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**Environmental Energy
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DISTRIBUTED ENERGY RESOURCES MARKET DIFFUSION MODEL

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ABSTRACT

Distributed generation (DG) technologies, such as gas-fired reciprocating engines and microturbines, have been found to be economically beneficial in meeting commercial-sector electrical, heating, and cooling loads. Even though the electric-only efficiency of DG is lower than that offered by traditional central stations, combined heat and power (CHP) applications using recovered heat can make the overall system energy efficiency of distributed energy resources (DER) greater. From a policy perspective, however, it would be useful to have good estimates of penetration rates of DER under various economic and regulatory scenarios. In order to examine the extent to which DER systems may be adopted at a national level, we model the diffusion of DER in the US commercial building sector under different technical research and technology outreach scenarios. In this context, technology market diffusion is assumed to depend on the system's economic attractiveness and the developer's knowledge about the technology. The latter can be spread both by word-of-mouth and by public outreach programmes. 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 then predicted via two scenarios: a baseline scenario and a programme scenario, in which more research improves DER performance and stronger technology outreach programmes increase DER knowledge. The results depict a large and diverse market where both optimal installed capacity and profitability vary significantly across regions and building types. According to the technology diffusion model, the West region will take the lead in DER installations mainly due to high electricity prices, followed by a later adoption in the Northeast and Midwest regions. Since the

DER market is in an early stage, both technology research and outreach programs have the potential to increase DER adoption, and thus, shift building energy consumption to a more efficient alternative.

1. INTRODUCTION

Distributed energy resources (DER), small-scale power generating technologies close to energy loads, are expected to become an important part of the future power system. Recent improvements, in particular for small-scale thermal electricity generation and combined heat and power (CHP) technologies, are enabling a dramatic 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 distributed generation (DG) adoption could have on the design and operation of building and utility systems, quality forecasts of DG market diffusion are vital, and developing them poses a major research challenge. This effort aims to develop a bottom-up model of economic DG adoption that can deliver reasonable forecasts of technology market diffusion and provide estimates of the benefits of alternative possible enhancements to DG 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 [1]. This property has commonly been modelled 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 adoption. In the Distributed Energy Resources Market Diffusion Model (DER-MaDiM), it is assumed that what determines DER market diffusion is a combination of knowledge about the technology and the economic attractiveness of the systems. The spread of DG 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 modelled 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 annual energy costs resulting from electricity, DG, and natural gas purchases as well as DG operating and maintenance (O&M) costs [2]. 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 DG capacity is growing in the U.S., the market for DG is still in an early phase as a small share of buildings has installed DG. The developed diffusion model has been applied to a study to estimate DG market diffusion in the U.S. commercial building sector under two different research and outreach scenarios. The work focuses on two of the most promising technologies, reciprocating engines and microturbines. 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 U.S. 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 DG knowledge to estimate market diffusion. The model suggests there can be a significant, and possibly imminent, DG adoption in the U.S. There are large regional differences in DG attractiveness; in particular, DG is attractive in the West region, but adoption is followed also in the Northeast and in the Midwest regions, while there is no signs of any market potential the South. Heat recovery, especially with thermally activated cooling, is an

essential technology for DG 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.

NOMENCLATURE

Indices

- i = Results (capacity, energy use, cost savings)
- j = Region (Northeast, Midwest, South, West)
- k = Building type (healthcare, lodging, mercantile, education, office)
- l = Building size (small, large)
- m = Time period (year)

Variables

- $A_{Ej,k,l,m}$ = Annual existing floorspace that adopts DG
- $A_{Nj,k,l,m}$ = Annual new floorspace that adopts DG
- $A_{Tj,k,l,m}$ = Annual total floorspace that adopts DG
- $F_{Dj,k,l,m}$ = Total floorspace with DG
- $F_{Nj,k,l,m}$ = Net new floorspace with DG potential
- $F_{Tj,k,l,m}$ = Total floorspace with DG potential
- $R_{Ai,j,k,l,m}$ = Annual change in result metrics
- $R_{Ti,j,k,l,m}$ = Cumulative result metrics over time
- X_m = Fraction of floorspace with DG

Parameters

- a_E, b_E, c_E = Adoption function parameter for existing buildings
- a_N, b_N, c_N = Adoption function parameter for new buildings
- $d_{i,j,k,l,m}$ = Annual DER-CAM results
- $f_{Ej,k,l,m}$ = Adoption function for existing buildings
- $f_{Nj,k,l,m}$ = Adoption function for new buildings
- $z_{j,k,l}$ = Building size
- $s_{j,k,l,m}$ = Percentage cost savings on energy bill
- α = Fraction of buildings without DG that gets knowledge from outreach programs
- β = Strength of the word-of-mouth process

2. MODELLING APPROACH

A bottom-up approach is chosen to model DG market diffusion. Optimal DG 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 modelling approach can be viewed as the following three-stage process as shown below in Figure 1:

1. Development of prototypical commercial building load profiles, with the use of the building energy simulation program DOE-2, specific to various representative U.S. locations, including data
2. Collection of tariffs and DER technology cost and performance data to run the Distributed Energy Resources Customer Adoption Model (DER-CAM) to estimate economic attractiveness of DG in a given building type, region, and in a set of forecast years
3. Application of the Distributed Energy Resources Market Diffusion Model (DER-MaDiM) to estimate the likely annual DG market diffusion from the modeled economic attractiveness for the different building types and regions

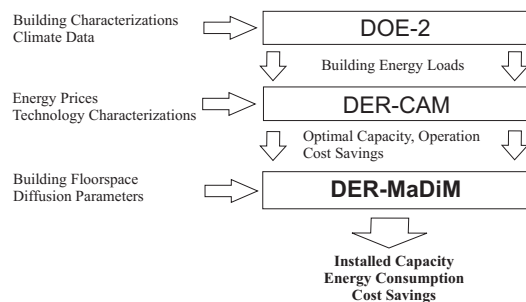


Figure 1: Modelling approach

2.1 External Modelling Tools

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 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. Building characteristics are taken from Huang et al. [3].

This study used DER-CAM to examine the economic potential for DG in the various building types, regions and years. Developed at LBNL, DER-CAM is a mixed integer linear program (MILP) written in GAMS (General Algebraic Modeling System) designed to factor many variables into determining the DG investment decision that minimize building energy costs with a given payback constraint. The DER-CAM solution provides both the generating equipment and the optimal operating schedule so that DG energy costs, utility electricity consumption, and carbon emissions are minimized. Input to DER-CAM includes the site's hourly end-use energy load,

electricity and natural gas supply costs, and DG technology adoption options. DG generation technology options include photovoltaics, natural gas fueled reciprocating engines, microturbines, gas turbines, and fuel cells. By matching thermal and fuel cell generation to heat exchangers and absorption chillers, heat recovered from natural gas driven generators can be used to offset heating and cooling loads. Figure 2 shows a high-level schematic of DER-CAM.

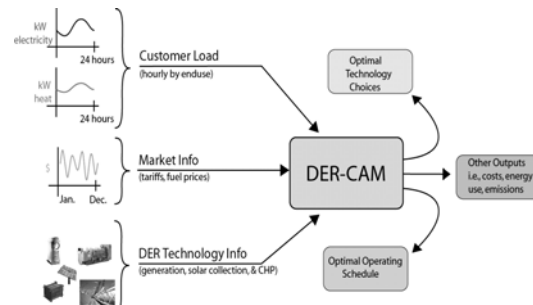


Figure 2: DER-CAM schematic

3. MATHEMATICAL MODEL DESCRIPTION

The objective of DER-MaDiM is to model the actual market diffusion of the technologies that may result from the optimal DG systems found by DER-CAM. In accordance with a study by Geroski [1], it is assumed that the introduction of a technology into a market is dependent on not only the cost attractiveness, but also the level of knowledge and trust in the technology. The introduction of a new technology in a market usually follows an S-curve. Two competing ways for addressing this logistic function are through epidemic models and probit models [1]. The former explain the introduction of new technologies with the means knowledge of the technology propagates to potential users. Probit models, on the other hand, focus on customer characteristics as an explanatory factor of why some firms adopt new technologies before others. Customer characteristics, such as building energy profiles, will affect the investment profitability, and therefore the decision to adopt the technology.

The model developed in this work is a combination of all three approaches. The central source of information is assumed to be outreach programs and research devoted to increase the understanding of DG, and in addition knowledge is spread by word-of-mouth. Further, individual building characteristics and DG economic attractiveness are modelled directly as described in the previous sections. The fact that DG systems are more suitable in some buildings than others 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 DG.

This assumption is implemented using a logistic adoption function where buildings with large savings are assumed to adopt DG at a faster rate than buildings with marginal savings.

Each year a constant fraction of buildings, α , without DG get information about the technologies from outreach programs. The remaining fraction of buildings can get knowledge by word-of-mouth. The factor that decides the strength of the word-of-mouth process, β , is proportional to the fraction of commercial buildings with DG 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 DG only a fraction, which increases with percentage savings on the energy bill, will actually install systems. Hence, the existing floorspace that adopts DG each year, m , is the product of the percentage of the market with DG knowledge, the adoption function for existing buildings, $f_{E,j,k,l,m}$, and the total floorspace with DG potential, $F_{T,j,k,l,m}$, less the existing floorspace with DG, $F_{D,j,k,l,m}$, shown below

$$A_{E,j,k,l,m} = (\alpha + \beta X_{m-1}) f_{E,j,k,l,m} (F_{T,j,k,l,m} - F_{D,j,k,l,m-1}) \quad (1)$$

New buildings adopt DG systems using the same process, but based on the adoption function in new buildings, $f_{N,j,k,l,m}$, and the new floorspace with economic potential for DG

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

The upper limit, or constraint 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 DG economic potential have DG information. The adoption function for both existing and new buildings is a logistical function given as

$$\begin{aligned} f_{E,j,k,l,m} &= \frac{c_E}{1 + a_E e^{-b_E s_{j,k,l,m}}} - \frac{c_E}{1 + a_E} \\ f_{N,j,k,l,m} &= \frac{c_N}{1 + a_N e^{-b_N s_{j,k,l,m}}} - \frac{c_N}{1 + a_N} \end{aligned} \quad (3)$$

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

$$A_{T,j,k,l,m} = A_{E,j,k,l,m} + A_{N,j,k,l,m} \quad (4)$$

Net new floorspace, $F_{N,j,k,l,m}$ is added to the total floorspace

$$F_{T,j,k,l,m} = F_{T,j,k,l,m-1} + F_{N,j,k,l,m} \quad (5)$$

Cumulative floorspace with DG, $F_{D,j,k,l,m}$, is floorspace with DG last period added the new adoption

$$F_{D,j,k,l,m} = F_{D,j,k,l,m-1} + A_{T,j,k,l,m} \quad (6)$$

The fraction of buildings with DG is total floorspace with DG divided by floorspace with potential in U.S. commercial building sector

$$X_m = \frac{\sum_j \sum_k \sum_l F_{D,j,k,l,m}}{\sum_j \sum_k \sum_l F_{T,j,k,l,m}} \quad (7)$$

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

$$R_{A,i,j,k,l,m} = \frac{d_{i,j,k,l,m}}{z_{j,k,l}} A_{T,j,k,l,m} \quad (8)$$

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

$$R_{T,i,j,k,l,m} = R_{T,i,j,k,l,m-1} + R_{A,i,j,k,l,m} \quad (9)$$

Results over different dimensions are obtained by summing over the indices.

4. MODEL DATA

Logistically, it is impossible to simulate the broad range of buildings that characterize all commercial buildings in the U.S. 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. Four cities are chosen to represent four U.S. regions: Boston represents the Northeast, Chicago the Midwest, Atlanta the South and San Francisco the West region. Figure 3 shows the total U.S. floorspace in the five buildings categories used in the study. As can be seen, mercantile and office buildings dominate U.S.

commercial floorspace. However, DG possesses varying degrees of potential with varying building size

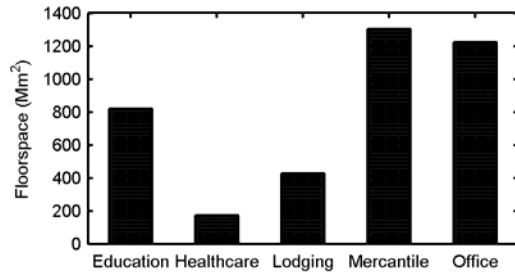


Figure 3: U.S. floorspace by building type [4]

To determine which building sizes to model in DER-CAM, a simple analysis to estimate the peak loads of each selected building type was conducted. The Commercial Building Energy Consumption Survey (CBECS) [5] categorizes each building type by area and also reports the energy intensity 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.

Reciprocating engines and microturbines are typically attractive for buildings with peak electricity load from a few hundred 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 300-2,000 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 (with peak load over 300 kW) and the largest size bin (with peak load under 2 MW) in the CBECS size distribution respectively, were selected for analysis in DER-CAM. Boston electricity intensity was used to define the two building sizes. The same building sizes are used for all regions. For this attractive DG size range 80 percent of existing and 90 percent of new floorspace are assumed to have DG potential. For buildings with a lower peak, DG incurs high investment costs and low capacity factor and is 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 DG site. For buildings with peak electricity loads under 300 kW, 16 percent of existing and 18 percent of new floorspace are assumed to have DG potential. 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. For buildings with a peak load over 2 MW, 32 percent of existing and 36 percent of new floorspace is assumed to have DG potential. Similarly, buildings larger than the largest modelled 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

Figure 4 is an example of the energy load data input to DER-CAM. It shows the weekday profiles for the large San Francisco office building. The load input 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 have the average load profile for remaining non-holiday weekdays and weekend days have the average load profile for weekend days and holidays. There are large differences in electricity capacity factors between the building types. Healthcare buildings have by far the highest capacity factor while lodging buildings have the lowest.

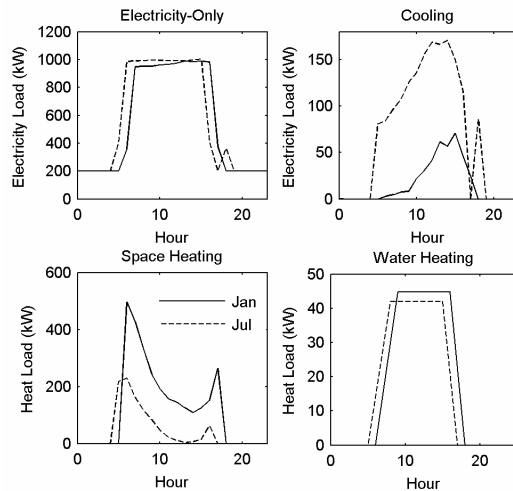


Figure 4: January and July weekday energy loads for the large San Francisco office building

Three gas-fired DG technology types were considered in the analysis: reciprocating engines, 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 [6] with additional data provided from work done at LBNL [7]. 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 cooling via an absorption chiller. Cost and performance data for the technologies in 2004 are

summarized in Table 1. For this project, heat exchangers used to convert waste heat from DG 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.

Table 1: 2004 technology cost and performance data used in the DER-CAM analysis

	Gas Turbine	Micro-turbines	Reciprocating Engines		
Capacity (kW)	1000	100	250	200	500
Capital Costs (\$/W)					
<i>El. only</i>	1.4	1.7	1.4	0.9	0.8
<i>Heat exch.</i>	1.9	2	1.7	1.2	1.1
<i>Abs. cooling</i>	2.1	2.4	2	1.6	1.3
O&M Costs					
<i>Fixed w/ abs. cooling (\$/kW)</i>	12	17	13	16	11
<i>Variable (\$/MWh)</i>	10	15	15	15	12
Lifetime (years)	20	10	10	20	20
Electrical efficiency	0.22	0.26	0.28	0.31	0.33
Heat-to-power ratio	2.45	2.29	2.29	1.88	1.55

The 2004 electricity tariffs for electric utilities serving the four cities of consideration are obtained from the LBNL Tariff Analysis Project's database of U.S. electricity rates [8]. 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 the month, regardless of how often the maximum rate 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. Table 2 shows the 2004 electricity rates for all four cities.

Table 2: Assumed 2004 electricity rates for commercial buildings (summer/winter) [8]

	Atlanta	Boston	Chicago	San Francisco
Volumetric (\$/MWh)				
<i>on-peak</i>	61/61	82/69	56/56	164/-
<i>mid-peak</i>	61/61	-/-	-/-	100/108
<i>off-peak</i>	61/61	59/56	23/23	89/89
Demand (\$/kW)				
<i>on-peak</i>	-/-	-/-	14/11	12/-
<i>mid-peak</i>	-/-	-/-	-/-	3/3
<i>non-coincident</i>	-/-	25/12	-/-	3/3

The 2004 natural gas rates for the regions containing the four cities under consideration were obtained from the AEO2005 Reference Case [9], and are shown in Table 3. The rate used for non-DG natural gas consumption is the average commercial rate for each respective region. The rate for DG consumption is the average of the commercial rate and the core electricity generator rate. This reflects the lower volumetric cost of natural gas when it is consumed in higher quantities and more consistent rates of prime power DER rather than typical commercial building consumption.

Table 3: AEO2005 natural gas rates in 2004 (\$/MWh, HHV) [9]

	For Heating Purposes	For Electricity Generators
Atlanta	37	29
Boston	40	29
Chicago	32	27
San Francisco	32	29

The AEO2005 Reference Case [9] is used to determine the change in electricity and natural gas prices in the two other years DER-CAM is solved for, 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 [8] to estimate rates for 2012 and 2022. All components of the electricity tariff are multiplied by these scaling factors to obtain the future electricity tariffs used in DER-CAM.

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 4. 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 4: Scaling factors for 2012 and 2022
DER-CAM technology data

	Gas Turbine	Micro-turbines	Recip. Engines
2012 Baseline Case			
Capital costs	0.890	0.737	0.882
Maintenance costs	0.834	0.907	0.928
Efficiency	1.112	1.324	1.045
Heat-to-power ratio	1.017	0.892	0.994
2012/2022 Program / 2022 Baseline Cases			
Capital costs	0.837	0.479	0.807
Maintenance costs	0.834	0.773	0.800
Efficiency	1.215	1.389	1.080
Heat-to-power ratio	1.043	0.950	1.011

In the Baseline case, two percent of buildings with DG potential are assumed to get DG information from outreach programs, while in the Program case ten 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 DG information that actually install systems for a given cost-effectiveness, are assumed to be equal in both cases. Figure 5 is a plot of the adoption function for existing and new buildings. This figure illustrates a more aggressive DG 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 DG systems. The maximum adoption rate for new buildings is 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 DG knowledge.

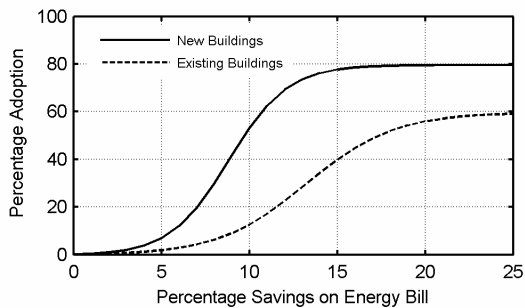


Figure 5: Relative adoption in new and existing buildings where owners has DG knowledge

5. RESULTS

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. The results are used as input to DER-MaDiM.

Figure 6 shows the modelled installed DG capacity in U.S. commercial buildings from 2005 to 2025. The Program case leads to an earlier and greater adoption of DG than the Baseline case. Cumulative capacity follows an S-curve with the highest growth in DG 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 DG knowledge in periods where prices are favorable for DG can lead to an increase in capacity that will not be made up for later. A commercial building DG capacity of 20 GW in 2025 can correspond to around 1.5 percent of U.S. electric capacity [9].

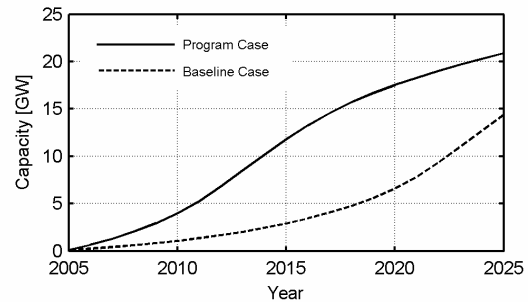


Figure 6: Cumulative installed DG capacity in U.S. commercial sector in Baseline and Program cases

Reciprocating engines are expected to experience 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 Figure 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.

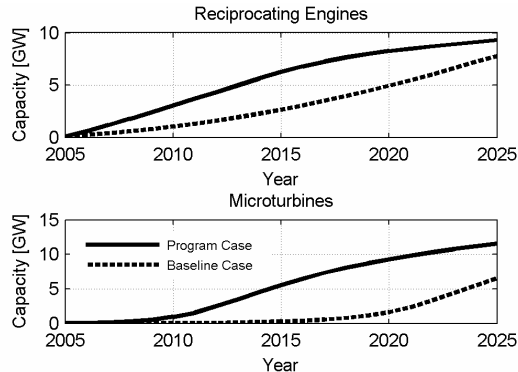


Figure 7: Cumulative installed capacity by technology

Electricity consumption decreases because of on-site electricity generation and the use of recovered heat through absorption chillers to offset electricity otherwise used for cooling. Natural gas consumption increases from on-site generation, but is partially offset by heat recovery for heating loads. Figure 8 shows that the reduction in electricity purchases and the increase in natural gas purchases follows the same S-curved pattern 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. The ratio of electricity generation to increased natural gas consumption can be viewed upon as an efficiency metric, which can be compared to the central efficiency for delivery to the end-user. In Figure 8 the ratio is around 0.5. Combined heat and power systems have the potential to generate at 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, DG 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.

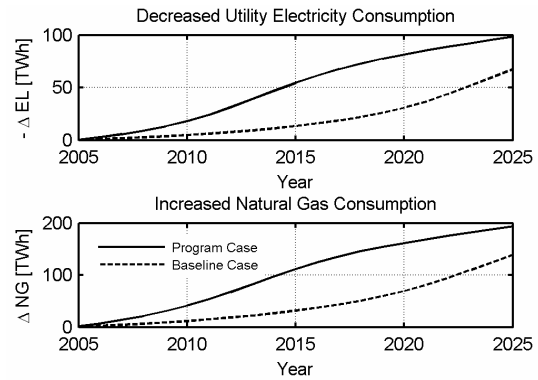


Figure 8: Changes in utility energy consumption

When buildings install DG systems, they reduce their energy costs. The cumulative annual private cost savings from building energy use for all U.S. commercial buildings with DG is shown in Figure 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.

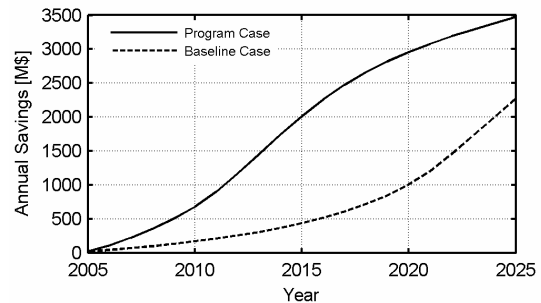


Figure 9: Annual private cost savings from DG

The U.S. consists of regions with diverse climates and energy markets. These differences are of major importance for DG attractiveness. As seen in Figure 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 DG expansion. Also, the Northeast seems to be an area suited for DG with a later, but significant, development. DG expansion in the Midwest is expected to be more modest, while the low electricity rates in the South are a barrier to any DG 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 DG capacity in the Baseline case, but toward the end of the forecast period. In the Midwest, DG development is delayed 10 years and is considerably slower.

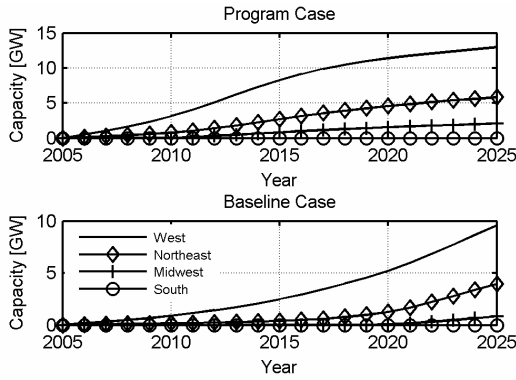


Figure 10: Cumulative installed DG capacity in U.S. regions

In the Program case, most DG is expected in office buildings followed by mercantile buildings (see Figure 11). Although the total floorspace for education buildings is much higher than for the healthcare and lodging buildings, the installed DG capacity is only slightly higher in the education buildings. Healthcare buildings are among the most attractive for DG sites, but they constitute a relatively small portion of U.S. commercial floorspace. The Baseline case shows a similar, but not identical, pattern. Mercantile buildings are leading DG adopters until 2018 when healthcare buildings install more DG than both education and lodging. An explanation for this can be that office buildings are more suited to the improved microturbines than reciprocating engines.

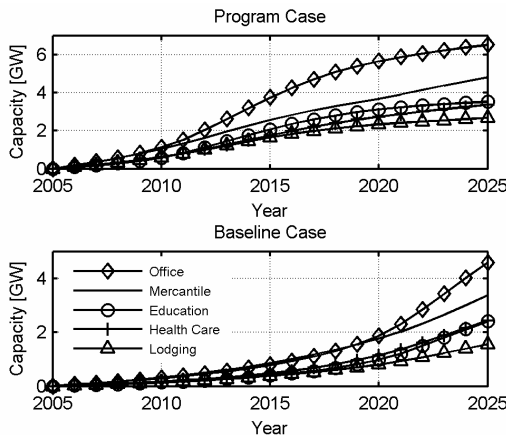


Figure 11: Cumulative installed DG capacity for building types

Most of the installed capacity in both the Baseline and the Program cases comes with systems for heat recovery, as can be seen in Figure 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 1). 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 2).

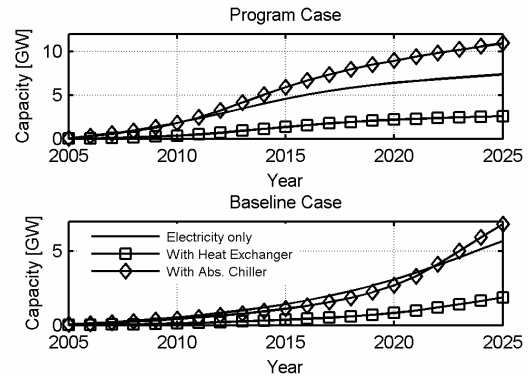


Figure 12: Cumulative installed capacity with only electricity generation, heat recovery and absorption cooling

6. CONCLUSIONS AND FURTHER WORK

The results from the DER-MaDiM model suggest that there can be a large market for DG in U.S. commercial buildings, even with only a modest research program and little technology outreach. It reveals how significant an impact a stronger research program combined with more technology research can have on the potential to accelerate and increase DG 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 DG 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 DG. The West and Northeast are the regions where most DG capacity expansion is expected. The office and mercantile buildings can play a key role in wide-scale DG development.

A weakness in the DER-MaDiM modelling approach is that the model does not directly allow for operational changes in the DG systems after they are installed as 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. Neither the vintage structure of the existing building stock nor the demolition of buildings is included in the analysis, but only a fraction of the entire building stock is included as potential DG buildings, and most buildings have an expected lifetime far beyond the analysis horizon. Competition from other DER technologies is included to some extent. This is accounted for by reducing the floorspace with DG potential, such as including a low fraction of the floorspace for larger buildings where gas turbines can be a strong competitor. It could also be possible to include more technologies, such as photovoltaic systems, directly as a competing technology if either they prove to be more competitive or there is a strong regulatory support for them.

Predicting market diffusion of new technologies is not straightforward, and finding appropriate parameters for the model is a challenge. A possible approach could be to base parameters on empirical data from the introduction of similar technologies such as energy efficiency equipment, but each technology is itself unique and has a unique market, which makes comparisons difficult. Another possibility is to base parameters on surveys of building owners' knowledge of DG and their willingness to invest under various cost-saving levels. Also, as DG capacity increases, there will be more data available to estimate parameters for the diffusion processes.

Despite the inherent challenges in modelling technology diffusion, DER-MaDiM captures the major dynamics of technology diffusion for DG in modelling 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 DG attractiveness for specific sites. The modelling approach can further be used to analyze the effect of other energy market policies in future studies.

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