LBNL-60590 JART

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Environmental Energy
Technologies Division

April 2007

http://eetd.lbl.gov/EA/EMP/emp-pubs.html

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

ELSEVIER

Energy Policy 35 (2007) 4471–4484

ENERGY POLICY

www.elsevier.com/locate/enpol

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Received 29 September 2006; accepted 8 March 2007
Available online 27 April 2007

Abstract

Distributed energy resources (DER) technologies, such as gas-fired reciprocating engines and microturbines, can be economically beneficial in meeting commercial-sector energy loads. Even with a lower electric-only efficiency than traditional central stations, combined heat and power (CHP) applications can increase overall system energy efficiency. From a policy perspective, it is useful to have good estimates of penetration rates of DER under different economic and regulatory scenarios. We model the diffusion of DER in the US commercial building sector under various technical research and technology outreach scenarios. Technology market diffusion is assumed to depend on the system's economic attractiveness and the developer's knowledge about the technology. To account for regional differences in energy markets and climates, as well as the economic potential for different building types, optimal DER systems are found for several building types and regions. Technology diffusion is predicted via a baseline and a program scenario, in which more research improves DER performance. The results depict a large and diverse market where the West region and office building may play a key role in DER adoption. With the market in an early stage, technology research and outreach programs may shift building energy consumption to a more efficient alternative.

Keywords: Distributed generation; Technology market diffusion; Research valuation

1. Introduction

Distributed energy resources (DER), small-scale power-generating technologies close to energy loads, currently have a small market share but investments are expected to increase in the future, leading to a much more decentralized energy system (IEA, 2002). Recent improvements, in particular for small-scale thermal electricity generation and combined heat and power (CHP) technologies, are enabling a shift from traditional monopolistic electricity supply to empowered, semi-autonomous self-generation. While small-scale generators by themselves do not match the electrical efficiency of centralized power generation, they enable overall system energy efficiency to be higher once used together with CHP technologies, which allow waste heat to be recovered to meet heating loads. Because of the significant effect widespread DER adoption could have on the design and operation of building and utility systems, quality forecasts of DER market diffusion are vital, and developing them poses a major research challenge. This effort aims to develop a bottom-up model of economic DER adoption that can deliver reasonable forecasts of technology market diffusion and provide estimates of the benefits of alternative enhancements to DER equipment under different policy and economic scenarios. The method is generic in the sense that it allows for the inclusion of all types of DER equipment, including renewables, which are expected to see cost reductions and potentially increased public support in the future.

Technology introductions typically follow an S-curved pattern of diffusion with initial slow adoption followed by exponential growth and a later decline in the adoption rate (Rogers, 1962). This property has commonly been modeled with the use of an epidemic model with word-of-mouth as a driving underlying process, while other models have focused on the profitability for different actors as a main driver for technology adoption (Geroski, 2000). In the

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doi:10.1016/j.enpol.2007.03.005

Distributed Energy Resources Market Diffusion Model (DER-MaDiM) developed in this paper, it is assumed that DER market diffusion is driven by a combination of knowledge (its existence and performance) about the technology and the economic attractiveness of the investment in the technology. Distributed generation knowledge is assumed to be spread by a central information source, here assumed to be a federal outreach program, and by word-of-mouth. The economic attractiveness is modeled with the use of the Distributed Energy Resources Customer Adoption Model (DER-CAM), an optimization model developed at Ernest Orlando Lawrence Berkeley National Laboratory (LBNL). The objective function in DER-CAM is to minimize the total annual energy costs resulting from electricity and natural gas purchases, the best (if any) DER investment as well as DER operating and maintenance (O&M) costs (Siddiqui et al., 2005). The program output is an idealized set of DER technologies to install along with operating schedules for the equipment, including patterns of heat recovery. Building energy loads are obtained via DOE-2, a building energy load simulation program developed at LBNL.

Although DER capacity is growing in the USA, the market for DER is still in an early phase as a small share of buildings has installed DER. The developed diffusion model has been applied to a study to estimate DER market diffusion in the US commercial building sector under two different research and outreach scenarios. The work focuses on two of the most common technologies, reciprocating engines and microturbines, where reciprocating engines represent a well-established technology while microturbines are not yet fully developed. Optimal systems, cost and energy savings and optimal operation are found with DER-CAM for small and large versions of five building types: education, healthcare, lodging, mercantile, and office. Four regions are chosen to represent the diversity in US climate and energy rates: Atlanta, Boston, Chicago, and San Francisco. DER-CAM is solved for both research scenarios for a discrete number of years and annual results are found by linear interpolation between the years. DER-MaDiM combines the annual DER-CAM estimates of annual savings and optimal systems with the processes for spread of DER knowledge to estimate market diffusion. The model suggests there can be a significant, and possibly imminent, DER adoption in the USA. There are large regional differences in DER attractiveness; in particular, DER is attractive in the West region, but adoption is followed also in the Northeast and in the Midwest regions, while there is no sign of any near term investment in the South due to low electricity tariffs. Heat recovery, especially with absorption cooling, seems to be an essential technology for DER adoption. Research and outreach can play an important role in speeding up adoption, and funds spent on research can potentially be paid back via private savings and reduced emissions.

Section 2 presents the approach in more detail and describes the external modeling tools used in the analysis and explains the intuition and mathematical detail behind the diffusion model, DER-MaDiM. Section 3 presents the data used in the model, while Section 4 presents results of both the DER-CAM runs and the predicted market diffusion from DER-MaDiM. In Section 5, the assumptions and the modeling approach are discussed, and Section 6 concludes the analysis.

2. Modeling approach and modeling tools

The goal of the work is to predict the likely adoption of distributed generation in the US commercial building sector under various technology research, outreach and policy assumptions. A bottom-up approach is chosen, where the optimal systems and profitability are found for a set of representative buildings, while market diffusion depends on a combination of economics attractiveness and market knowledge of the technologies. The modeling approach can be viewed as the following three-stage process as shown below in Fig. 1:

(1) Development of prototypical commercial building load profiles, with the use of the building energy simulation program DOE-2, specific to various representative US locations, including data.
(2) Collection of energy tariffs and DER technology cost and performance data for present and future years and run of the DER-CAM to estimate the economic attractiveness of DER and optimal system size for all building types, regions, scenarios and a set of years.
(3) Application of the DER-MaDiM to estimate the likely annual DER market diffusion from the modeled economic attractiveness for the different building types and regions.

2.1. DOE-2 building simulations

To generate the load profiles, the widely used building energy simulation program, DOE-2, which was developed and is maintained by LBNL, was used. DOE-2 is a public

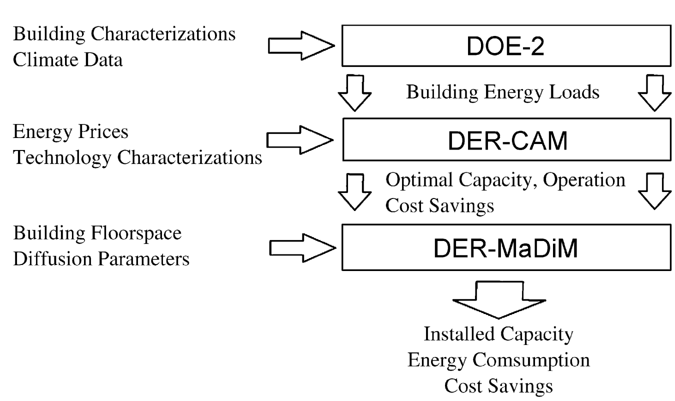

Fig. 1. Overview of the modeling approach.

domain computer program written in FORTRAN77 designed for analyses of energy consumption in buildings. DOE-2 estimates the hourly energy consumption in a building, given hourly climate data and information of the building heating ventilation and air conditioning (HVAC) equipment.

Logistically, it is impossible to simulate the broad range of buildings that characterize all commercial buildings in the USA using DOE-2 and DER-CAM. The data and computational demands would simply be too burdensome; therefore, judicious selection of representative buildings in representative locations is necessary. Based on the availability of weather data and a desire to include a representative range of climates and electricity and fuel cost environments, a set of buildings and regions is chosen for the analysis.

Basic input data such as building size are obtained from the Commercial Building Energy Consumption Survey (CBECS) 1999 building characteristic data (EIA, 2003), as will be discussed in the parameter section. The location of the building is defined by the typical meteorological year (TMY) data sets derived from the 1961–1990 National Solar Radiation Data Base and building characteristics are taken from Huang et al. (1991).

2.2. DER-CAM: DER adoption and operation via optimization

The profitability and optimal DER systems are found using the optimization model DER-CAM (Siddiqui et al., 2005) for the various building types, regions, years and scenarios. DER-CAM uses available data on a site's electric and heat loads along with tariff information, fuel prices, and candidate DER technologies characteristics to select a cost-minimizing set of discrete-sized DER technologies and determine their operating schedule over a given time horizon. In particular, the test site has several types of end-use loads that must be met. These are illustrated in the right-hand side of Fig. 2. The available resources to meet these end-use loads are indicated in the left-hand side of the same figure and are subject to thermodynamic laws governing the flow of energy. It is then the objective of DER-CAM to ensure that the end-use loads are satisfied during each time step of the horizon at minimum cost. For example, the cooling load may be met in one of four different ways: via electricity (that may be either purchased from the utility or generated on site), recovered heat (by employing absorption chillers), or direct burning of natural gas. Note that the Sankey diagram in Fig. 2 accounts for efficiency losses associated with energy conversion at each step.

In deciding how best to meet its energy requirements, the customer faces a trade-off between the capital cost of DER and the benefits of a lower energy bill (and greater overall system energy efficiency) in the future as a result of using DER. The latter is possible because even though on-site generation is not as efficient as central-station generation, the application of CHP in recovering heat enables the customer to reduce the cost of meeting its heat loads drastically. Furthermore, due to high demand charges in most energy tariffs, it is worthwhile to use on-site generation to meet electric loads since it enables the customer to reduce its peak load as presented to the utility.

DER generation options include natural gas fueled reciprocating engines, microturbines, gas turbines, fuel cells, and photovoltaics in different sizes. Given the large number of possible technology adoption and scheduling combinations, it is not computationally efficient to approach this problem using an exhaustive trial-and-error method. Mathematically, the customer adoption problem is a mixed-integer linear program that includes not only the DER technology adoption decision variable (which can take on non-negative integer values), but also the continuous operation decision variable (see Fig. 3). Since commercial algorithms exist to solve this type of problem, we implement it as DER-CAM in General Algebraic Modeling System (GAMS) and use CPLEX to solve it for

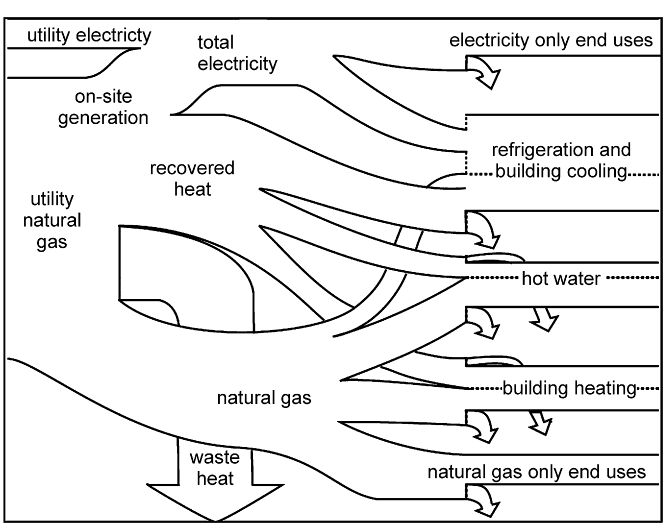

Fig. 2. Energy Flows in DER-CAM.

MINIMIZE

Annual energy cost

Electricity bill + Natural gas bill + DER amortized capital cost + DER O&M cost

CONSTRAINTS

Energy balance

Energy purchased + energy produced on site = energy demand

Operational constraints

Equipment must operate within rated capacity

Heat recovered is limited by electricity generated

Fig. 3. DER-CAM mathematical representation.

given parameters. Specifically, the solution to DER-CAM yields the DER investment decision and hourly operating schedule for the installed equipment over a test year. The run times are on the order of 10 min on a typical desktop PC.

2.3. Description of the technology diffusion model DER-MaDiM

This section introduces a way to model market diffusion as a function of the profitability and optimal systems found in the previous section. It is reasonable to assume that profitability is a factor that can help predict technology market diffusion. At the same time, it is a well-known fact that profitable projects are not necessarily adopted. A typical example from the energy sector is the slow diffusion of energy efficiency projects (Jaffe and Stavins, 1994). With this in mind, it should be clear that it cannot be assumed that all buildings where DER-CAM finds a profitable DER-system will actually adopt one. The slow investment in energy efficiency has been explained by the fact that such investments are not the core competence and focus for the potential developers and that the return might not be sufficient for all investors. In general, new technology, even if superior to existing alternative, typically experiences a slow initial adoption followed by an exponential growth until the market matures and growth slows down, thus producing the well known S-curve of market diffusion (Rogers, 1962).

Two competing ways of modeling the commonly observed technology patterns are through epidemic models and probit models (Geroski, 2000). Epidemic models explain the introduction of new technologies with the way knowledge about the technology (knowledge of its existence, how it works and trust in its performance) propagates to potential users. One version of epidemic models assumes a central source that transmits knowledge to a constant percentage of the potential users each year. However, the model fails to produce the commonly observed S-curve since growth will be largest in the beginning. A second epidemic model assumes that information is spread by word-of-mouth. This model produces an S-curve but fails to explain how the successful introduction of a new technology can be explained without initial installations. Geroski (2000) suggests using a mixed information source model with both a central source of information and a word-of-mouth process. Probit models, on the other hand, focus on the potential developer's characteristics to explain why some actors adopt new technologies before others. Characteristics, such as building energy profiles and local tariff structures, will affect the investment profitability, and therefore, the decision to adopt the technology. Such a model may produce an S-shaped diffusion curve depending on the assumptions of how profitability is distributed among potential adopter, how it evolves over time and the relationship between profitability and adoption.

The model developed in this work is a combination of an epidemic and a probit model. For the epidemic part, the central source of information is assumed to be outreach programs and research devoted to increase the understanding of DER, and in addition, knowledge is spread by word-of-mouth, which increases as installed capacity increases. Furthermore, individual building characteristics and DER economic attractiveness are modeled directly as described in the previous sections. That DER systems are more suitable for some particular buildings is reflected in the variability of energy bill savings found from the DER-CAM analysis. Hence, it is reasonable to assume that buildings with a higher percentage of energy bill savings are more likely to install DER. This assumption is implemented using a logistic adoption function where buildings with large savings are assumed to adopt DER at a faster rate than buildings with marginal savings. In addition, to take into account that some building will never adopt systems even with information and profitability in place either due to the building characteristics not captured by the model or a general lack of interest in the technology, the potential floorspace available for DER is lower than total commercial floorspace.

Each year a constant fraction of buildings, α, without DER receives information about the technologies from outreach programs. The remaining fraction of buildings obtains knowledge by a word-of-mouth process. The factor that decides the strength of the word-of-mouth process, β, is proportional to the fraction of commercial buildings with DER potential that has installed systems, X_m. Thus, the word-of-mouth process is increasing in strength as more users become aware of the technology. Of the buildings with knowledge of DER only a fraction, which is increasing with percentage savings on the energy bill, will actually install systems.

It then follows that the existing floorspace that adopts DER each year, m, is the product of the percentage of the market with DER knowledge, the adoption function for existing buildings,$f_{Ej,k,l,m}$, and the residual available floorspace, which is the total floorspace with DER potential, $F_{Tj,k,l,m}$, less the existing floorspace with DER, $F_{Dj,k,l,m}$, shown below:

$$A_{Ej,k,l,m} = (\alpha + \beta X_{m-1}) f_{Ej,k,l,m} (F_{Tj,k,l,m} - F_{Dj,k,l,m-1}). \quad (1)$$

New floorspace is added each year as new buildings are constructed. Because DER-MaDiM does not include the vintage structure of existing buildings and no buildings were phased out, new buildings were defined as the amount of gross new floorspace less the reduction to the existing floorspace due to retirements. New buildings adopt DER systems using the same process, but adoption is based on the adoption function in new buildings,$f_{Nj,k,l,m}$, and the new floorspace with economic potential for DER, $F_{Nj,k,l,m}$,

$$A_{Nj,k,l,m} = (\alpha + \beta X_{m-1}) f_{Nj,k,l,m} F_{Nj,k,l,m}. \quad (2)$$

The upper limit of the parameters α and β is that the sum must be lower than one, to ensure that less than 100 percent of buildings with DER economic potential have DER information. The adoption function for both existing and new buildings is a logistical function given as

$$f_E = \frac{c_E}{1 + a_E e^{-b_E s_{j,k,l,m}}} - \frac{c_E}{1 + a_E},$$
$$f_N = \frac{c_N}{1 + a_N e^{-b_N s_{j,k,l,m}}} - \frac{c_N}{1 + a_N}, \tag{3}$$

where a_E, a_N, b_E, b_N, c_E, c_N, are parameters and $s_{j,k,l,m}$ is annual savings on energy bill from DER. Total annual floorspace that adopts DER is the sum of adoption in existing and new buildings:

$$A_{Tj,k,l,m} = A_{Ej,k,l,m} + A_{Nj,k,l,m}. \tag{4}$$

Net new floorspace is added to the total floorspace:

$$F_{Tj,k,l,m} = F_{Tj,k,l,m-1} + F_{Nj,k,l,m}. \tag{5}$$

Cumulative floorspace with DER is floorspace with DER last period added the new adoption:

$$F_{Dj,k,l,m} = F_{Dj,k,l,m-1} + A_{Tj,k,l,m}. \tag{6}$$

The fraction of buildings with DER is total floorspace with DER divided by floorspace with potential in US commercial building sector:

$$X_m = \frac{\sum_j \sum_k \sum_l F_{Dj,k,l,m}}{\sum_j \sum_k \sum_l F_{Tj,k,l,m}}. \tag{7}$$

The different result metrics (see Table 1) in each time period, are defined as the DER-CAM results, $d_{i,j,k,l,m}$, divided by building size, $z_{j,k,l}$, multiplied by the floorspace that actually adopts DER

$$R_{Ai,j,k,l,m} = \frac{d_{i,j,k,l,m}}{z_{j,k,l}} A_{Tj,k,l,m}. \tag{8}$$

Cumulative values over time of the different results, installed capacities, changes in energy consumption and private cost savings, $R_{Ti,j,k,l,m}$, are given as

$$R_{Ti,j,k,l,m} = R_{Ti,j,k,l,m-1} + R_{Ai,j,k,l,m}. \tag{9}$$

Results over different dimensions are obtained by summing over the indices. For example, results for the US commercial building sector as a whole are obtained as a summation over all Census Divisions, building types and building sizes that the floorspace is allocated to

$$R_{Ti,m} = \sum_j \sum_k \sum_l R_{Ti,j,k,l,m}. \tag{10}$$

3. Model data

Table 1 gives a description of the indices used in the study. All 4 US census regions are modeled and five building types in two sizes. Results are reported over nine dimensions. Four cities are assumed to represent the whole USA, in terms of climate and energy rates. The Midwest is represented by Chicago, the Northeast Boston, the south by Atlanta and the West by San Francisco.

3.1. Building data

Five buildings categories are used in the study. US commercial floorspace is dominated by mercantile (1300 Mm^2), office buildings (1200 Mm^2) and educational buildings (800 Mm^2). The two remaining categories, lodging (400 Mm^2) and healthcare (200 Mm^2) contribute less to the commercial floorspace. However, DER possesses varying degrees of potential with varying building size.

Table 2 displays the size distribution of US commercial floorspace in the five building types. Notice that healthcare buildings have most of the floorspace in the largest categories, while mercantile buildings have a low share in the two largest categories. The remaining building types have more even size distributions.

To determine which building sizes to model in DER-CAM, an analysis to estimate the peak loads of each selected building type was conducted. The CBECS (EIA, 2003) categorizes each building type by area and also reports the energy intensity per square meter of each building type. The building area and energy intensity are used to determine the buildings sizes where peak electricity is more important than other characteristics. The peak load to total energy consumption ratio and intensity were applied to estimate the peak load of each building type in each building size category defined by CBECS.

Table 3 presents the peak load by building type and size and the selected range of building size for candidate small-scale DER. This paper focus on DER is in the range of the

Table 1
Description of indices used in DER-MaDiM

	Result dimensions, i	Census regions, j	Building type, k	Building size, l
1	Total installed capacity	Midwest	Education	Small
2	Total installed capacity, reciprocating engines	Northeast	Healthcare	Large
3	Total installed capacity, microturbines	South	Lodging	
4	Installed capacity, electricity generation only	West	Mercantile	
5	Installed capacity with heat exchangers		Office	
6	Installed capacity with absorption cooling			
7	Change in electricity purchases			
8	Change in natural gas purchases			
9	Annual private cost savings			

smallest DER systems currently being installed, i.e. 100 s of kW, to the largest sites where reciprocating engines are still preferable to turbines, i.e. 1–2 MW. Motivated by this, buildings with peak demand in the range 300–2000 kW are considered attractive sites for microturbines and reciprocating engines. Two buildings, one large and one small, corresponding to the midpoint in the smallest size bin and the largest size bin in the CBECS size distribution, respectively, were selected for analysis in DER-CAM. The peak loads shown in bold indicate the minimum and maximum building sizes considered for each building type. Boston electricity intensity was used to define the two building sizes. The same building sizes are used for all regions. Table 3 shows that there are large differences in electricity intensity between the building types. Healthcare buildings have by far the highest electricity intensity while lodging buildings have the lowest intensity.

As there is little available information of regional building size distributions, it is assumed that the national size distribution is valid regionally. Buildings with a peak electricity load in the medium-size range of 300–2000 kW, are assumed to be most suitable for reciprocating engines and microturbines (80% of existing and 90% of new building). For buildings with a lower peak, DER system incurs high investment costs and low capacity factor and are not likely to be cost-effective for most buildings. However, some niche markets might exist and some development might come from the introduction of microgrids, where neighboring buildings can add their loads together to become an attractive DER site. It is assumed that 16% of existing and 18% of new buildings have a DER potential.

For buildings with peak loads over 2 MW, gas turbines can be strong competitors to reciprocating engines and microturbines. In addition, some large buildings have installed DER systems already. However, there is a potential market in some buildings where investment in large gas turbines does not provide a sufficient return, assumed to be 32% of existing and 34% of new building floorspace.

One building represents the minimum and the other represents the maximum size building likely to have a peak load in the 300 kW–2 MW range. Smaller buildings are assumed to adopt systems at the same capacity and energy consumption changes per floorspace as the small building and with the same percentage savings on the energy bill. Similarly, buildings larger than the maximum size building are assumed to adopt systems with a capacity and energy consumption per square meter equal to the large building, and have the same percentage annual savings on the energy bill. For building types with an intermediate size in installed capacity, changes in energy consumption and the percentage savings on the energy bill is a linear interpolation between the small and the large building. Instead of interpolating the results, an equivalent interpolation where the floorspace is shared between the buildings was performed. Hence, the total floorspace for each building type is allocated to the two building sizes.

Comparisons of the peak electricity load, total annual energy use, and fuel-to-electricity (F/E) ratio are shown in Table 4. The F/E ratio is highest for the educational building, followed by healthcare and lodging for all four cities. Notice the very low F/E ratio for mercantile buildings.

The load input to DER-CAM is given as hourly loads in three representative days for each month. Peak days have the average energy profile for the three non-holidays weekdays with the highest electricity demand, weekdays

Table 2
Size distribution of commercial building floorspace, percentage of floorspace in CBECS size bins (EIA, 2003)

Size (m^2) Median (m^2)	93–465 233	465–930 698	930–2325 1628	2325–4650 3488	4650–9300 6975	9300–18,600 13,950	18,600–46,500 32,550	>46,500 60,450	Sum
Education	3.5	4.6	9.1	18.6	22.1	15.3	13.5	13.5[a]	100
Healthcare	6.6	5.7[a]	4.7	9.6	9.2	11.0	26.4	26.8	100
Lodging	2.2[a]	6.3	9.6	25.3	16.8	11.7	17.6	10.6[a]	100
Mercantile	8.9	10.1	20.5	9.6	14.4	17.0	4.1	15.4	100
Office	10.1	8.8	12.3	9.9	16.2	14.3	13.0	15.5	100

[a]Assumed value. Data withheld in [3] because the relative standard error was greater than 50 percent, or fewer than 20 buildings were sampled.

Table 3
Commercial building peak load (kW electricity) for CEBECS size bins for Boston with modeled buildings in bold type (EIA, 2003)

Size (m^2) Median (m^2)	93–465 233	465–930 698	930–2325 1628	2325–4650 3488	4650–9300 6975	9300–18,600 13,950	18,600–46,500 32,550	>46,500 60,450
Education	11.5	34.5	80.5	172.5	**345**	690	**1610**	2990
Healthcare	18.25	54.75	127.75	273.75	**547.5**	**1095**	2555	4745
Lodging	7	21	49	105	210	**420**	980	**1820**
Mercantile	8.75	26.25	61.25	131.25	262.5	**525**	**1225**	2275
Office	10.75	32.25	75.25	161.25	**322.5**	645	**1505**	2795

Table 4
Electricity (EL) load, natural gas (NG) load and fuel-to-electricity ratio (F/E)

		Healthcare		Lodging		Mercantile		Education		Office	
		Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
Atlanta											
Peak EL load	kW	576	1193	460	1974	543	1230	360	1620	348	1401
Total EL load	MWh	3446	7082	2090	9012	2562	5881	627	2871	1175	4809
Total NG load	GJ	7057	11,934	3629	15,705	710	1143	2142	8997	1635	3826
F/E ratio		0.6	0.5	0.5	0.5	0.1	0.1	1.0	0.9	0.4	0.2
Boston											
Peak El load	kW	557	1150	420	1804	530	1202	332	1502	349	1385
Total EL load	MWh	3224	6591	1855	8027	2351	5413	586	2657	1100	4529
Total NG load	GJ	9789	17,188	49,67	21,504	1681	2867	3847	16,028	2551	6094
F/E ratio		0.8	0.7	0.7	0.7	0.2	0.2	1.8	1.7	0.6	0.4
Chicago											
Peak EL load	kW	584	1207	448	1925	536	1219	335	1507	350	1422
Total EL load	MWh	3252	6656	1886	8169	2373	5466	603	2726	1123	4615
Total NG load	GJ	9920	17,270	5486	23,758	1954	3406	4345	18,038	2750	6533
F/E ratio		0.9	0.7	0.8	0.8	0.2	0.2	2.0	1.8	0.7	0.4
San Francisco											
Peak EL load	kW	539	1112	383	1646	498	1133	304	1382	338	1342
Total EL load	MWh	3223	6597	1828	7890	22,93	5300	559	2577	1081	4457
Total NG load	GJ	7731	12,776	3324	14,404	278	396	1959	8322	1650	3707
F/E ratio		0.7	0.5	0.5	0.5	0.0	0.0	1.0	0.9	0.4	0.2

have the average load profile for remaining non-holiday weekdays and weekend days have the average load profile for weekend days and holidays. In Fig. 4, the weekday profiles for the large San Francisco office building in January and August can be seen. Most of the seasonal variation is in cooling and heating.

3.2. Distributed generation technology

Three gas-fired DER technology types were considered in the analysis: reciprocating engines, larger gas turbines and microturbines. Cost and performance data for these technologies in 2004 are interpolated from data provided in a study by the National Renewable Energy Laboratory (Goldstein et al., 2003) with additional data provided from work done at the LBNL (Firestone, 2004). Reciprocating engines and microturbines are considered in two sizes. In DER-CAM, each device can be purchased in one of three packages: as an electricity generation unit, as an electricity generation unit with heat recovery for space and water-heating applications or as an electricity generation unit with heat recovery for space and water heating applications and for cooling via an absorption chiller. Cost and performance data for these technologies in 2004 are summarized in Table 5. For this project, heat exchangers used to convert waste heat from DER equipment to useful end-use heat are assumed to be 80 percent efficient, as are combustors used to convert natural gas to useful end-use heat. The coefficient of performance (COP) of electric chillers is assumed to be 5 and that of absorption chillers to be 0.7.

3.3. Energy tariff data

The 2004 electricity tariffs for electric utilities serving the four cities under consideration are obtained from the LBNL Tariff Analysis Project's database of US electricity rates (LBNL, 2005). The three main components of a typical electricity tariff are: volumetric charges, demand charges, and monthly fees. Volumetric charges are in proportion to the electricity consumed each month; there are often different rates for different times of the day. Demand charges are in proportion to the maximum power of electricity consumption during each month, regardless of how often the maximum consumption occurs. There are often different rates for different times of the day, as well as occasionally a non-coincident rate, which is applicable to all hours of the day. The monthly fee is a fixed charge each month. Table 6 shows the 2004 electricity rates for all four cities.

The 2004 natural gas rates for the regions containing the four cities of consideration were obtained from the Annual Energy Outlook (AEO) 2005 Reference Case (EIA, 2005a), and are shown in Table 7. The rate used for non-DER natural gas consumption is the average commercial rate for each respective region. The rate for DER consumption is the average of the commercial rate and the core electricity generator rate. The core electricity rate reflects the lower volumetric cost of natural gas when it is consumed in the

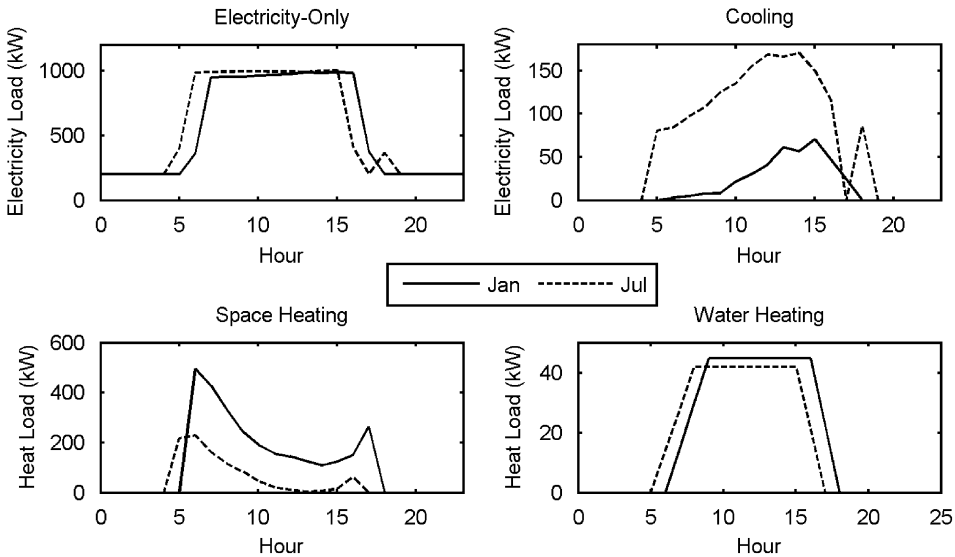

Fig. 4. January and July energy loads for the large San Francisco office building.

Table 5
2004 technology cost and performance data used in the DER-CAM analysis

	Gas turbine	Microturbines		Reciprocating engines	
	1 MW	100 kW	250 kW	200 kW	500 kW
Capital costs ($/kW)					
Electricity only	1403	1700	1400	900	795
Heat exchangers	1910	1980	1650	1225	1065
Absorption cooling	2137	2419	1976	1629	1339
Maintenance costs					
Fixed w/absorption cooling ($/kW)	11.9	17.1	12.8	15.9	11.0
Variable ($/kWh)	0.010	0.015	0.015	0.015	0.012
Lifetime (years)	20	10	10	20	20
Energy output					
Electrical efficiency	0.219	0.260	0.280	0.308	0.332
Heat to electricity ratio	2.45	2.29	2.29	1.88	1.55

Table 6
Assumed 2005 electricity rates for the commercial buildings (LBNL, 2005)

	Atlanta		Boston		Chicago		San Francisco	
	Summer	Winter	Summer	Winter	Summer	Winter	Summer	Winter
Volumetric ($/kWh)								
On-peak)	0.061	0.061	0.0815	0.693	0.056	0.056	0.1647	—
Mid-peak	0.061	0.061	—	—	—	—	0.1	0.1083
Off-peak	0.061	0.061	0.0594	0.56	0.0234	0.0234	0.0891	0.0891
Demand ($/kW)								
On-peak	—	—	—	—	14.24	11.23	11.8	—
Mid-peak	—	—	—	—	—	—	2.65	2.65
Non-coincident	—	—	24.72	11.54	—	—	2.55	2.55
Monthly fee ($)	2750	2750	166.67	166.67	39.93	39.93	175	175

higher quantities and more consistent rates of prime power DER rather than typical commercial building consumption. The AEO2005 (EIA, 2005a) was also used to estimate natural gas prices for 2012 and 2024. The scaling factors used to convert 2004 natural gas rates to 2012 and 2022 rates are shown in Table 10.

Table 7
AEO2005 natural gas rates in 2004 ($/kWh, HHV[a]) (EIA, 2005a)

	Heating purposes	For electricity generators
Atlanta	0.037	0.029
Boston	0.040	0.029
Chicago	0.032	0.027
San Francisco	0.032	0.029

[a]HHV refers to higher heating value. 1 kWh of natural gas contains 3412 Btu.

Table 8
Scaling factors for 2012 and 2022 electricity and natural gas prices (EIA, 2005a)

	Electricity		Natural gas		Natural gas (DER)	
Year	2012	2022	2012	2022	2012	2022
Atlanta	0.89	0.95	0.82	0.92	0.80	0.93
Boston	0.76	0.84	0.83	0.91	0.81	0.92
Chicago	0.88	0.98	0.81	0.93	0.77	0.93
San Francisco	0.84	0.83	0.87	0.97	0.86	0.93

The AEO2005 Reference Case (EIA, 2005a) is used to determine the change in electricity and natural gas prices in 2012 and 2022 relative to these same prices in 2004. The change in each region for the two future years is represented as a scaling factor; this scaling factor is applied to the 2004 rates from the LBNL Tariff Analysis Project (LBNL, 2005) to estimate rates for 2012 and 2022 as shown in Table 8. All components of the electricity tariff are multiplied by these scaling factors to obtain the future electricity tariffs used in DER-CAM. The natural gas volumetric price for DER service is less than that for standard (i.e. heating, cooking) service because DER consumption is more regular throughout the year; infrastructure costs can be spread out over a larger volume of gas consumption. As is apparent from Table 8 all multipliers are below 1.0; both electricity and natural gas prices are expected to stay under 2004 levels in all regions and all time periods. Natural gas fueled DER profitability depends on the difference between natural gas and electricity prices. A larger fall in natural gas prices than in electricity prices will thus improve DER economics.

3.4. Technology research scenarios

Forecasted estimates of technology cost and performance in 2004 and 2022 that reflect the Baseline and Program case assumptions are used to estimate the percentage improvements in cost and performance from 2004 to 2022. These percentage improvements were then applied to the 2004 technology data to obtain the 2022 data for both the Baseline and Program cases.

For the Baseline case, technology improvement from 2004 to 2022 is assumed to progress linearly; data for 2012 are, therefore, interpolated from the initial and final years. For the Program case, the technology is assumed to reach maturation in 2012, so that cost and performance data for 2022 are also used for 2012. The scaling factors used to convert 2004 cost and performance data to 2012 and 2022 data are provided in Table 9. Note that microturbines are predicted to improve in electrical efficiency and capital cost to a much greater extent than reciprocating engines, while gas turbine improvement is intermediate to these two technologies. Microturbines are expected to improve the most because they are the least developed of the three technologies.

Table 9
Scaling factors for 2012 and 2022 DER-CAM technology data

	Gas turbines	Microturbines	Reciprocating engines
2012 Baseline case			
Capital costs	0.890	0.737	0.882
Maintenance costs	0.834	0.907	0.928
Electrical efficiency	1.112	1.324	1.045
Heat to power ratio	1.017	0.892	0.994
2012/2022 Program case and 2022 baseline case			
Capital costs	0.837	0.479	0.807
Maintenance costs	0.834	0.773	0.800
Electrical efficiency	1.215	1.389	1.080
Heat to power ratio	1.043	0.950	1.011

Table 10
Adoption function parameters

	α	β	a_E	a_N	b_E	b_N	c_E	c_N
Baseline case	0.02	0.98	200	200	0.4	0.6	60	80
Program case	0.1	0.9	200	200	0.4	0.6	60	80

3.5. Technology diffusion parameters

Table 10 summarizes the parameters that determine the spread of DER knowledge and adoption as a function of percentage annual savings on the energy bill. In the Baseline case, two percent of buildings with DER potential are assumed to get DER information from outreach programs, while in the Program case 10 percent are reached. In both cases, the factor determining the strength of the word-of-mouth process, β, is at its maximum. The parameters determining the adoption function, which are the percentage of customers with DER information that actually install systems for a given cost-effectiveness, are assumed to be equal in both cases.

Fig. 5 is a plot of the adoption function for existing and new buildings. This figure illustrates a more aggressive DER adoption rate in new buildings. This is based on the assumption that when new buildings are constructed it is more likely that energy considerations are made, and that new buildings can be more flexible in incorporating DER systems. The maximum adoption rate for new buildings is

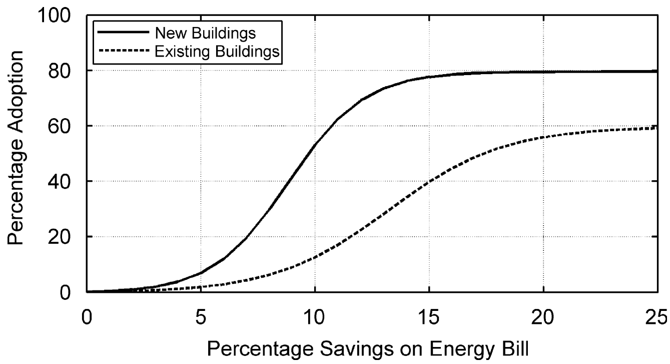

Fig. 5. Adoption curves for owners of new and existing buildings with DER knowledge.

80 percent and for existing buildings 60 percent. Note that the percentage of all considered buildings that adopt systems can be much lower, because actual relative adoption is calculated as the product of the adoption function and the floorspace with DER knowledge.

4. Results

4.1. Optimal distributed generation systems for the modeled buildings

This section presents the results from the DER-CAM optimization model, and thus, provides an overview of profitability and optimal DER system size across US regions, building types and technology scenarios. DER-CAM is solved for the 2004, the 2012 Baseline case, the 2012 Program case and for the 2022 case. In the 2022 case, there is no difference between the Baseline and Program case as technology improvements from the baseline case have caught up with the program case. Four scenarios, five building types in two sizes and four regions leave 160 different problems for DER-CAM to solve. Table 11 displays the optimal DER capacity found with DER-CAM for the 160 runs. DER systems are in general largest in San Francisco and in Boston while in Atlanta there is no optimal DER capacity in any of the cases. Table 12 shows the expected percentage savings in the energy bill in the same runs. San Francisco also has the highest savings on the energy bill for most building types, followed by Boston. The savings range from 4.5 to 31.8 percent of the annual energy costs. A comparison of Tables 4 and 12 suggests that the most important indicator of DER profitability in the US commercial sector is the building peak electricity load, as the two least attractive buildings are the two smallest and the larger version of both are attractive buildings for DER installations. That peak electricity load seems more important than energy load profiles can mean that DER is used widely to reduce peak demand. The large education buildings have the highest percentage savings on energy bill in Boston and Chicago, while the large healthcare building has the highest in San Francisco.

Table 11
Optimal installed capacity (kW) in the modeled buildings

	Healthcare		Lodging		Mercantile		Education		Office	
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
Atlanta										
2004 both cases	0	0	0	0	0	0	0	0	0	0
2012 baseline	0	0	0	0	0	0	0	0	0	0
2012 program	0	0	0	0	0	0	0	0	0	0
2022 both cases	0	0	0	0	0	0	0	0	0	0
Boston										
2004 both cases	200	1000	200	1200	0	0	0	700	0	500
2012 baseline	250	500	0	750	0	0	0	700	0	200
2012 program	250	750	250	1200	0	500	100	850	100	500
2022 both cases	250	1000	200	1250	250	500	100	1100	100	750
Chicago										
2004 both cases	0	0	0	0	0	0	0	0	0	0
2012 baseline	0	0	0	0	0	0	0	0	0	0
2012 program	250	250	100	750	0	0	0	600	0	250
2022 both cases	250	500	100	750	0	250	0	500	0	250
San Francisco										
2004 both cases	200	1000	200	1000	500	1200	0	500	0	1200
2012 baseline	200	1000	200	1000	500	1200	0	500	0	1200
2012 program	500	1000	250	1500	500	750	0	600	100	1200
2022 both cases	500	1000	100	1000	500	750	0	600	100	1200

4.2. Predicted DER market diffusion

Fig. 6 shows the modeled installed DER capacity in US commercial buildings from 2005 to 2025. The installed capacity in 2025 reaches 14.2 GW in the Baseline case and 20.7 GW in the Program case. This compares to the AEO2005 (EIA, 2005a) estimate of 1.8 GW. Several assumptions made in the AEO2005 estimate that is based on the National Energy Modeling System (NEMS) (EIA, 2005b) can help explain the difference in the results. Firstly, the AEO2005 estimate mainly based on adoption in new buildings, while DER-MaDiM allows for significant investment also in existing building stock. Secondly, payback periods are estimated based on only one capacity version per technology, which does not allow buildings to optimize systems as with the DER-CAM modeling. Lastly, the NEMS modeling does not allow for absorption cooling.

Table 12
Percentage savings on building energy bill

	Healthcare		Lodging		Mercantile		Education		Office	
	Small	Large	Small	Large	Small	Large	Small	Large	Small	Large
Atlanta										
2002 both cases	0	0	0	0	0	0	0	0	0	0
2012 baseline	0	0	0	0	0	0	0	0	0	0
2012 program	0	0	0	0	0	0	0	0	0	0
2022 both cases	0	0	0	0	0	0	0	0	0	0
Boston										
2002 both cases	13.5	14.1	11.1	16.1	0	0	0	23.2	0	14.2
2012 baseline	10.2	14.4	0	13.1	0	0	0	20.4	0	5.5
2012 program	18.7	14.9	12.3	16.7	0	9.2	12.0	29.8	13.4	13.9
2022 both cases	21.0	18.4	13.4	17.5	10.3	8.6	14.9	27.3	14.2	18.2
Chicago										
2002 both cases	0	0	0	0	0	0	0	0	0	0
2012 baseline	0	0	0	0	0	0	0	0	0	0
2012 program	10.8	12.1	6.7	13.0	0	0	0	17.2	0	7.3
2022 both cases	10.6	10.5	5.6	13.7	0	4.5	0	13.5	0	7.6
San Francisco										
2002 both cases	19.7	27.3	16.1	21.9	15.5	20.5	0	15.4	0	22.5
2012 baseline	19.7	28.3	15.8	23.8	15.3	20.0	0	15.4	0	22.1
2012 program	28.8	31.3	27.8	31.8	19.0	24.7	0	24.7	16.6	26.3
2022 both cases	24.7	27.3	19.7	26.8	14.2	20.5	0	22.9	14.0	21.9

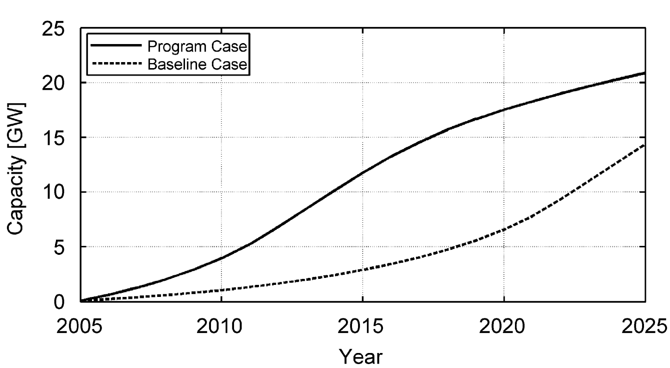

Fig. 6. Cumulative installed DER capacity in US commercial sector in Baseline and Program cases.

The Program case leads to an earlier and greater adoption of DER than the Baseline case. Cumulative capacity follows an S-curve with the highest growth in DER capacity around 2014. In the Baseline case, installed capacity shows exponential growth during the forecast period with a potential inflection point around 2025. The largest difference in installed capacity is in year 2019 at 11.1 GW. After 2019, growth is higher in the Baseline case because technology advancement is catching up to the Program case and because there is a larger undeveloped potential than in the Program case. Furthermore, observe that there is path dependence in these curves, whereby the difference between the Program and Baseline cases is not only a delayed development, but the path has also changed. This is due to two factors: first, stronger outreach programs create higher growth, and second, increased DER knowledge in periods where prices are favorable for DER can lead to an increase in capacity that will not be made up for later.

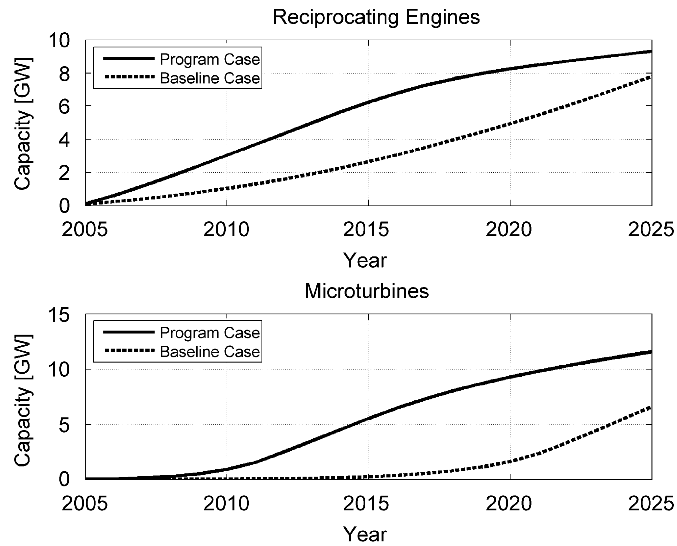

Fig. 7. Cumulative installed capacity of reciprocating engines and microturbines in the Program and Baseline cases.

Reciprocating engines are expected to experience only marginal improvements in performance during the forecast horizon. However, these improvements combined with a stronger technology outreach program and increased word-of-mouth from the successful implementation of microturbines leads to a higher installed capacity in the Program case than in the Baseline case (see Fig. 7). Microturbines represent a promising technology with expected cost reductions and performance improvements over time. In the Program case, investments in microturbines are expected to grow rapidly from 2010 and exceed the capacity of reciprocating engines by 2017. Notice the difference in the diffusion curves for reciprocating engines and microturbines in the Program case. Reciprocating engine capacity grows fast initially, but as microturbines become more competitive they take a larger share of the market. However, there is still a market growth for both, reflected by different buildings suitability to each technology. For example, in the Baseline case reciprocating engines are superior to microturbines.

Electricity consumption is decreased with on-site generation and the use of recovered heat through absorption chillers to offset electricity otherwise used for cooling. Natural gas consumption increases with on-site generation, but is partially offset by DER heat recovery that serve heating loads previously served by natural gas combustion. Fig. 8 shows that the reduction in electricity purchases and the increase in natural gas purchases follow the same S-curved patterns as installed capacity. In the Program case, 100 TWh of electricity is expected to be produced in commercial buildings in 2025. The largest difference in the two graphs is in 2017 when 67 TWh are produced in the Program case and 19 TWh in the Baseline case. From the figure, it can also be seen that the ratio of net changes in electricity purchases to net changes in building natural gas purchases is between 0.4 and 0.5. This ratio can be viewed upon as an efficiency metric, which can be compared to the central efficiency for delivery to the end-used. CHP systems have the potential to produce higher overall efficiencies. The reason for this discrepancy is that some of the recovered heat is used for cooling, which has a lower efficiency than direct heat use and that the generators are allowed to produce without any heat recovery if prices justify such operation. A considerable amount of the on-site generation occurs at peak hours when the efficiency is lower and the grid is heavily strained. In comparison to a central system, where some electricity will be lost under transmission and distribution, DER provides electricity on-site. The results represent a laissez-faire solution, exclusive of any policies to improve efficiency, such as a lower bound on efficiency or promotion of the use of waste heat.

When buildings install DER systems they reduce their energy costs. The cumulative annual private cost savings from building energy use for all US commercial buildings with DER is shown in Fig. 9. In 2015 the annual savings are $2.0 billion in the Program case and $0.5 billion in the Baseline case. In 2025 the difference in savings is reduced with savings of $3.5 billion in the Program case and $2.3 billion in the Baseline case.

The US consists of regions with diverse climates and energy markets. These differences are of major importance for DER attractiveness. As seen in Fig. 10, the West region, which is dominated by the dense population of California and high electricity prices and a cooling demand, is in position to be the leader in DER expansion. Also, the Northeast seems to be an area suited for DER with a later, but significant, development. DER expansion in the Midwest is expected to be more modest, while the low electricity rates in the South are a barrier to any DER potential. Both the Baseline and the Program cases show the same regional pattern. The West and Northeast are still expected to develop the majority of DER capacity in the Baseline case, but toward the end of the forecast period. In the Midwest, DER development is delayed 10 years and is considerably slower.

In the Program case, most DER is expected in office buildings followed by mercantile buildings (see Fig. 11).

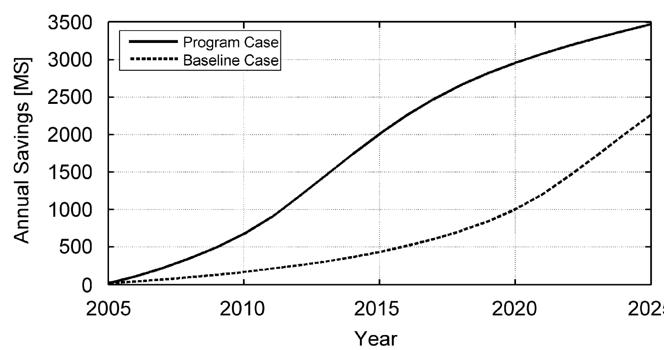

Fig. 9. Annual private cost savings from DER in Program and Baseline cases.

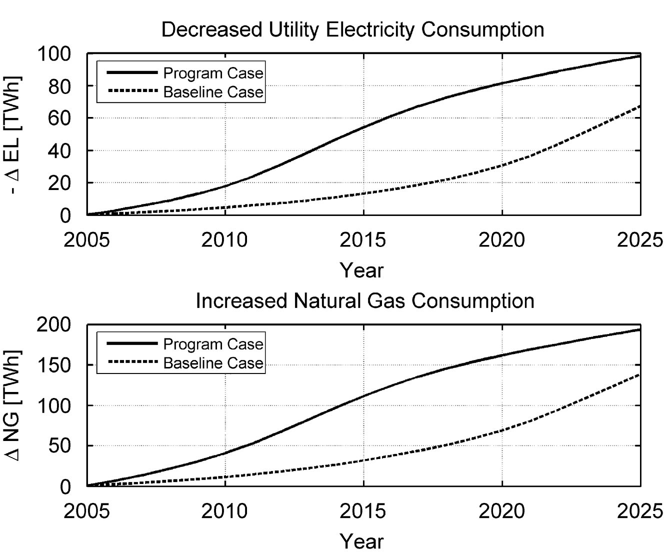

Fig. 8. Electricity produced on-site and increased natural gas consumption.

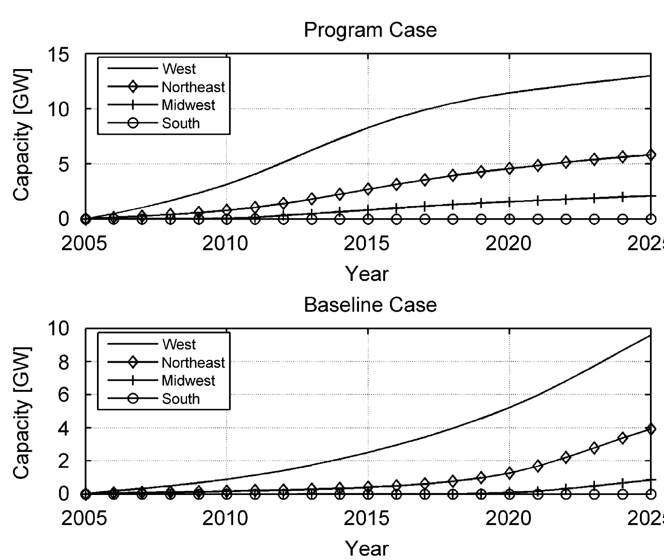

Fig. 10. Cumulative installed DER capacity in Census regions in the forecast period in Program and Baseline cases.

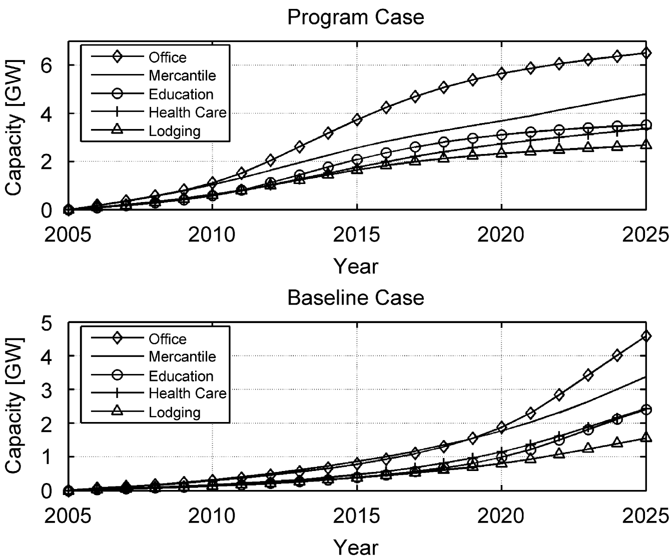

Fig. 11. Cumulative installed DER capacity for building types in Program and Baseline cases.

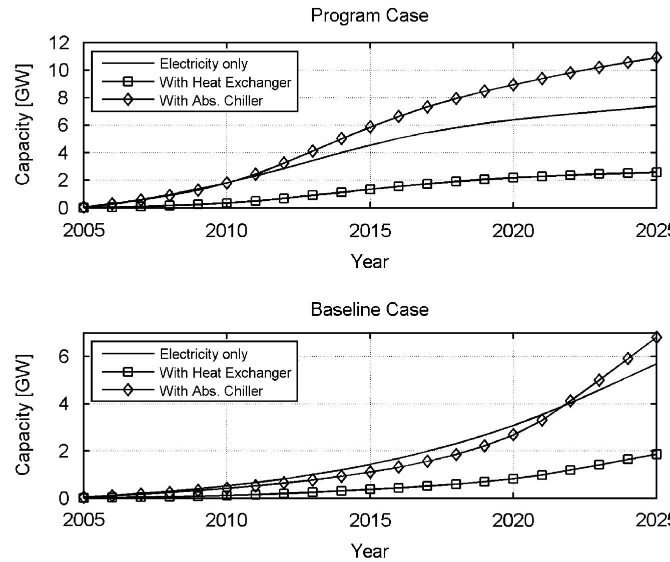

Fig. 12. Cumulative installed capacity with electricity generation only, heat recovery and absorption cooling in Program and Baseline cases.

Although the total floorspace for education buildings is much higher than for the healthcare and lodging buildings, the installed DER capacity is only slightly higher in the education buildings. Healthcare buildings are among the most attractive for DER sites, but they constitute a relatively small portion of US commercial floorspace. The Baseline case shows a similar, but not identical, pattern. Mercantile buildings are leading DER adopters until 2018 when healthcare buildings install more DER than both education and lodging. An explanation for this can be that office buildings are more suited to the improved microturbines than reciprocating engines.

Most of the installed capacity in both the Baseline and the Program cases comes with systems for heat recovery, as can be seen in Fig. 12. The most common installations have thermally activated cooling, which also comes with a heat exchanger and can be used to supply both cooling and heating loads. Notice that in the Baseline case, the most common technology until around 2022 can be used for electricity generation only while this is never the case in the Program case. Although most of the installed capacity has the ability to recover heat, a large share of the installed capacity does not. Capacity without the ability to recover heat does not have a high potential efficiency (see Table 5). The electricity-only generators profitability is reflected in the high volumetric electricity rates and demand charges for several utilities, probably due to expensive and, therefore, inefficient on-peak power and high transmission and distribution costs (see Table 6).

5. Modeling discussion

Predicting market diffusion of new technologies is not straightforward, which means that finding correct parameters for the model is a challenge. A possible approach to improving parameter estimation could be to estimate them from empirical data from the introduction of similar technologies such as energy efficiency equipment. However, each technology is itself unique, which makes comparisons difficult, as a lack of interest in energy efficiency equipment does not necessarily transfer to a lack of interest in DER. Another possibility is to estimate parameters based on surveys of building owners knowledge of DER and their willingness to invest under various cost-saving levels. In the early years of DER, it is hard to predict if building owners will embrace the technology and the word-of-mouth will be positive towards DER. If building owners have negative experiences with DER performance, then negative word-of-mouth could be a barrier to DER diffusion. This approach includes word-of-mouth as a net positive addition. When and if DER capacity increases, there will be more data available to estimate parameters for the diffusion processes and the modeling can provide more robust results.

Due to the difficulties in estimating investor behavior and the many uncertainties related to the driving variables of DER profitability, such as energy costs and technology cost developments, there is clearly significant uncertainty in forecasts of DER market diffusion. Several events have the potential to change diffusion rates rapidly. For example, a technological breakthrough in competing technologies, such as photovoltaics or large-scale power technologies, can easily change the future of reciprocating engines and microturbines. Likewise, a rapid change in natural gas costs could be a barrier to DER development, unless electricity prices increase concomitantly. A more comprehensive sensitivity analysis than comparing two DER research scenarios could reveal more of the effect of the assumptions underlying the forecast.

A potential improvement to the DER-MaDiM modeling approach is to allow for operational changes in the DER systems after they are installed when market conditions change. Similarly, the investment decision is based only on the energy prices in a particular year and does not include any expectation of future price developments. On the other hand, competition from other DER technologies is included to some extent by reducing the floorspace with DER potential, such as including a low fraction of the floorspace for larger buildings where gas turbines can be strong competitors. It could also be possible to include other technologies, such as photovoltaic systems and fuel cells, directly as competing technologies, if either they prove to be more competitive or they receive strong regulatory support. Finally, it would be possible to expand the modeling scope to include the effects of other energy policies on capacity expansion, cost savings and emissions reductions.

6. Conclusions

The results from the DER-MaDiM model suggest that there can be a large market for DER in US commercial buildings, even with only a modest research program and little technology outreach. It still reveals how significant an impact a stronger research program combined with more technology research can have on the potential to accelerate and increase DER investments. Investment in the research and outreach programs can be balanced by private savings on the energy bill. Satisfying electricity, heat loads and cooling loads with DER leads to a net increase in building natural gas consumption that is approximately double the increase in electricity production on-site. Over half of the installed capacity has the ability to recover heat and absorption cooling is the most common technology. However, a large share of the installed systems only has electricity-generation capability. Regulation and incentives have the potential to further improve the environmental benefits of DER. The West and Northeast are the regions where most DER capacity expansion is expected. The office and mercantile buildings can play a key role in wide-scale DER development.

Despite the inherent challenges in modeling technology diffusion, DER-MaDiM captures the major dynamics of technology diffusion for DER in modeling the spread of information from a central source and from a word-of-mouth process combined with the bottom-up DER-CAM approach to decide DER attractiveness for specific sites. Furthermore, the modeling approach allows for future extensions to analyze the effect of other energy market policies on market diffusion, cost savings and emissions reductions.

Acknowledgments

The work described in this paper was funded by the Assistant Secretary of Energy Efficiency and Renewable Energy, Distributed Energy Program of the US Department of Energy under Contract No. DE-AC02-05CH11231. The authors would also like to thank our Program Manager, Patricia Hoffman, and other members of the DE staff, especially Debbie Haught. The authors would also like to thank Nan Zhou for providing the building energy loads and Kristina Hamachi LaCommare and Judy Lai for helpful comments and discussions during the work process. This work builds on prior work by Owen Bailey, Jennifer Edwards, Etan Gumerman and Michael Stadler. The first author is grateful for the financial support from the Norwegian Research Council for the stay at Lawrence Berkeley National Laboratory.

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