low, the microgrid CO_2 emission factor is comparable to that of the wholesale marketplace, and California retail electricity rates are relatively expensive. Further, the critical asset and campus integrate electric and thermal loads via CHP, thereby increasing consumption efficiencies and obviating much of the electricity and fuel purchases otherwise needed for direct heating and cooling.

All configurations include solar PV—driven in part by the coincidence of peak load and peak solar irradiance, as well as the assumption of clear weather days. The critical asset and campus invest in a maximum capacity of solar PV—that is, the solar PV space constraint caps investment.[9] The large commercial uses 33% of available space. Such large installations are cost effective because of the large daily load peak and the coincidence of peak load with peak solar.

The macro grid and microgrid customers are subject to competing costs (Fig. 5) per Eqs. (1)–(8). The former pays only for utility electric and gas service per applicable tariffs ("tariff costs" and "fuel costs"), while the latter pays the same tariff charges in addition to "DER costs" and "carbon taxes". The total cost is the sum of these four per Eq. (1). We find that, for the baseline case, microgrid adoption reduces the total cost relative to the macro grid customer—that is, the economic benefit is positive.

[9] When unconstrained by available space, the critical asset and campus see investment of an additional 40% (1750kW constrained, 1250kW baseline) and 177% (8600kW unconstrained, 3100kW baseline) respectively. These results are detailed in the Supplementary information.

3.3. Simple sensitivity analysis

Now we turn to sensitivity analysis. In this section we vary all 13 of the significant parameters in the model within ranges detailed in Table 4. For this "simple sensitivity" we leave the configuration of installed DERs on each iconic microgrid unchanged from the baseline. In the next section we look at a subset of the most important factors and offer full blown re-optimizations around those variables to show the deeper implications for investment decision-making.

The 13 sensitivities span the major clusters of factors that vary in ways that affect the viability of microgrid investment: technological advance, which generally lowers costs; utility tariff costs, which generally rise and vary widely with geography and regulation; carbon costs, which vary jurisdictionally; and financing and fuel costs, which reflect market conditions. We also vary the magnitude of electric and thermal loads to reflect the uncertainties omnipresent in energy service that affect load—factors such as climate zone, energy efficiency measures, and load growth.

Fig. 6 shows results for the simple sensitivity analysis. While results are nuanced, several trends are common across the three microgrids:

- In general, sensitivity is greatest to four factors: gas price, carbon cost, DER costs, and tariff costs.
- Sensitivities to volumetric and demand charges are small because the microgrids primarily self-generate electricity. Put differently, once a customer invests in a microgrid, the optimal configuration reduces the cost of grid service (demand charges, volumetric charges) massively.
- Sensitivities to the carbon cost and gas price are high and exceed those to DER costs. In other words, opex can impact the total cost to a greater degree than capex (cf. the relative magnitude of DER and fuel costs in Fig. 5).
- The sensitivity to the electric load is large. The systems have reserve generation (gas generators are sized to meet the peak critical load and do not run at 100% output during non-peak hours). Hence the systems can supply the majority of load growth without additional capex, thereby increasing the economic benefit.

Regarding the last bullet, the means to supply load growth is highly dependent on the volumetric charge and gas price—if volumetric charges are sufficiently low and/or gas prices high, the models instead revert to purchasing electricity. Note that variation (positive vs. negative) is reversed in Fig. 6 for the electrical and thermal load sensitivities—once investment is fixed, less load decreases the economic benefit.

The range of cost deviations shows that the business case for all microgrids is very robust—that is, only extraordinarily high values for the carbon cost and gas price (approaching 100-120 \$/tCO_2 and 12-16 \$/mmbtu) make microgrid adoption uneconomical. Yet high carbon taxes and gas prices would likely increase retail electricity rates commensurately and move the parity point to the right.

3.4. Strategically important variables: markets, technology, policy

Four variables have a large strategic effect on the business case for microgrid adoption: natural gas price, electric tariff charges, carbon cost, and electric storage cost. Gas prices are inherently variable and important because of the dominance of gas generators in the baseline optimal configurations. Carbon costs are expected to increase, while storage costs are declining rapidly. Tariff charges ultimately make it economical (or not) to invest in technologies that peak shave and/or supply base load in place of utility service; it other words, investment decisions must balance avoided costs from volumetric and demand charges while considering standby charges and fuel costs. Moreover, tariff charges and structures vary widely by utility and region. Each is a policy variable and possible pathway for policy intervention. Gas and carbon prices may push investment toward gas or renewable generators, while the magnitude of tariff charges may impose a "barrier to entry" if too low, and high storage costs may impose an analogous barrier for low-carbon configurations.

Electric storage in particular is widely seen as an important tool for integrating renewables and facilitating deployment of low-carbon microgrids. Storage costs are decreasing rapidly, though the point at which deployment becomes cost-effective varies and is an open question, which others have investigated (Nottrott et al., 2013).

In what follows we run greenfield analyses for varying gas price, tariff charges, carbon cost, and electric storage cost (with justification for parameter variation as in Section 3.3). For each variable, we re-determine the optimal system. We compare the total cost for the two customer types and distinguish electricity provision by resource. We present emission totals for the microgrid customer, which includes direct emissions from on-site generation as well as indirect emissions—the result of purchased electricity derived from generators in the wholesale market.

3.4.1. Natural gas price

We vary the gas price from 4 to 16 \$/mmbtu (Fig. 7). Here we perform a "scenario analysis"—so-called because we vary multiple parameters to capture feedback.[10] The total cost for both microgrid and macro grid service increases with gas price because both customer types must purchase gas to meet the gas load $L_{\cdot ng \cdot}$. Across the full range of prices microgrids incur a smaller total cost when compared with utility service—with the largest differences occurring when prices are low (here the microgrids have the most flexibility to reduce costs).

Low prices drive investment in gas generators; as prices increase those are replaced with renewable sources as well as purchased electricity—a transition that decreases the economic benefit. Beyond 9 \$/mmbtu the large commercial system adopts a low-carbon configuration, and thereby maintains a positive (and increasing) economic benefit (i.e., it insulates itself from further gas price increases). The critical asset and campus systems, on the other hand, see a persistently diminishing economic benefit as prices increase—they do not transition to low-carbon configurations, but rather revert to purchasing electricity. Higher gas prices make it harder for these microgrids to utilize one of the chief advantages of local production: the on-site use and storage of thermal energy via CHP.

Across all three optimal systems there is a sharp transition in the source of electricity provision from gas-fired self-generation to purchased electricity. The transition points—at 7–9, 11–13, and 9–11 \$/mmbtu for the large commercial, critical asset, and campus systems—have significant implications for the optimal configuration, business case, and policy decision-making if low-carbon systems are preferred. More research is needed to investigate whether these knife-edge transitions—particularly prominent in the smaller microgrids—reflect real-world conditions or are a standard discontinuity that often arises with optimization models.

3.4.2. Electric tariff charges

Volumetric rates are varied fractionally from 0.4 to 1.4 in increments of 0.1 (Fig. 8), where unity is the rate in the baseline analysis. Rather than varying each element of the tariff separately, which would yield a highly complex sensitivity analysis, we vary the whole cluster of related volumetric charges so that potential investors and policy makers can understand better the fundamental impact of such charges on microgrid configuration and viability.

We find that volumetric rates greatly affect the total cost and

[10] We increase the volumetric charge with the gas price to account for a corresponding increase in natural gas-generated wholesale electricity. Marginal generators are typically gas-fired in the California wholesale market. We increase only the generation portion of the volumetric rate and scale the increase by the fraction of wholesale electricity generated from natural gas plants in California (45% at the time of this work).

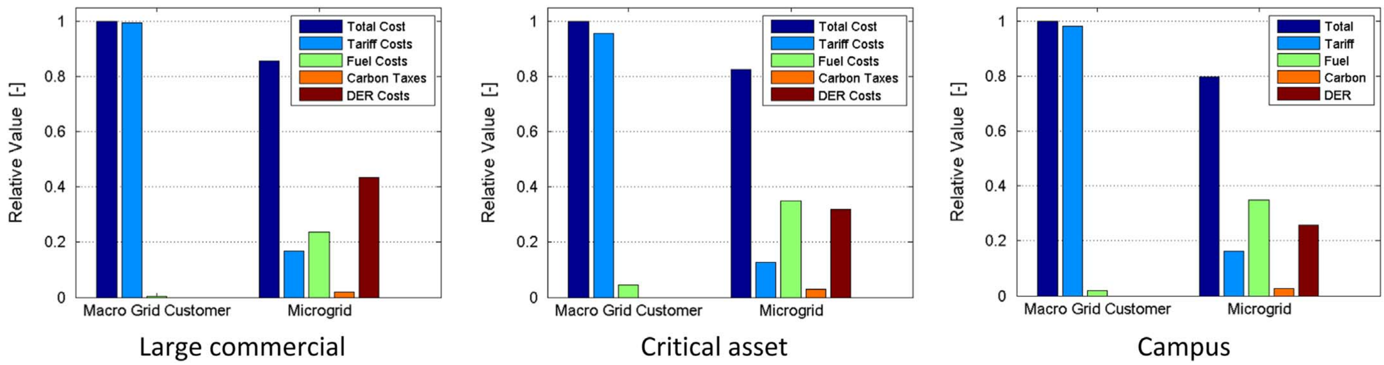

Fig. 5. The disaggregation of the year-one total cost shows how microgrid adoption shifts the source of cost from tariff-based to DER- and fuel-based. In doing so adoption reduces the total cost—by 14%, 17%, and 21% for the large commercial, critical asset, and campus, respectively. Costs are normalized to the macro grid customer's total cost.

Table 4
Variation of 13 parameters in the simple sensitivity analysis.

Parameter Varied	−/+ variation (nominal, range)	Justification	Reference
Interest rate	-/+25% (7, 5.25–8.75%)	Reflects a typical discount rate for lower medium grade (BBB- to BBB+) corporate bonds at the time of this work; the sensitivity range further covers high-yield and upper medium grade bonds.	
Carbon cost	−100/+1000% (12, 0-132 \$/tCO$_2$)	Captures the 95th-percentile cost for the out-year 2020 (129 \$/tCO$_2$). At the time of this work the price of California Carbon Allowance futures is trading at 12–13 \$/tCO$_2$e.	(Interagency Working Group on Social Cost of Carbon, 2013)
Natural gas price	−50/+100% (8, 4–16 \$/mmbtu)	Captures the full range of AEO2015 projected Henry Hub spot prices[a] while further allowing for a range of retail prices which vary according to local natural gas infrastructure spending.	(Conti et al., 2015)
Volumetric charge	−45/+15% (multiple, varies)	Captures the wide range of US average retail electricity rates for commercial customers.[b]	(Conti et al., 2015)
Demand charge	−45/+15% (multiple, varies)	For simplicity, we vary the demand charge −45/+15% to align with the variation in volumetric charge.[c]	
Standby charge	−45/+15% (13.76, 7.57–15.82 \$/kW)	As noted for the demand charge.	
Gas generator capital cost	−20/+10% (varies, see SI)	Captures cost projections for 2010–2030 for small (< 1 MW) generators while allowing for emissions treatment equipment costs for compliance with potential future stringent emissions regulations. Though both capital and emissions treatment equipment costs vary by generator type and capacity, for generality we apply the sensitivity range across all generator types.	(Hedman et al., 2012)
Gas generator O & M cost	−20/+10% (varies, see SI)	As noted for the gas generator capital cost.	
Electric storage capital cost	−50/+300% (350, 175–1050 \$/kWh)	Captures existing and projected costs over the next 5–10 years.[d]	(Shah and Booream-Phelps, 2015)
Thermal storage capital cost	-/+20% (50, 40–60 \$/kWh)	Considers potential technology advances or unforeseen policy changes affecting thermal storage.	
Solar PV capital cost	-/+50% (2390, 1195–3585 \$/kW)	The sensitivity decrease nears the DOE SunShot Initiative goal of 1 \$/W installed cost; the increase nears the cost of smaller rooftop solar PV systems (5–10 kW, 3740 \$/kW). The nominal cost assumes large (~200 kW) rooftop installations.	(Kann et al., 2016)
Electrical load	-/+20% (varies)	Captures potential load growth and energy efficiency measures implemented over the microgrid lifetime. Growth assumes a 1% annual rate (per EIA forecasts) and loss a −1% annual rate.	
Thermal loads	-/+50% (varies)	Captures other climate zones outside of the nominal climate zone 3B-coast.[e]	

[a] Annual Energy Outlook 2015 (AEO2015) forecasts for 2030 range from 4 \$/mmbtu in the "High Oil and Gas Resource" scenario to 8 \$/mmbtu in the "High Oil Price" scenario.

[b] Captures the 5th- and 95th-percentile for the average retail electricity rate for commercial customers across all 50 states and the District of Columbia over the period 2013–2033, assuming the 2013 average retail price for commercial customers in California as the baseline and an annual increase of 0.6% per the AEO2015 "Reference case" scenario. We project the price to 2033 to capture variation over the 20-year plausible lifetime of the microgrid. See the Supplementary information for detailed treatment.

[c] The EIA frequently publishes data on monthly average retail electricity prices (through the AEO) based on collected utility revenues and sales—a metric that amalgamates all utility charges—but does not report demand charges or standby charges separately. Surveying the range of demand and standby changes across utilities to generate a sensitivity range is not straightforward because those charges are closely tied to volumetric charges in the ratemaking process, and, further, it is unclear how to normalize utility charges against the volumetric charge.

[d] Today's hardware cost for battery storage ranges widely across manufacturers (and chemistries)—from 350 to > 2000 \$/kWh (lead-acid may be as low as 200 \$/kWh while lithium-ion may be 500 \$/kWh)—but are forecasted to fall sharply over the next 5–10 years. For reference, as of 2015 T Motors sells its Powerwall stationary battery storage product for 350 \$/kWh (the offering excludes inverter and soft costs).

[e] The climate of coastal southern California is moderate and requires relatively little building heating and cooling. Climate zones in the US range from 1 A (hot and humid, e.g. Miami, Florida) to 8 (cold, e.g. Fairbanks, Alaska).

optimal configuration. As with the gas price, sharp transition points exist in which gas-based self-generation and purchased electricity are substituted. When rates are low (< 0.5), the microgrid total cost exceeds that to the macro grid customer; that is, the economic benefit is negative.

Microgrids realize an economic benefit beginning with rates > 0.5 that increases with rising rates. We observe scenarios with near 100% self-generation. Notably, these occur under present-day electricity rates in southern California. Purchasing electricity is the dominant mode of supply for rates near 0.6–0.9 (depending on the microgrid).

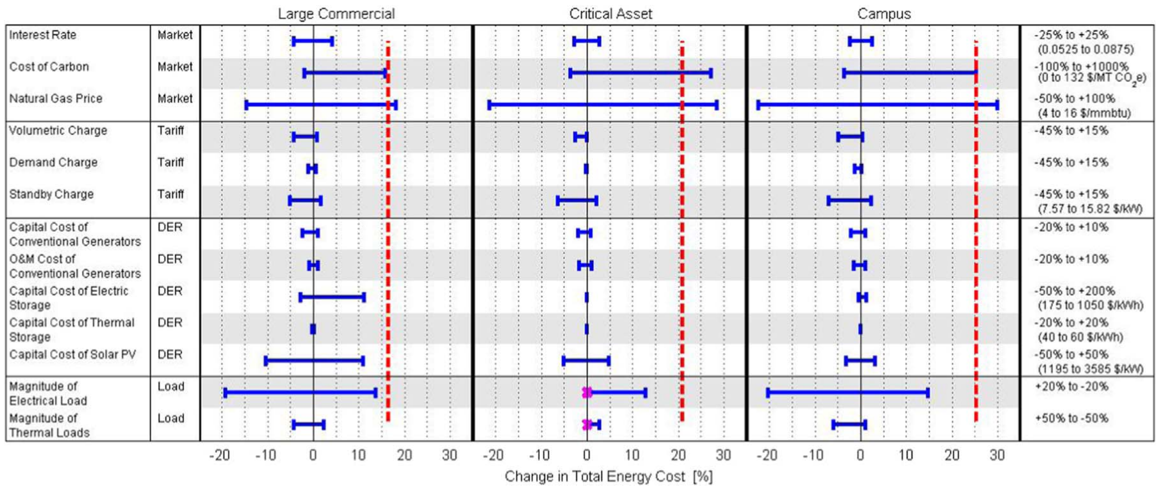

Fig. 6. Change in total cost due to variation in the 13 simple sensitivities. The red dashed line denotes the "parity point"—the cost increase that reaches the total cost to the macro grid customer. For some market parameters (gas price, carbon cost) the parity point shifts because variation affects electricity rates for the macro grid customer, though such shifts are not noted. The models do not converge in two instances (marked in purple); in these cases the magnitude of electric and thermal load for the critical asset do not meet the resource adequacy constraint because the fixed configuration does not have sufficient capacity to supply the increase in critical load. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

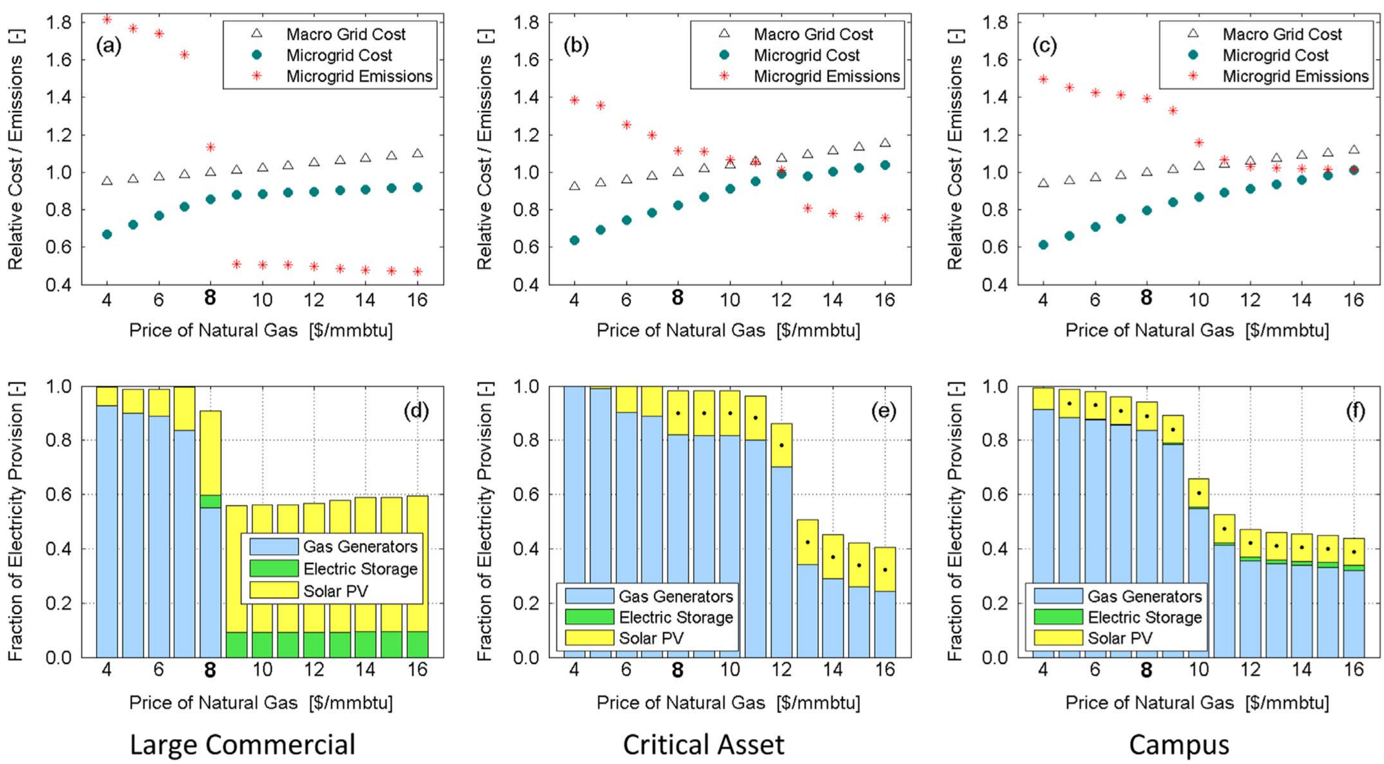

Fig. 7. (a)–(c) The total cost and total CO_2 emissions are normalized by the total cost to and total emissions of the macro grid customer, respectively, for the nominal gas price (8 $/mmbtu; bolded); and (d)–(f) the fraction of electricity supplied by microgrid resource across variation in gas price. Each bar shows results from a single model run. The uncolored portion above a bar represents purchased electricity. A dot in the solar PV bar denotes that the solar PV space constraint has capped installations.

Optimal configurations fit broadly within two domains—low-carbon and gas-based configurations—separated by a transition point. The large commercial system is low-carbon for rates < 0.9 and gas-based for rates ≥ 0.9, with gas dominant with increasing rates. Similar transitions occur for the critical asset and campus microgrids—for rates 0.6–0.8 and 0.7–0.9 respectively. For these two systems, however, gas generators remain the dominant microgrid resource over the range of rates. They are the bedrock of investment and business case for larger systems.

Demand charges are varied fractionally from 0.4 to 1.4 in increments of 0.1 (Fig. 9). As before, unity is the nominal demand charge in the baseline analysis. All demand charges are varied concurrently.

We observe that peak shaving is key to the business case over the wide range of demand charges. For charges < 0.6, the economic benefit is negative, while for charges > 0.6 the total cost increases slightly and soon plateaus. Here the microgrids self-generate nearly 100% of electric load, and hence mitigate the demand charge to zero (or close to zero).

For present day charges (unity), it is economical to peak shave and, further, to self-generate nearly all electric load. The critical asset invests in gas generators to supply its large fraction of critical load in the event of outages independent of the demand charge, and hence sees

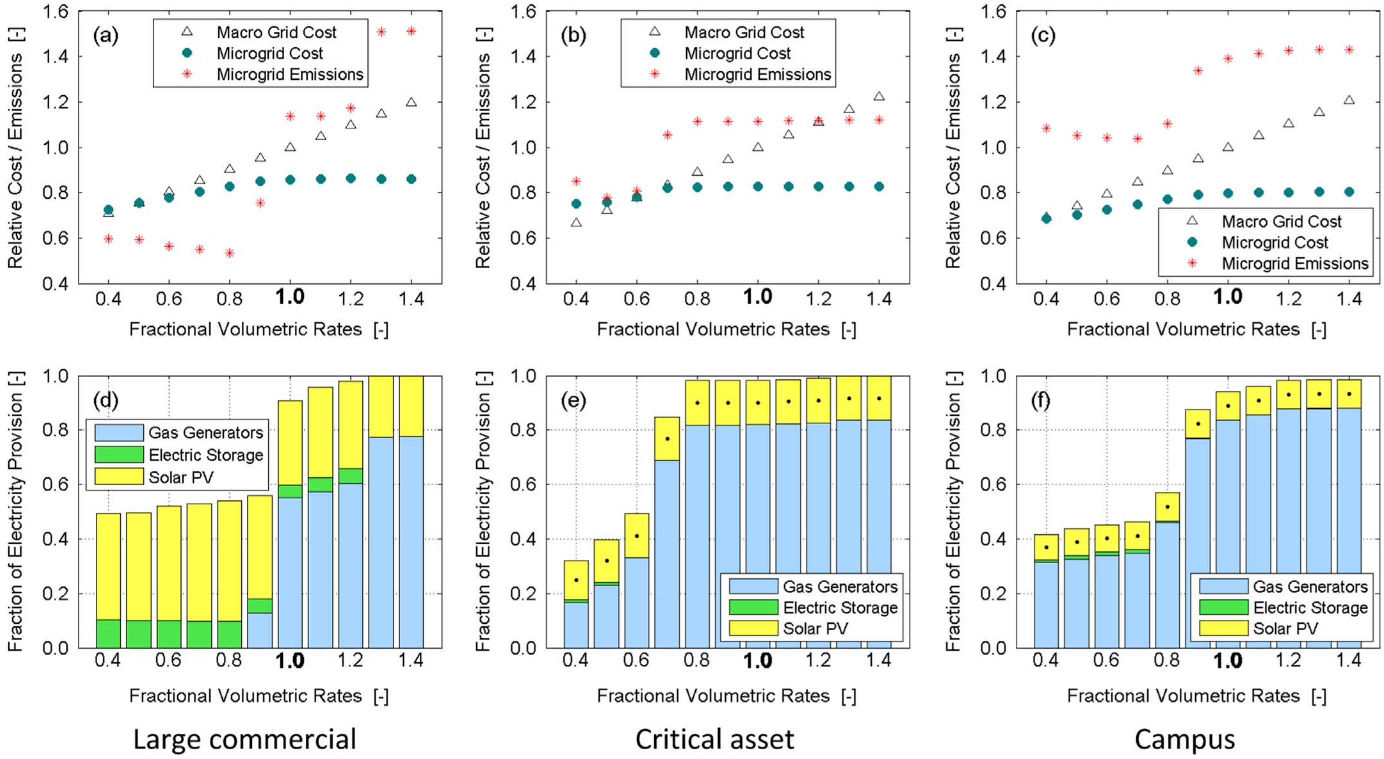

Fig. 8. (a)–(c) The total cost and total CO_2 emissions are normalized by the total cost to and total emissions of the macro grid customer, respectively, for the nominal volumetric charge (unity; bolded); and (d)–(f) the fraction of electricity supplied by microgrid resource across variation in volumetric charges. Each bar shows results from a single model run. The uncolored portion above a bar represents purchased electricity. A dot in the solar PV bar denotes that the solar PV space constraint has capped installations.

a business case for peak shaving for demand charges 0.4–1.4. The large commercial and campus have a smaller fraction of critical load—they revert to purchasing electricity when demand charges are small. For these two microgrids, we observe a sharp transition (0.8–1.0 and 0.7–0.9 respectively) separating two modes of electricity provision—purchased electricity when demand charges are small and gas generation when large. Present-day demand charges thus lie near this inflection point that separates two distinct investment cases—one based on renewables and partial self-generation, and another on gas generators and near 100% self-generation.

3.4.3. Carbon cost

We vary the carbon cost from 0 to 132 $/t$CO_2$ (Fig. 10) and, as with the gas price, run a scenario analysis.[11] We find that increasing carbon cost can shift investment from gas generators to renewables and that the onset of that shift arises at lower carbon costs for smaller microgrids (i.e. the large commercial). This is because such transitions are constrained by available space for PV in the two larger microgrids. These two, as well, make efficient use of gas with CHP—an efficiency advantage that is not offset until higher carbon prices.

The large commercial system supplies nearly 80% of electric load with gas generators at a carbon cost of 0 $/t$CO_2$ and only 15% at 30 $/t$CO_2$. For costs > 36 $/t$CO_2$, a low-carbon configuration with electricity purchases replaces gas generators. The critical asset and campus systems also divest in gas generators with rising carbon cost; however, they purchase additional electricity rather than transition to a low-carbon configuration. This is due in part to the solar PV space constraint.[12] This result suggests that for such configurations, decarbonizing the electricity system may best be achieved with centralized grids.

3.4.4. Electric storage cost

We use as the nominal turnkey electric storage cost a forecasted estimate (350 $/kWh) that aligns with estimates of current and projected costs over the next 5–10 years, and vary the electric storage cost 0–1150 $/kWh (Fig. 11) in increments of 50 $/kWh.

The large commercial system adopts additional storage as costs fall. Two transitions are salient. The first occurs when storage is first adopted, at 350 $/kWh, and the second when the microgrid reaches a low-carbon configuration, at 200 $/kWh. With these transitions the microgrid also purchases additional electricity, eventually supplying over 30% of load. At costs < 100 $/kWh, further storage does not provide a benefit (i.e., energy shifting is not needed) because the microgrid has already plateaued demand and achieved perfect on-peak/off-peak energy arbitrage.

The critical asset and campus also purchase additional storage as costs fall, but never adopt low-carbon configurations. Gas generators remain the dominant resource throughout. Even at 0 $/kWh, storage is used only to facilitate peak shaving, as observed in the baseline results. The solar PV space constraint caps installations, thereby restricting potential low-carbon transitions, in which storage might store significant excess solar PV generation for discharging at night.

4. Conclusion and policy implications

Under the right conditions, the supply of electric and thermal

[11] We increase the volumetric charge with the carbon cost to account for a corresponding increase in generation costs from fossil fuel power plants and subsequently the clearing price in the CAISO wholesale market and retail rates. We use AEO 2014 projections and compare the percent difference in economy-wide electricity generation costs between the "Reference case" and "Greenhouse gas $10" scenarios. We apply that difference as a percent increase to the generation portion of the volumetric charge (taken to be 7/16 in SDG & E's service territory).

[12] We run the same greenfield analysis without the space constraint. Results show that high carbon costs do cause a shift in investment—from gas generators to solar PV and electric storage—in the larger two microgrids. Consequently, it seems a lack of space in which to install an optimal low-carbon configuration may inhibit efforts to decarbonize the grid through single-owner, single-property microgrids.

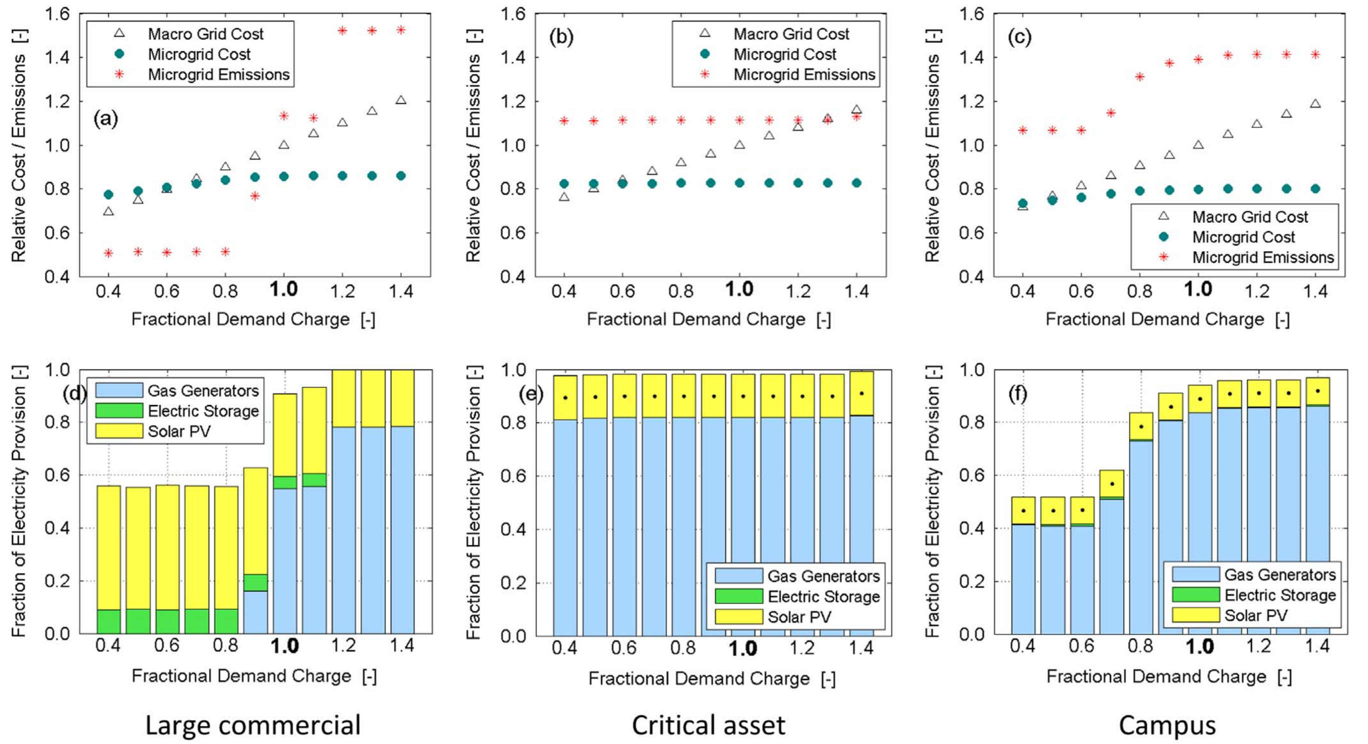

Fig. 9. (a)–(c) The total cost and total CO_2 emissions are normalized by the total cost to and total emissions of the macro grid customer, respectively, for the nominal demand charge (unity; bolded); and (d)–(f) the fraction of electricity supplied by microgrid resource across variation in demand charges. Each bar shows results from a single model run. The uncolored portion above a bar represents purchased electricity. A dot in the solar PV bar denotes that the solar PV space constraint has capped installations.

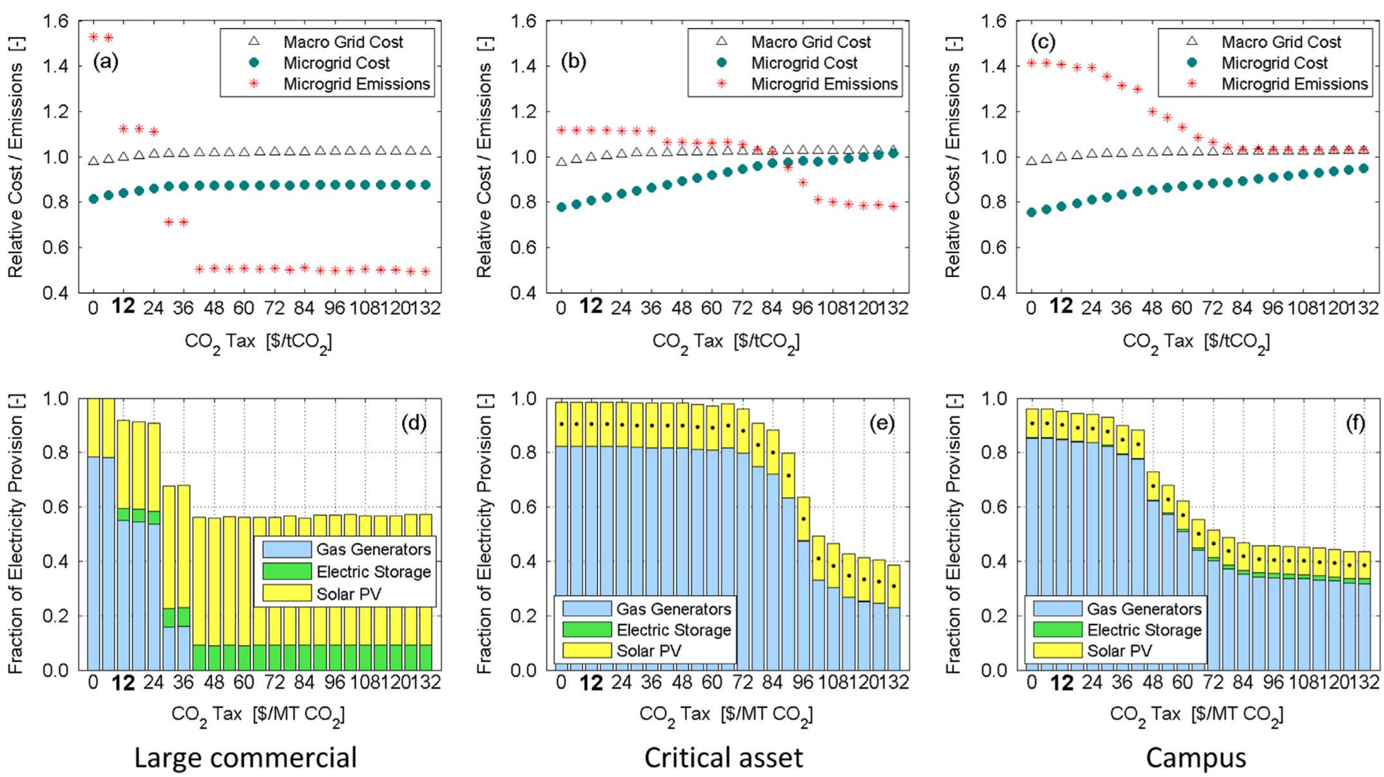

Fig. 10. (a)–(c) The total cost and total CO_2 emissions are normalized by the total cost to and total emissions of the macro grid customer, respectively, for the nominal carbon cost (12 \$/tCO_2; bolded); and (d)–(f) the fraction of electricity supplied by microgrid resource across variation in the carbon cost. Each bar shows results from a single model run. The uncolored portion above a bar represents purchased electricity. A dot in the solar PV bar denotes that the solar PV space constraint has capped installations.

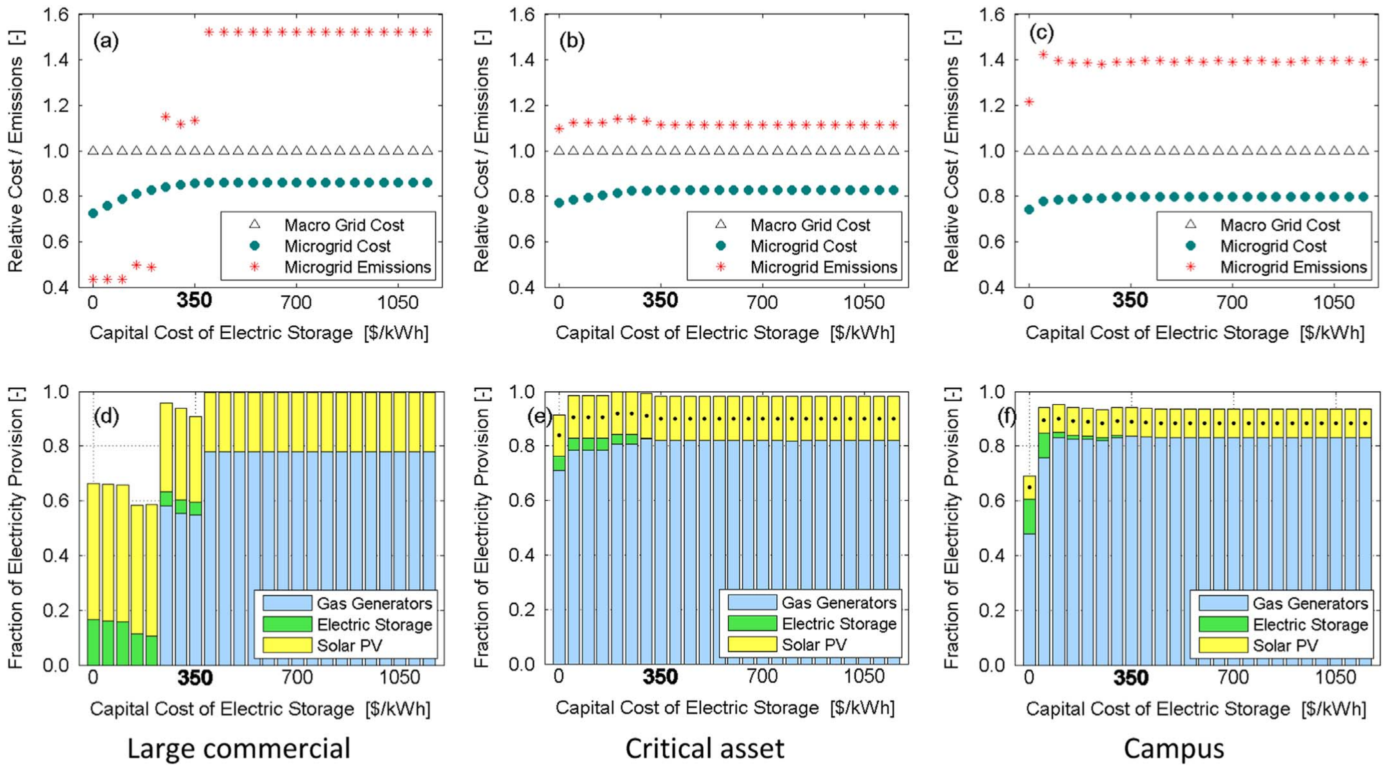

Fig. 11. (a)–(c) The total cost and total CO_2 emissions are normalized by the total cost to and total emissions of the macro grid customer, respectively, for the nominal electric storage cost (350 $/kWh; bolded); and (d)–(f) the fraction of electricity supplied by microgrid resource across variation in the electric storage cost. Each bar shows results from a single model run. The uncolored portion above a bar represents purchased electricity. A dot in the solar PV bar denotes that the solar PV space constraint has capped installations.

services from a microgrid can be cost-effective when compared with complete reliance upon macro grid utility service. Some of those conditions reflect changes in technology and market conditions; some are rooted in policy choices; and many reflect the interplay of technology, policy and markets.

We have focused here on the business case for investing in microgrids by focusing on the total cost of energy service for three different types of likely microgrid customers. Under prevailing conditions in southern California we find that the case for cost-effective shifts from pure utility service to microgrids is robust, and especially so for large customers who can utilize the intrinsic advantage that local production offers in managing electric and thermal loads in tandem. Centrally, the case for microgrids is a case for natural gas fired locally that also generates significant thermal energy. Though smaller microgrids by contrast rely relatively less on gas and more on renewables, across all microgrids gas generators supply the majority of on-site electric and thermal energy. While the work presented here looks only at the economics for energy provision, future work—including that planned by our team—can enhance this analysis by adding value streams derived from increasing reliability and resiliency. We are interested, as well, in exploring these new value streams in different climate and regulatory environments, as was done in (Maribu et al., 2007).

Through analyses of uncertainty we find that business cases are robust across a wide variation in parameters—costs of critical technologies, tariff rates, natural gas prices, and the price charged for carbon emissions—over which policy makers have some influence. Of particular importance for large microgrid systems is the price of natural gas, which regulators can influence only indirectly. Renewables and utility service are more attractive in a world with high gas prices, but gas remains an important player for larger systems even at 16 $/mmbtu. Preference for gas generators holds when carbon prices are independently high. In worlds where utility service costs are high and where DER technologies improve rapidly—plausibly, a world that California and other jurisdictions are now entering—the case for microgrids of all sizes is even more robust. This finding aligns with results in (Firestone et al., 2006), who similarly looked at the effect of tariff charge sensitivities on DER adoption.

For policy makers, there are at least two major implications of this work. The first concerns how policy makers might guide a nascent microgrid landscape by scaling up deployment. It is one thing for a scattered number of customers to switch to grid-tied microgrids for self-supply, but another for grid operations to be structured on a new topography of widespread distributed microgrids. Though more investigation is needed to explore how adoption may become widespread, our results indicate that microgrid deployment will likely resemble the former if left alone. Policy makers interested in the latter have the opportunity to shape deployment to align with larger social goals like reducing greenhouse gas emissions.

To this end policy makers have control over several important parameters—in particular, interconnection tariffs (which respond to regulatory decisions) and the cost of carbon (which is a policy choice). Policy makers also have the capacity to alter the cost of DER technologies—either directly with subsidies or indirectly through procurement mandates. We have been able to model some of these but the work presented here suggests the need for modelers to develop more sophisticated methods that capture both the full set of policy options available as well as of value streams policy makers might invoke to shape widespread deployment—for example as is happening in the northeast US states with resiliency-based systems. In jurisdictions such as California and New York that are actively pushing adoption of DERs it is that full set of policy options that will determine how markets could be developed.

The second implication for policy is perhaps more profound. Because the case for gas-based microgrids is so robust, policy makers may find that adoption of DER-friendly policy reforms leads to even more ubiquitous adoption of gas-based microgrids. Emissions from those systems are smaller when compared with some grids (those dominated by coal and gas generators) but they are not zero, and in many jurisdictions policy makers are setting goals for cutting emissions that probably require zero or negative emissions from electric power. California, for example, has a goal of 80% cuts in CO_2 emissions below 1990 levels by 2050. Assuming some emissions will continue to be needed from transportation, that economy-wide goal implies zero for the rest of the energy system. Policy makers who push DER and microgrids without simultaneously adopting a carbon price (or regulatory substitute) may unwittingly encourage the creation of a long-lived microgrid infrastructure that is incompatible with zero carbon.

Acknowledgements

The authors acknowledge and thank Michael Stadler and Gonçalo Cardoso from the Grid Integration Group at the Lawrence Berkeley National Laboratory for providing the DER-CAM model and consultation; Lukas Nonnenmacher, Bill Torre, Byron Washom, John Dilliot, and other team members at the University of California, San Diego for their comments and for providing data to aid the modeling process; a large California utility for providing real interconnection data; and numerous individuals at local utilities, the California Public Utilities Commission, and the California Independent System Operator, who contributed insightful guidance in the early stages of this work. The authors acknowledge also Ron Schoff and Robert Schainker of the Electric Power Research Institute (EPRI) for comments on a draft. This work was supported by EPRI, the Norwegian Research Foundation, and University of California, San Diego.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.enpol.2017.01.010.

References

Beer, S., Gómez, T., Dallinger, D., Momber, I., Marnay, C., Stadler, M., Lai, J., 2012. An economic analysis of used electric vehicle batteries integrated into commercial building microgrids. IEEE Trans. Smart Grid 3, 517–525. http://dx.doi.org/10.1109/TSG.2011.2163091.

Bronski, P., Creyts, J., Crowdis, M., Doig, S., Glassmire, J., Guccione, L., Lilienthal, P., Mandel, J., Rader, B., Seif, D., Tocco, H., Touati, H., 2015. The Economics of Load Defection: How Grid-connected Solar-plus-battery Systems Will Compete With Traditional Electric Service, Why it Matters, and Possible Paths Forward.

California Carbon Dashboard [WWW Document], 2015. URL ⟨http://calcarbondash.org/⟩ (accessed 5.28.15)

Christiansen, C., Murray, B., 2015. Energy Storage Study: Funding and Knowledge Sharing Priorities.

Conti, J.J., Holtberg, P.D., Diefenderfer, J.R., Napolitano, S.A., Schaal, A.M., Turnure, J. T., Westfall, L.D., 2015. Annual Energy Outlook 2015 With Projections to 2040.

Darrow, K., Hampson, A., 2013. The Effect of Departing Load Charges on the Costs and Benefits of Combined Heat and Power.

DeForest, N., Mendes, G., Stadler, M., Feng, W., Lai, J., Marnay, C., 2014. Optimal deployment of thermal energy storage under diverse economic and climate conditions. Appl. Energy 119, 488–496. http://dx.doi.org/10.1016/j.apenergy.2014.01.047.

Deru, M., Field, K., Studer, D., Benne, K., Griffith, B., Torcellini, P., Liu, B., Halverson, M., Winiarski, D., Rosenberg, M., Yazdanian, M., Huang, J., Crawley, D., 2011. US Department of Energy Commercial Reference Building Models of the National Building Stock.

Firestone, R.M., Marnay, C., Maribu, K.M., 2006. The Value of Distributed Generation under Different Tariff Structures.

Ghatikar, G., Mashayekh, S., Stadler, M., Yin, R., Liu, Z., 2016. Distributed energy systems integration and demand optimization for autonomous operations and electric grid transactions. Appl. Energy 167, 432–448. http://dx.doi.org/10.1016/j.apenergy.2015.10.117.

Hedman, B., Wong, E., Darrow, K., Hampson, A., 2012. Combined Heat and Power: Policy Analysis and 2011–2030 Market Assessment.

Interagency Working Group on Social Cost of Carbon, 2013. Technical Support Document: Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis Under Executive Order 12866.

Kann, S., Shiao, M., Honeyman, C., Perea, A., Jones, J., Smith, C., Gallagher, B., Moskowitz, S., Baca, J., Rumery, S., Holm, A., O'Brien, K., 2016. U.S. Solar Market Insight 2016 Q2.

Karl Magnus Maribu, S.-E.F., 2008. Combined heat and power in commercial buildings: investment and risk analysis. Energy J. 29, 123–150.

Maribu, K.M., Firestone, R.M., Marnay, C., Siddiqui, A.S., 2007. Distributed energy resources market diffusion model. Energy Policy 35, 4471–4484. http://dx.doi.org/10.1016/j.enpol.2007.03.005.

Marnay, C., Blanco, R., LaCommare, K.H., Kawann, C., Osborn, J.G., Rubio, F.J., 2000. Integrated Assessment of Dispersed Energy Resources Deployment.

Marnay, C., Venkataramanan, G., Stadler, M., Siddiqui, A.S., Firestone, R., Chandran, B., 2008. Optimal technology selection and operation of commercial-building microgrids. IEEE Trans. Power Syst. 23, 975–982. http://dx.doi.org/10.1109/TPWRS.2008.922654.

Maurovich-Horvat, L., De Reyck, B., Rocha, P., Siddiqui, A.S., 2016. Optimal selection of distributed energy resources under uncertainty and risk aversion. IEEE Trans. Eng. Manag..

Mendes, G., Feng, W., Stadler, M., Steinbach, J., Lai, J., Zhou, N., Marnay, C., Ding, Y., Zhao, J., Tian, Z., Zhu, N., 2014. Regional analysis of building distributed energy costs and CO_2 abatement: a U.S.-China comparison. Energy Build. 77, 112–129. http://dx.doi.org/10.1016/j.enbuild.2014.03.047.

Mendes, G., Marnay, C., Silva, C., Correia de Barros, M., Stadler, M., Ferrão, P., Loakimidis, C., 2013. Microgrid adoption patterns in Portugal and the U.S. In: Proceedings of the Santiago 2013 Symposium on Microgrids.

Momber, I., Gómez, T., Venkataramanan, G., Stadler, M., Beer, S., Lai, J., Marnay, C., Battaglia, V., 2010. Plug-in electric vehicle interactions with a small office building: An economic analysis using DER-CAM. IEEE PES Gen. Meet. pp. 1–8. ⟨http://dx.doi.org/10.1109/PES.2010.5589485⟩

New York State Energy Research and Development Authority, 2014. Toward a Clean Energy Future: A Strategic Outlook.

Nottrott, A., Kleissl, J., Washom, B., 2013. Energy dispatch schedule optimization and cost benefit analysis for grid-connected, photovoltaic-battery storage systems. Renew. Energy 55, 230–240. http://dx.doi.org/10.1016/j.renene.2012.12.036.

Nykvist, B., Nilsson, M., 2015. Rapidly falling costs of battery packs for electric vehicles. Nat. Clim. Chang. 5, 329–332. http://dx.doi.org/10.1038/nclimate2564.

Office of Energy Efficiency and Renewable Energy, 2015. Commercial Reference Buildings [WWW Document]. URL ⟨http://energy.gov/eere/buildings/commercial-reference-buildings⟩ (accessed 7.26.15).

Reitenbach, G., 2016. Emerging Microgrid Business Models. Power Mag.

Rocha, P., Kaut, M., Siddiqui, A.S., 2016. Energy-efficient building retrofits: an assessment of regulatory proposals under uncertainty. Energy 101, 278–287. http://dx.doi.org/10.1016/j.energy.2016.01.037.

Saadeh, O., 2015. North American Microgrids 2015: Advancing Beyond Local Energy Optimization.

Shah, V., Booream-Phelps, J., 2015. Crossing the Chasm.

Short-Term Energy Outlook (STEO), 2016.

Siddiqui, A., Marnay, C., Edwards, J., Firestone, R., Ghosh, S., Stadler, M., 2005. Effects of Carbon Tax on Microgrid Combined Heat and Power Adoption.

Siddiqui, A.S., Firestone, R.M., Ghosh, S., Stadler, M., Edwards, J.L., Marnay, C., 2003. Distributed Energy Resources with Combined Heat and Power Applications

Siddiqui, A.S., Marnay, C., Firestone, R.M., Zhou, N., 2007. Distributed generation with heat recovery and storage. J. Energy Eng. 133, 181–210. http://dx.doi.org/10.1061/(ASCE)0733-9402(2007)133:3(181).

Stadler, M., Groissböck, M., Cardoso, G., Marnay, C., 2014. Optimizing distributed energy resources and building retrofits with the strategic DER-CAModel. Appl. Energy 132, 557–567. http://dx.doi.org/10.1016/j.apenergy.2014.07.041.

Stadler, M., Kloess, M., Groissböck, M., Cardoso, G., Sharma, R., Bozchalui, M.C., Marnay, C., 2013. Electric storage in California's commercial buildings. Appl. Energy 104, 711–722. http://dx.doi.org/10.1016/j.apenergy.2012.11.033.

Stadler, M., Marnay, C., Siddiqui, A., Lai, J., Coffey, B., Aki, H., 2009a. Effect of Heat and Electricity Storage and Reliability on Microgrid Viability: A Study of Commercial Buildings in California and New York States.

Stadler, M., Marnay, C., Siddiqui, A.S., Lai, J., Aki, H., 2009b. Integrated Building Energy Systems Design Considering Storage Technologies.

Stadler, M., Marnay, C., Siddiqui, A.S., Lai, J., Coffey, B., Aki, H., 2008. Effect of Heat and Electricity Storage and Reliability on Microgrid Viability: A Study of Commercial Buildings in California and New York States.

Stadler, M., Siddiqui, A., Marnay, C., Aki, H., Lai, J., 2011. Control of greenhouse gas emissions by optimal DER technology investment and energy management in zero-net-energy buildings. Eur. Trans. Electr. Power 21, 1291–1309. http://dx.doi.org/10.1002/etep.418.

US Energy Information Administration, 2015. Natural Gas Prices [WWW Document]. URL ⟨http://www.eia.gov/dnav/ng/ng_pri_sum_dcu_SCA_m.htm⟩ (accessed 8.18.15).

von Appen, J., Marnay, C., Stadler, M., Momber, I., Klapp, D., von Scheven, A., 2011. Assessment of the economic potential of microgrids for reactive power supply. In: Proceedings of the 8th International Conference on Power Electron. – ECCE Asia. pp. 809–816. ⟨http://dx.doi.org/10.1109/ICPE.2011.5944700⟩.

Wilson, R., 2002. Architecture of power markets. Econometrica 70, 1299–1340. http://dx.doi.org/10.1111/1468-0262.00334.