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Modeling the Economics and Market Adoption of Distributed Power Generation

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Preface

This thesis is submitted in partial fulfillment of the requirements for the degree "Doktor ingeniør" (Dr. Ing) in the Department of Electrical Power Engineering at the Norwegian University of Science and Technology. My supervisor has been Ivar Wangensteen from the Department of Electrical Power Engineering, and my co-supervisor has been Bjørn Grinden at SINTEF Energy Research. A significant amount of the work was done when I was a visiting scholar at Ernest Orlando Lawrence Berkeley National Laboratory in Berkeley, California.

The thesis consists of a prologue and four separate papers that can be read independently of one another. The first three papers cover economic analyses of distributed power generation, while the third also models market diffusion of distributed generation technologies.

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Acknowledgements

Abstract

After decades of power generating units increasing in size, there is currently a growing focus on distributed generation, power generation close to energy loads. Investments in large-scale units have been driven by economy of scale, but recent technological improvements on small generating plants have made it possible to exploit the benefits of local power generation to a larger extent than previously. Distributed generation can improve power system efficiency because heat can be recovered from thermal units to supply heat and thermally activated cooling, and because small-scale renewables have a promising end-user market. Further benefits of distributed generation include improved reliability, deferral of often controversial and costly grid investments and reduction of grid losses. The new appeal of small-scale power generation means that there is a need for new tools to analyze distributed generation, both from a system perspective and from the perspective of potential developers. In this thesis, the focus is on the value of power generation for end-users. The thesis identifies how an end-user can find optimal distributed generation systems and investment strategies under a variety of economic and regulatory scenarios. The final part of the thesis extends the analysis with a bottom-up model of how the economics of distributed generation for a representative set of building types can transfer to technology diffusion in a market.

Four separate research papers make up the thesis. In the first paper, *Optimal Investment Strategies in Decentralized Renewable Power Generation under Uncertainty*, a method for evaluation of investments in renewable power units under price uncertainty is presented. It is assumed the developer has a building with an electricity load and a renewable power resource. The case study compares a set of wind power systems with different capacity and finds that capacity depends on the electricity price and that there under uncertain prices can be a significant value in postponing investment until larger projects are profitable. In the second paper, *Combined Heat and Power in Commercial Buildings: Investment and Risk Analysis*, a Monte Carlo simulation program to find the value and risk characteristics of combined heat and power units is presented. Using historical price data to estimate price process parameters, it is shown that uncertain prices should not be a barrier for investment, since on-site generators can adapt to uncertain prices and reduce the total energy cost risks. In, *Optimizing Distributed Generation Systems for Commercial Buildings*, which uses a mixed integer linear program, distributed generation portfolios that maximize profitability are tailored to a building's energy load. Distributed generation with heat recovery and thermally activated cooling are found profitable in an office and a health care building, using current generator data and energy tariffs from California. With the fourth paper, *Distributed Energy Resources Market Diffusion Model*, the analysis is taken a step further to predict distributed generation market diffusion. Market penetration is assumed to depend on economic attractiveness and knowledge and trust in the technologies. A case study based on the U.S. commercial sector depicts a large market for reciprocating engines and microturbines, with the West and Northeast regions driving market diffusion. Technology research and outreach programs can speed up and change the path of capacity expansion.

The thesis presents three different models for analyzing investments in distributed generation, all of which have benefits and disadvantages. Choice of model depends on the specific application, but the different approaches can be used on the

same problem to analyze it from different viewpoints. The cases in the thesis indicate that distributed generation can reduce expected energy costs while at the same time improve cost predictability. Further, the thesis identifies several important factors and potential barriers to distributed generation adoption. Analyzing distributed generation from the end-user perspective is important also for policy makers, because of the importance of estimating how the market will react to potential policy measures. The thesis shows that small-scale generating capacity has the potential to increase in the near future. Further research should increase the understanding of economic and environmental issues related to distributed generation, while policy makers should aim to construct and implement measures that make it attractive for end-users to invest in efficient local generating capacity.

List of Papers

I   Optimal Investment Strategies in Decentralized Renewable Power Generation under Uncertainty

Stein-Erik Fleten, Karl Magnus Maribu and Ivar Wangensteen

II   Combined Heat and Power in Commercial Buildings: Investment and Risk Analysis

Karl Magnus Maribu and Stein-Erik Fleten

III   Optimizing Distributed Generation Systems for Commercial Buildings

Karl Magnus Maribu

IV   Distributed Energy Resources Market Diffusion Model

Karl Magnus Maribu, Ryan M Firestone, Chris Marnay and Afzal S Siddiqui

Contents of Prologue

Introduction

Traditionally, electricity has been generated centrally in large power plants and transported to end-users through the grid system. In the future, the electricity system might consist of a combination of large central units and small autonomous power units distributed in the grid [1]. Distributed generation (DG), power generation close to electricity loads, offers end-users increased flexibility in provision of electricity as they can generate electricity on-site or buy from suppliers. When DG is economically attractive, the progress of the electricity system will be based on decisions made by a larger number of dispersed decision makers, as compared to the situation with the conventional central electricity system. Such a fundamental change in the electricity system creates a demand for new analytic tools and analyses to evaluate the economics of DG. This thesis aims to develop tools to evaluate the economics of distributed generation from the perspective of end-users and develop a method to predict how the economics for individual end-users can lead to market diffusion of the technologies.

The restructuring of the electricity system, which opened competition for electricity generation, has created a market for end-user technologies such as DG, which can provide lower energy costs and higher reliability. More frequent use of pricing schemes with incentives for end-users to change their consumption patterns has made DG more attractive. Technological progress has made several small-scale generation technologies competitive in many regions. Further cost reductions are expected as many of the technologies are not yet mature but have promising performances [2]. Generation closer to energy loads can supply electricity at high efficiency because otherwise wasted heat can be utilized and because grid losses can be avoided. Distributed generation can further provide an alternative to expensive and often controversial grid capacity investments. In addition, the end-user market is a potentially important market for renewable generation, which can be essential in the transition to a sustainable energy system.

This thesis consists of four separate papers, of which the first three apply three different methods to evaluate DG system economics from an end-user perspective, and the fourth is a bottom-up approach to predict DG market diffusion. In the first paper, *Optimal Investment Strategies in Decentralized Renewable Power Generation under Uncertainty,* a model for finding optimal capacity and investment thresholds for small-scale renewables, under uncertain wholesale electricity prices, is presented. The model is applied to a case where a land owner can invest in small-scale wind power and shows how investment in different capacities and waiting for new information is the optimal decision for different wholesale price levels. The second paper, *Combined Heat and Power in Commercial Buildings: Investment and Risk Analysis,* analyzes the risk characteristics and investment value of combined heat and power (CHP) applications under uncertain electricity and natural gas wholesale prices using Monte Carlo simulation. Since a CHP system has operational flexibility, and therefore protection against unfavorable prices, it is expected that value can increase with price uncertainty and that CHP systems can reduce the energy cost risk, which is confirmed in the paper. The third paper, *Optimizing Distributed Generation systems for Commercial Building*, introduces a mixed-integer linear program to find optimal DG systems for building energy loads. In the analysis of two commercial buildings in California, DG systems with heat recovery and absorption cooling are profitable in all price scenarios, and have

a carbon emission reduction potential. In the last paper, *Distributed Energy Resources Market Diffusion Model*, the analysis is taken a step further by trying to predict how the economics of DG technologies will results in market diffusion under various research and outreach scenarios. The model is applied to the U.S. commercial building sector and displays a large market with a forthcoming adoption in the West and Northeast. Further research and outreach has a potential to speed up and also change the path of market diffusion of efficient DG technologies.

This introductory chapter is divided into four main sections. The next section presents the various DG technologies with current costs and performance, and provides an overview of the driving forces behind DG adoption and the benefits and challenges of increased DG market penetration. Then the third chapter gives and introduction to the research questions and methodologies presented in the thesis. The last chapter summarizes the major findings in the thesis and suggests some policy recommendations and areas for further work in the DG economic modeling space.

Distributed Generation

Distributed generation is broadly defined as power generation close to energy loads [1]. Pepermans et al. [3] have reviewed the definitions of DG currently used in the literature. They found that more specific definitions of DG vary widely. Some definitions focus on capacity as the most important characteristic of DG, however, some include generating units with a capacity up to ten MW while others allow for up to 100 MW. Several DG definitions claim that distributed generation must be connected to the low-voltage distribution grid, while some also allow for connection at the high-voltage transmission grid. Other definitions vary according to technology and some even use the term solely for renewable generation. After studying the various definitions, Pepermans et al. [3] suggest to define distributed generation as, "An electric power source that is connected directly to the distribution network or at the customer side of the meter." This thesis will generally use this definition of distributed power generation. Distributed energy resources (DER) is a term often used with the same meaning as DG but the International Energy Agency (IEA) defines DER as DG plus demand side measures. Yet another commonly used term is microgrid, which usually refers to two or more DG units connected to the grid through one common connection. Microgrids can be established to allow several end-users to share their load and utilize DG units together.

Figure 1 displays both a central and a distributed power system. In the central power system, power is generated at a central source and then transmitted to end-users, while in the distributed power system part of the energy is generated at or close to the energy loads. DG can be installed in industrial, commercial and residential sector as shown in the figure.
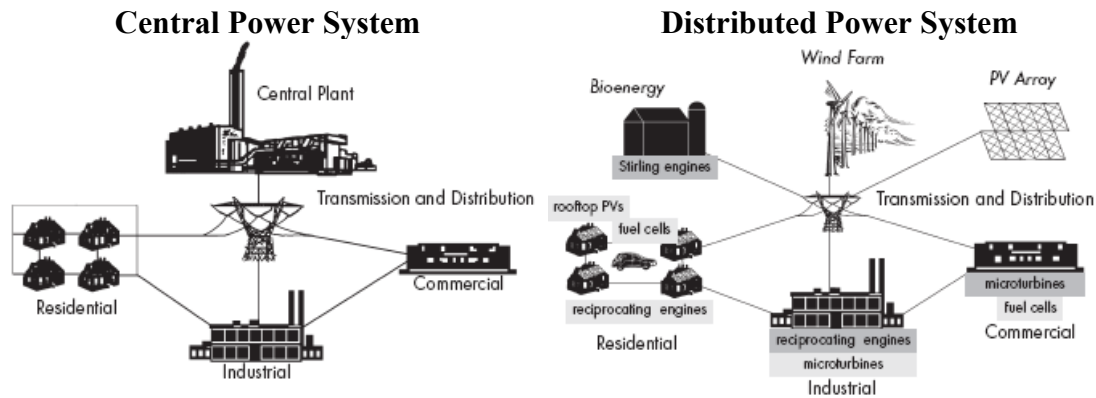
Figure 1: Central versus distributed power system, from [4]

Technologies and Applications

This section gives an overview of the most common DG technologies, which here are grouped into thermal and renewable generation technologies. Other related technologies such as storage and solar heating are also sometimes defined as DER but do not have electricity generating capabilities, which is the focus of this thesis.

Thermal Technologies

Thermal DG is mainly based on fossil fuels but can also be based on bio-fuels - therefore also thermal technologies can be renewable. The reason why thermal units or units that are based on combustion are separated from renewable technologies is that they have important common characteristics. Thermal generating units can be equipped to recover the heat that results from combustion, and such combined heat and power (CHP) systems can have high total efficiencies. CHP systems can provide heat and power for both industrial and commercial buildings. Tri-generation systems, which can utilize recovered heat in absorption chillers in addition to in heat exchangers, can have a large potential in regions with sufficient cooling loads [2]. Thermal DG technologies can successfully be applied for stand-by power for customers with high reliability needs, such as hospitals, elevator loads and water pumping. Customers with poor load factors and high demand charges can use thermal DG for peak-shaving by producing at peak electricity load hours. Also electricity utilities use thermal technologies increasingly for grid support and peak-shaving, which can defer grid investments. Thermal DG includes the following technologies:

- Reciprocating engines
- Gas Turbines
- Microturbines
- Fuel Cells
- Sterling Engines

Reciprocating engines (internal combustion engines) are widely used in automobiles and for marine transportation. Reciprocating engines are also presently the most common DG technology because they, as a well-developed technology, have relatively low costs. They are especially competitive in sizes under 1 MW but can be ordered in sizes up to 30 MW [1]. There are two main types of reciprocating engines: spark ignition and compression ignition based engines. Spark ignition units are typically fueled by natural gas when used for continuous operation but systems can also operate on bio-gas and landfill gas. Compression ignition units can operate on heavy fuel oil and diesel [5]. The technology of choice for most continuous power generating applications is spark ignited natural gas units, available in sizes from 10 kW to 7 MW. Reciprocating engines have many attractive characteristics: they generally have a high reliability, low start-up costs, they can follow electricity load well and have high part-load efficiencies [5]. The low start-up costs make reciprocating engines the technology of choice for stand-by and peak shaving purposes. There are alternatives with low investment costs but lower efficiencies, which can be particularly suitable for such applications. A negative aspect of reciprocating engines is nitrogen oxide and particle emissions, which can deteriorate air quality, making them inappropriate in populous areas [6]. However, these emissions can be reduced with catalytic converters.

Gas turbines are commonly used for propulsion of airplanes but have also, from as early as the late 30s, been used for electricity generation. While they for a long time have been used for peak power plants, technological advances have made them an attractive choice also for base-load power. For sizes over a few MW, gas turbines are often a more cost-effective alternative for continuous operation. In addition to having lower installation costs in comparison to reciprocating engines in that size range, they can be particularly attractive for industrial purposes due to the high temperature in the recoverable heat. Although the overall efficiency can be high when heat is recovered, the electric efficiency can be slightly lower than that of reciprocating engines [1]. Gas turbines have higher start-up costs than reciprocating engines, which make them less suitable for emergency and peak-shaving use. Therefore, the main application is CHP for industrial purposes and commercial buildings. One of the largest benefits of gas turbines is that they can generate electricity with very low carbon and nitrogen dioxide emissions [5].

Microturbines represent a less mature technology than reciprocating engines and gas turbines, and are therefore usually not competitive on a pure cost basis. Yet, prospects are optimistic for microturbines because costs are expected to fall and because they have low emissions of nitrogen oxides, due to a low combustion temperature. Microturbines can have as much as eight times lower emissions than diesel engines and 50 percent lower emissions than the best natural gas engines [5]. Microturbines are also attractive because they are relatively silent in operation and have higher reliability than reciprocating engines. The major application is for CHP in commercial buildings and for light industrial purposes, but they can also be used for peak shaving.

Fuel cells can generate electricity at high electric efficiencies (up to 60 percent) using hydrogen as the fuel. They are like microturbines, silent in operation and have very low emissions. The fuel cell technology is, however, in an early stage of development and costs are presently very high. Still, fuel cells are available on the market and systems are installed, but in 2001 the worldwide capacity was no more than 70 MW [7]. The commercially available units are a few hundred kW but several

companies have launched plans to introduce household sizes in a few kW. Potential applications will depend on the development in equipment performance; to date reliability has not been validated although some tests have been promising [5].

Sterling engines use an external combustion process to change the pressure of a gas that drives a piston to generate electricity, which makes them flexible in fuel use. They have their potential market in the residential and small commercial building sector. Models that are currently under development are in the size from 1-55 kW. Although they have a very high potential efficiency, available units have efficiencies comparable or lower than microturbines. Because of current costs the technology must overcome large technological hurdles before commercial applications can be commonplace [5].

Table 1 displays approximate costs and performance of the thermal DG technologies.

Table 1. Approximate costs and performance of thermal DG technologies [1], [5], [8]

	Reciprocating Engines	Gas Turbines	Micro-turbines	Fuel Cells	Sterling Engines
Fuels	*diesel, natural/bio gas, oil*	*natural / bio gas*	*natural/ bio gas*	*hydrogen*	*natural/ bio gas, oil,*
Size Range (kW)	20-5000 +	1000-	30-200	50-1000 +	1 -55 +
Efficiencies (%)	28-42	21-41	25-30	35-60	25 +
Turnkey Costs ($/kW)	350-1000	650-900	1000-1300	1500-3000	-
Heat Recovery Costs ($/kW)	200-400	100-500	200-400	200 +	-
Absorption Chiller Costs* ($/kW)	300-1000	250-800	400-800	300 +	-
O&M Costs ($/MWh)	5-15	3-8	5-10	5-10	-
CO_2 Emissions (kg/MWh)	500-650	580-680	~720	430-490	low
NOx - Emissions (kg/MWh)	0.2-10	0.3-0.5	~0.1	0.005-0.01	low

*Includes heat recovery

Renewable Technologies

The most important renewable DG technologies include

- Hydropower
- Photovoltaics
- Wind Power

Renewable distributed generation can be used to provide part or all of the electricity for residential and commercial buildings. Often renewables are used in rural areas without grid connection, but they can increasingly compete with central power generation on a pure cost basis. Renewable generation is typically very capital intensive but has low operating costs since there no fuel costs. In general, renewable generation is intermittent with the exception of small hydropower installations, which sometimes have some storage potential in small reservoirs. Hydropower is currently the most competitive small-scale renewable energy resource. In Norway, capacity is growing and systems have been found competitive at current electricity wholesale prices, without serving

private loads for which electricity must be purchased at end-user prices that also includes transmission costs [9].

Photovoltaic (PV) systems' costs are currently too high for a wide-spread commercial adoption. An advantage with photovoltaics is that their production profile coincides with the load profile and, therefore, also peak electricity prices in summer peaking electricity systems. However, capacity factors are fairly low, ranging from 10 % in Germany to 22 % in California [1]. Despite the costs, PV capacity is growing exponentially due to governmental support and high electricity prices in several regions. Most PV potential is assumed to be in the household size range because costs are similar for all sizes while the competing technologies have relatively higher costs for small installations. The state of California recently passed a bill that intends to promote installations on a million rooftops, or a total of 3000 MW PV installations by 2020 [10]. Such investments driven by subsidies can reduce PV costs because of expected learning effects. Combined with the currently intense research efforts in the field, the future can be bright for PV.

Small-scale wind turbines represent another currently immature technology that can expect significant cost reductions the coming years. The American Wind Energy Association [11] expects the costs for 5-15 kW wind generators to be reduced from around 3500 $/kW in 2002 to 1200-1800 $/kW in 2020 and the annual production for an average U.S. sites to be increased from 1200 kWh/kW to 1800 kWh/kW. Slightly larger wind turbines are currently profitable in good sites and in regions with high electricity costs. Several U.S. states have net metering regulation for small renewable energy installations, which allows the meter to run backwards, effectively allowing electricity generated at low load periods displace expensive retail priced electricity purchases. In Norway, case studies have found currently installed wind power projects with a positive net present value (NPV); in several of the cases, some of the load displaces electricity purchases from the local utility and the remaining electricity is sold at wholesale prices [9]. Large wind turbines are often clustered in large wind parks and connected to the grid at the transmission level. Such systems would not usually be considered distributed generation.

If costs are reduced, storage technologies can enhance the economics of renewable energy because the electricity generated at off-peak hours can be used at peak-hours and smaller systems can generate a larger share of the local demand.

Table 2 displays approximate costs and performance of small-scale renewable DG technologies. For wind power and hydro power, the costs especially depend a lot on the size due to economy of scale in production. The installation costs for PV systems are the main reason why there is a slight decrease in costs with size, as PV systems are modular. PV systems have the lowest capacity factors because generation is limited to daylight hours while hydropower units can have the highest capacity factors in cases with abundance of running water.

Table 2. Approximate costs and performance of renewable DG technologies [1], [12]

	Hydropower	Photovoltaics	Wind Power
Size (kW)	0.5+	0.2+	0.2+
Turnkey Costs ($/kW)	1000-6000	5000-9000	1000-3500
O&M Costs ($/MWh)	0.3-4	1-4	1-9
Capacity Factor	0.1-0.8	0.1-0.2	0.1-0.3
Expected Lifetime (years)	30	20-30	20

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Driving Forces, Benefits and Challenges

The International Energy Agency suggests that there are five main drivers behind the increased interest and policy attention given to DG: electricity market liberalization, developments of DG technology, constraints on construction of new power lines, increased customer demand for reliable power and concerns about climate change [1].

In a liberalized power market, electricity is sold in a competitive market and investments in generation capacity must recover the investment costs through uncertain electricity prices. This contrasts with a regulated environment where the investment risk usually is passed on to the end-user because electricity utilities can recover their costs through regulated electricity tariffs. Small units with lower investment lead times can have less associated risk than larger units because investment strategies based on them can be more flexible in adapting to uncertain prices. Further, with the liberalization process, time varying price signals are increasingly sent directly to end-users with electricity rates, such as real time pricing, which can be beneficial for DG units that typically operate during peak hours. The restructured market also allows for new niche DG markets such as supplying generators for increased end-user reliability [1].

Improvements in power electronics have made it possible to interconnect DG safely and a low cost to the grid [2]. In many regions of the world, distributed generation technologies such as reciprocating engines, gas turbines and small scale wind power are currently cost-effective alternatives to central power generation [6]. Several immature technologies have promising efficiency and emissions performance, and further investments and research can make them cost-competitive in the near future. Historically, the most efficient electricity generating units have been the largest units, but currently the most efficient gas turbines, for example, are around 40 MW [13].

Investments in power lines are lumpy by nature, often capital intensive and controversial due to health and esthetic concerns. DG can be an alternative to grid investments, and can be particularly beneficial under uncertain load forecasts because of their modularity. Several studies ([14];[15];[16]) have shown that DG can be used to defer investments in grid capacity thereby reducing system costs.

Modern power electronics can allow grid-connected DG to be utilized also after a grid outage, and thus, increase the reliability in electricity supply for a building with DG [17]. Electricity supply outages can infer large losses to certain groups of customers, and they will therefore often have a willingness to pay for the reliability improvements.

One of the largest environmental challenges facing us today is climate change, and the electricity sector is one of the largest emitters of greenhouse gases from the combustion of fossil fuels [2]. Distributed generation is important because it creates a market for renewable power generation, which has no operational greenhouse gas emissions. Further, distributed generation, which by definition is close to energy loads, allows for the utilization of the heat created by combustion that would be waste heat in a central power plant. The opportunity to use the recovered heat gives DG a high energy efficiency potential, and therefore an ability to reduce emissions of greenhouse gasses compared to central generation. DG can also improve energy system efficiency because there are no transmission losses; for example, in the U.S. energy system the average electricity grid losses are 9 percent [2]. In areas with cooling loads, absorption chillers, provide an opportunity to use heat also in periods and regions where heat loads are low.

A review of DER benefits by National Renewable Energy Laboratory [18] further lists the potential for voltage control and provision of ancillary services as important DER application and value.

Although distributed generation has several benefits, there are also many related challenges. One of the major challenges is operation of the grid with a high share of electricity generators outside the control of the system operator [5]. A high share of intermittent DG can be a particular challenge for the future reliability of the system. It should, however, be noted that the availability of standby generators also provides an additionl capacity which can be valuable under high demand periods; this was the case in New York in the summer of 2001 where DG generators helped avoid large outages [1].

Distributed generation can provide electricity without losses, but the effect on the distribution losses in the grid is more complicated. A study [19] found that low DG penetration usually decreases losses while a high penetration could increase losses. However, losses could be minimized with a high penetration if DG was sufficiently dispersed.

It is also important to realize that even though DG has a potential for a high efficiency when heat is recovered, the electrical efficiency for most resources are lower than modern central units. Therefore, improved system efficiency depends on the operation of DG. At the same time, central efficiency can be low at peak hours and even DG systems electrical efficiency can be higher than then central peaking units, especially when grid losses are accounted for. An increased share of DG, therefore, makes it even more important that the end-user see the real marginal price in the system because incorrect tariffs can lead to inefficient operation of the system as a whole.

Another challenge with DG is the fact that some of the units can lead to local emissions, which can be a realistic health concern. A study by Heath et al. [20] finds that the mass of pollutant inhaled per kWh of electricity generated can be up to a three orders of magnitude greater of DG units than by central Californian power stations due to the proximity of the generation to the population centers. The study question the common embrace of DG technologies that can increase public health burden. Thorough analysis should find balance in local and global emission concern and set regional emission standards.

Electricity utilities might see DG as competitor in supply of electricity and might, therefore, discourage DG, which has been seen in Japan [1]. Many countries have complicated connection rules which can be a barrier to DG adoption. Some countries have simple connection standards and several countries are currently establishing them to make DG adoption simpler [1]

Distributed generation has several benefits but also many related challenges. Most likely, capacity will increase in the coming years. Distributed generation market adoption and environmental and economic impact depend on technological progress, but also on research on DG system benefits and the willingness of policy makers to transform the knowledge of DG benefits to implementation of intelligent market design and energy policy.

Thesis Focus and Methodology

This section introduces the four papers and the methodologies that have been used in the analyses. The focus in the first three papers is on modeling investment strategies and economic value of distributed generation to end-users, whereas the fourth paper additionally models the relationship between the economic value for potential adopters and actual market diffusion. In a restructured market, the value of distributed generation is based on uncertain future electricity prices, and for thermal technologies, also uncertain fuel prices. Wholesale prices of electricity, in a restructured market, are set in the market place in the same way as prices of most other commodities, such as the common DG fuel natural gas.

The first paper, *Optimal Investment Strategies in Decentralized Renewable Power Generation under Uncertainty*, presents a method for evaluation of investments in renewable DG under price uncertainty, for a building owner with an electricity load and a renewable power resource. The owner of the building has a deferrable opportunity to invest in one power generating unit. It is assumed that the developer's objective is to maximize the profits from the renewables. A set of alternative power units, with different capacities and costs are compared for this analysis. The distributed power that is produced displaces local electricity load when they coincide, and the surplus electricity is exported to the grid. Increase in generator capacity means more power generation and a lower investment cost per kW, but at the same time, a larger share of the electricity is exported and thus valued at the lower export price. Since small units can produce most of the electricity at times when it is valued at the retail price, capacity choice is not straightforward and the capacity that maximizes NPV can be a function of the electricity price. With an uncertain and growing price it can be beneficial to wait for larger projects to be profitable. The problem is to find the price triggers, at which it is optimal to invest, and in which capacity to invest. The long-term electricity price is modeled as a geometric Brownian motion, a simple stochastic process commonly used for financial applications, and price process parameters are estimated from Nord Pool, the Nordic electricity market.

The paper uses real options methodology, a method to evaluate investment under uncertain market prices. The methodology has been developed from pricing methods for valuing stock options [21]. A stock option gives the holder the option to buy an underlying asset at a given price, the exercise price. European options only allow the owner to exercise the option at a specific time, while American options allow the owner to exercise the option anytime within over a given time horizon. Holders of a European option will exercise it if the asset price is over the exercise price while the holder of an American option only will exercise it if it has sufficient return. An opportunity to invest in a generating plant can be viewed upon as an American option with an infinite horizon if a concession is not setting a time limit on construction. The discounted value of the power plant is the underlying asset and the investment cost is the exercise price. Because DG developers usually can postpone the investment and because the underlying price that determines the value of the project follows a stochastic process, real option analysis provides a useful framework for evaluating DG investments. The use of a simple stochastic process, such as Brownian motion, allows for closed form solutions to the investment timing problem. In the paper, future electricity prices are estimated from the electricity forward markets. A forward market allows producers and

consumers of electricity to agree on prices for delivery in the future. Therefore, forward markets provide a risk-adjusted price forecast and historic data can indicate price volatility. For an introduction to the real option literature, the text books Dixit and Pindyck [21] and Trigeorgis [22] are good starting points. For further readings on stochastic price processes applied to energy commodities see Clewlow and Strickland [23].

Thermal DG profitability depends on stochastic fuel prices as well as electricity prices. Thermal generation technologies are different from renewables because they have operational flexibility, meaning that the power output levels can be controlled. With uncertain prices, flexibility usually has a value and such equipment can therefore be beneficial. As a simple illustration, every hour of operation of a DG plant can be viewed upon as a European option to generate electricity. The electricity price is the underlying asset, and the sum of the natural gas price and the operational costs represents the exercise price. The value of the plant is then simply the integral of all European options over the lifetime. Since operation can be viewed upon as options, it is natural to hypothesize that the value, as with financial options, increase with uncertainty and that DG, as financial options, can hedge the building cost risks. For most commercial buildings, the electricity tariff structure often includes a demand component that is proportional to the maximum electricity load over a month or a shorter period. Therefore, hourly operation is not independent of operation in other hours and operation levels must be found by optimization or by choosing the best of a set of alternatives. Still, operation has operational flexibility, since operation will depend on the stochastic prices. Another real option method for evaluating investments under uncertain prices is to use Monte Carlo simulation. In Monte Carlo simulation of stochastic prices, random numbers are drawn from a distribution to estimate price changes. Simulations of price paths are performed a number of times, and in each time step operational decisions are made and used to estimate profitability. After the simulations are completed, distributions of the plant profitability can be found. A strength of Monte Carlo-based methods is that they can be applied to more sophisticated price processes and models, for which there exist no closed form solution. For a broad introduction to Monte Carlo simulation with applications to finance, see the text book by Glasserman [24], and for applications to modeling energy prices see Clewlow and Strickland [23].

The second paper, *Combined Heat and Power in Commercial Buildings: Investment and Risk Analysis,* uses Monte Carlo simulation of the electricity and natural gas price to determine value and risk characteristics of investments in CHP systems. While the first paper considers the option to invest, this paper considers the option to operate, and it values the investment as a sum of the value of the options to operate. The analysis is from a developer's perspective, who would decide to invest based on a NPV criterion, that is invest in the project with the highest positive NPV with the required rate of return. Both electricity and natural gas prices are modeled as two correlated mean reverting processes, a process where it is assumed that prices have a tendency to revert back to a long-term average if they drift over the equipment lifetime. A set of alternative CHP systems with different capacity are compared in the analysis. On-site generation has operational flexibility, and will therefore operate when expected income is larger than expected cost. It is assumed that the building electricity consumption is subject to a daily demand charge and that on-site generators only can satisfy the local load, thus there are no exports to the grid. Operation levels are found as the level of a set

of discrete alternatives, which maximize profits for every time step and in every simulation. The results from the case study reveal that both investment value and standard deviation of the investment increase with uncertainty in the electricity price and that CHP has a potential to reduce building energy cost risk. The optimal size is sensitive to demand charges and energy costs.

A shortcoming of the real option analyses, both the one based on a closed form solution and the one based on Monte Carlo simulation, is that they only compare a discrete set of investment options. For an end-user who wants to invest in distributed generation systems there may be many different combinations of power generating equipment. Optimization or mathematical programming is concerned with finding the maximum or minimum of an objective function, often given constraint on the variables in the objective function. In linear programming, the objective function and constraints are linear while in integer programming the variables can only hold certain integer values. Uncertainty can be included in optimization programs by including price scenarios and probabilities. For an introduction to mathematical programming a good starting point can be the text book by Bertsimas and Tsitsiklis [25].

The model presented in the paper *Optimizing Distributed Generation Systems for Commercial Buildings* finds optimal systems and operation of distributed generation systems. Because DG units are sold in discrete capacities and because the operation levels of the generators are discontinuous the chosen methodology is mixed-integer linear programming. Several units with various cost and performance are considered for investment and the program can chose a combination of units as the optimal generating portfolio. The objective function in the model is to maximize annual benefits of DG systems. Important constraints are that displaced energy loads must be lower than the building load and that generators must produce within upper and lower limits if turned on. The model is applied to simulated load data for a health care and an office building in California. Important factors for distributed generation profitability under various price and regulatory assumptions are identified in the paper. With time-of-use (TOU) electricity prices with monthly demand charges, the ability to reduce demand charges can be a critical factor for the profitability of generating systems. In all modeled price scenarios, DG systems with heat recovery are profitable and have carbon emission reducing potential.

The first three papers have shown how individual end-users can evaluate investments in distributed generation. From a policy maker point of view it is essential to have an understanding of how DG economic attractiveness for the various building classes relates to actual technology diffusion. Different end-users will have different expectations of return on investment and different knowledge and trust in a new technology, which complicates prediction of DG diffusion. New technologies are usually diffused into the market with a slow initial adoption followed by an exponential growth and a later decline due to market saturation. Such S-curved market diffusion cannot be explained by economic attractiveness alone, but are due to the spread of technology knowledge and trust by word-of-mouth and sometimes outreach programs. The fourth paper, *Distributed Energy Resources Market Diffusion Model,* presents a model that can be used to predict market diffusion of distributed generation. The model is applied to a case to predict diffusion of distributed generation in the U.S. commercial building sector under different technical research and technology outreach scenarios. The work has focused on the most promising technologies in a short and medium term,

reciprocating engines and microturbines. Distributed generation market diffusion is assumed to depend on a combination of economic attractiveness and the knowledge about the technology in the market. Economic attractiveness is modeled with a bottom-up approach using a mixed-integer optimization program to find optimal systems, operation and profitability for a number of representative buildings. Optimal systems are found in five building types, two sizes and in four regions to account for differences in building characteristics, energy markets and climate. Technology knowledge can be spread by word-of-mouth and by information programs. Technology diffusion is predicted in two scenarios: a baseline scenario and a program scenario where additional research improves technology performance and stronger outreach programs increase the level of technology knowledge. The case shows that DG systems can be a profitable in for several building types and regions of U.S., and that DG adoption can increase substantially with continued technology research and outreach.

Thesis Conclusions and Recommendations

The first three papers in the thesis analyze investments in DG from the perspective of the end-user. The first paper, *Optimal Investment Strategies in Decentralized Renewable Power Generation under Uncertainty*, uses real options methodology to evaluate investments in wind power turbines of different sizes under uncertain electricity prices. Uncertain prices make it attractive to wait for a higher price in the market than the NPV break-even price. In the case study, wind turbines can displace electricity at a retail price, that includes both wholesale prices and transmission costs, and sell excess electricity at a lower wholesale price. The results suggest it is optimal to wait for significantly higher prices than the net NPV break-even price due to uncertainty and price growth. The optimal capacity choice depends on the current market price, expected price growth and price volatility because it can be valuable to wait for larger capacities to be more profitable. Reductions in price volatility will shrink the price levels where waiting is optimal. The model shows that developers of renewable DG may have incentives to postpone investment considerably to wait for larger units to be more profitable than the smaller units. Regulation that sets time limits on DG subsidies and the concession to install DG or that allows for net metering might give incentives to invest earlier.

The second paper, *Combined Heat and Power in Commercial Buildings: Investment and Risk Analysis,* uses Monte Carlo simulation to evaluate the value and risk characteristics of investments in CHP systems. The analysis suggests that uncertainty in wholesale prices should not be a barrier for investment in CHP because both the value and the CHP energy costs potential can increase with increased electricity price volatility. Value increases with uncertainty because CHP generators can adapt to the uncertain prices by changing operation levels; the on-site generators can benefit from high prices while they shut down when prices are low and thereby capture only the upside of the price volatility. Further, a large share of CHP value comes from transmission and distribution charges which often are more predictable than wholesale prices. A high correlation in the electricity and natural gas prices leads to a low standard deviation in the simulated NPV of the CHP systems; a reduction in the price correlation can increase the standard deviation in the NPV and expected NPV, because of

operational flexibility, and decrease the total building energy costs standard deviation. The analysis has shown that CHP units both can decrease expected energy costs and standard deviation under several electricity price parameter scenarios. Demand charges and transmission and distribution costs are important for choosing the size of on-site generating systems.

In the third paper, *Optimizing Distributed Generation Systems for Commercial Buildings,* optimal DG system are found with a mixed-integer linear program. The case study, based on San Francisco energy rates and climate, find DG to be profitable in a set of price scenarios for both a health care and an office building. Cooling technologies are found to be attractive in the temperate climate and with the high electricity tariffs. The DG systems can reduce carbon emissions compared to central generation. In the paper, the sensitivity in profitability to monthly demand charges shows that they can be of vital importance for DG profitability. Monthly demand charges are potentially risky for DG developers because the case of an unexpected outage in q peak electricity demand hour can lead to great losses. Therefore, demand charges can be barriers to DG development. The current tariff structure was created before widespread DG adoption and has assumed that buildings have predictable load profiles over the month. Distributed generation installation can make demand for utility electricity much more variable, therefore the tariff structure needs a review to make sure it gives the right incentives for adoption of efficient DG.

The first three papers introduce three different methods to evaluate DG investments, all of which have their benefits and disadvantages. The closed form real option method has the benefit of suggesting the timing of the investment, the Monte Carlo method can evaluate risk characteristics of an investment and are able to incorporate complex stochastic processes, while the optimization program can find the optimal combination of units. The different methods fit different problems and a main challenge lies in finding the correct method for each problem. If Monte Carlo simulation was applied to the renewable DG investment, risk characteristics of the investment could also be added. Monte Carlo analysis can also be applied to value the investment option by least squares Monte Carlo simulation, which includes a calculation of the expected NPV at different price levels [24]. Optimization would not be necessary in the wind turbines analysis because only investments in wind turbines were possible. The closed form real option method could be applied to the CHP problem, but only with a simpler price process assumption. The Monte Carlo and the optimization program are applied to similar problems and an investment evaluation could include both methods. The major drawback with the optimization program is that optimization programs only find optimal system based on maximization of the profits and will not report a next-best solution that can have a very close solution in terms of expected value and much more favorable risk-characteristics. For further work, more sophisticated simulation and optimization programs that allows for investment in several periods could be constructed, both least squares Monte Carlo simulation methods and multistage optimization programs. Although there will exist very many strategies for investment over many periods, a set of qualitatively different strategies compared with Monte Carlo methods and few systems with investment option only in a few stages for the optimization program could provide a DG developer with additional knowledge for choice of investment strategy.

The fourth paper, *Distributed Energy Resources Market Diffusion Model*, suggests a way of modeling how distributed generation can diffuse into markets under various technology research and outreach scenarios. The model is applied to the U.S. commercial market and the results depict a large and diverse market where both optimal installed capacity and profitability varies significantly across regions and building types. The technology diffusion model suggests that the West region will take the lead in on-site installations, and that the Northeast and Midwest regions will follow, while the low electricity costs in the South makes it impossible for on-site generation to compete with utility purchases. The analysis further describes a market in an early stage, where research and information outreach can shape the future. Technology research has the potential to increase distributed generation adoption and revolve technology adoption to a more efficient alternative. Outreach programs and marketing can speed up adoption.

This thesis develops three models for valuation and finding investment strategies in DG and one model for predicting DG market diffusion. The case studies show that DG can have a high economic value to end-users, and that DG can have beneficial risk characteristics. Several factors that are important for DG economics and potential barriers to DG adoption are identified in the thesis. Knowledge of how DG is seen from an end-user standpoint is as important for policy makers as it is to the end-users themselves. The case with market diffusion commercial building sector shows a large DG potential in the U.S. commercial building sector. An important challenge for further research is to develop models that analyze system benefits of distributed generation. Combined with an increased understanding of system benefits of DG, further research should suggest tariff structures, subsidies and taxes that give DG developers incentives to develop DG systems that improve the electricity system's environmental impact and reduce system costs.

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PAPER I

Optimal Investment Strategies in Decentralized Renewable Power Generation under Uncertainty

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Optimal Investment Strategies in Decentralized Renewable Power Generation under Uncertainty

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Abstract

This paper presents a method for evaluation of investments in decentralized renewable power generation under price uncertainty. The analysis is applicable for a building owner with an electricity load and a renewable resource that can be utilized for power generation. The owner of the building has a deferrable opportunity to invest in one local power generating unit, with the objective to maximize the profits from the opportunity. Renewable electricity generation can serve local load when generation and load coincide in time, and surplus power can be exported to the grid. The problem is to find the price intervals and the capacity of the generator at which to invest. Results from a case with wind power generation for an office building suggests it is optimal to wait for higher prices than the net present value break-even price under price uncertainty, and that capacity choice can depend on the current market price and the price volatility. With low price volatility there can be more than one investment price interval for different units with intermediate waiting regions between them. High price volatility increases the value of the investment opportunity, and therefore, makes it more attractive to postpone investment until larger units are profitable.

Keywords: Distributed generation, renewables, small-scale wind power, investment appraisal, real option valuation

1. Introduction

With increasing emissions and rising volatile oil prices, both large-scale and small-scale renewable power generation will be key ingredients in the electricity future. In the past decade there has been a trend towards liberalizing electricity markets, which has created exchanges for spot trading and financial markets. Driven by electricity market liberalization and cost improvements for small-scale power units, the future electricity system can include significant generation at end-users. This change increases the demand for market-based valuation and decision support tools for generation capacity for electricity customers. The following will present a method for finding optimal investment strategies in decentralized renewable power generation with an uncertain future electricity price, from the perspective of the developer. Finding optimal investment strategies includes finding both the optimal capacity and the timing of the investment. The setting of the analysis is in a liberalized power market with a market for trading electricity on spot and forward contracts (contracts for delivery in the future). The methodology can be applied to all types of decentralized renewable power generation, including wind power, photovoltaic power and hydropower. These technologies share some important properties such as the high initial investment cost and the intermittent uncontrollable power generation.

Distributed generation has many potential system benefits, such as reducing power losses from the grid, deferring grid capacity investments, reducing emissions and reducing the costs of electricity generation [1]. Much of the present literature on investment in distributed generation (e.g. [2] and [3]) takes the utility and societal perspective and focuses on wider system benefits. This paper instead takes the perspective of a building owner who wants to maximize private profits, with a building that consumes electricity and has a renewable resource available. We compare different systems and find optimal timing for renewable power generation under electricity price uncertainty. The investment model developed is based on the real option literature, and uses the text book by Dixit and Pindyck [4] as the main reference. The real options methods can be used to find the value of flexible investment strategies under uncertainty, such as being able to postpone an investment, value that is not included in a now-or-never investment evaluation. Another recommended reference is the textbook by Trigeorgis [5].

In the model, we assume that the plant is metered hourly in such a way that the electricity generated from a local power generating unit will displace electricity bought from the grid, and excess electricity can be sold back to the grid. Displaced electricity is valued at a retail price (including grid tariffs and taxes), and exported electricity is valued at a price close to the wholesale price. The model we develop can also be applied to cases with different metering regulations such as net metering, where the retail price is received also for the generated power that does not coincide with the building load. In a situation with hourly metering, the time correlations between generation, consumption and prices are important for the profitability of the power generating unit because displaced electricity and exports are valued at different prices. At the same time, power generation that is positively correlated with the electricity price variations will have a higher value. This can for example be the case for wind power in Norway because both wind speeds and spot prices are highest during the winter months.

We assume the owner of the plant can choose between different discrete capacity choices up to a maximum capacity, which is constrained by resource availability or regulation. With a low installed capacity a large portion of the power generation will be for building consumption, which has the retail electricity price value, but small units typically have a high investment cost per kW. Larger systems have a lower investment cost per kW but the added generation can for a large part be exported, and hence, is only valued at the export price that is lower than the retail price. Therefore capacity choice is not straightforward. The optimal capacity is the capacity with the highest net present value. However, the optimal capacity can vary with the electricity price, and therefore, with time.

We derive an expression for the net present value of each investment alternative, using the price information from the forward market which directly reveals the value of future delivery of electricity. The long-term electricity price is assumed to be uncertain, while all other inputs are modeled deterministically. We assume capacity choice is a choice between mutually exclusive capacities, and we derive a method for valuing the investment opportunity for each capacity. If an investment opportunity for any capacity is worth more than the expected net present value, investment is postponed. Investment is optimal when the most valuable investment opportunity has the same value as the expected net present value of the underlying project. We illustrate the model using an example with small-scale wind power alternatives for an office building in Norway.

The paper is organized as follows; in section 2 we present our stochastic long-term electricity price process, and in section 3 we show how we model the expected net present value of the investment in power generating units. Section 4 introduces valuation under uncertainty and shows how to find optimal investment thresholds and capacity choice under uncertainty. Section 5 presents the input data used for the analysis, and section 6 presents the results from the wind power example, which together with the limitations and potential applications of the research, are discussed in Section 7.

Nomenclature

Indices

h	Time (h)
i	Power generating unit considered in preliminary analysis (*1..N*)
j	Power generating unit considered for investment under uncertainty (*1..M*)
m	Indifference point where two net present value function of different power units have the same value
t	Time (y)

Endogenous Variables and Constants

A_j	Constant in option value function
B_1	Constant in option value function around an indifference point
B_2	Constant in option value function around an indifference point
$F_j(S)$	Value of the investment opportunity before investing in plant j ($)
G_{Di}	Annual power generation that displaces electricity load for unit i (MWh/y)

G_{Ei}	Annual power generation that are exported for unit i (MWh/y)
K_{Di}	Correction factor for the annual average price of displaced electricity for unit i
K_{Ei}	Correction factor for the average price of exports for unit i
$NPV(S)$	Net present value of the most profitable capacity ($)
$P_{Di,t}(S)$	Annual effective price of displaced electricity load for unit i ($/MWh)
$P_{Ei,t}(S)$	Annual effective export price for unit i ($/MWh)
S	Electricity start price adjusted for short-term deviations ($/MWh)
$V_j(S)$	Value of unit j after investment and in perpetuity ($)
Z_j	Optimal investment interval for power generating unit j ($/MWh)
$g_{Di,h}$	Hourly substituted electricity load for unit i (MWh)
$g_{Ei,h}$	Hourly power generation for exports for project i (MWh)
$npv_i(S)$	Net present value of investment in power generating unit i ($)
u	Control decision (invest or wait)
$v_i(S)$	Present value of a power plant during the lifetime of one unit ($)
$x_{i,t}$	Annual cash flow for project i ($/y)
z_j	Optimal investment threshold for power plant j ($/MWh)
$z*$	Lowest price at which investment is optimal ($/MWh)
β_1	Positive solution to quadratic equation from differential equation
β_2	Negative solution to quadratic equation from differential equation
ε_t	Normally distributed random continuous process with a mean of zero and a standard deviation of one
Θ_i	Simplifying variable in the equation for the annual cash flow $x_{i,t}$
Υ_j	Simplifying variable in equation for $V_j(S)$
Φ_i	Simplifying variable in equation for the annual cash flow $x_{i,t}$
Ω_j	Simplifying variable for the equation for $V_j(S)$

Input Data

C_i	Capacity of the power plant i (kW)
D_i	Hourly electricity load (kWh)
I_i	Turn-key investment cost for power generating unit i ($)
O_i	Annual operation and maintenance costs of power generating unit i ($/y)
S_0	Electricity start price adjusted for short-term deviations at time of analysis ($/MWh)
T_i	Expected lifetime of power generating unit i (y)
$g_{i,h}$	Hourly power generation for power generating unit i (MWh)
r	Risk-free nominal interest rate (1/y)

s_h	Hourly historic spot price ($/MWh)
$\bar{s}$	Annual average historic spot price ($/MWh)
α	Expected annual risk-adjusted growth in the electricity price (1/y)
γ	Grid tariff ($/MWh)
δ	Value added tax
λ	Supplier mark-up ($/MWh)
σ	Annual volatility in the electricity price (1/y)

2. Stochastic Long-Term Electricity Price Process

The choice of price description is important in an investment analysis. Stock prices are often described by random walk models where price changes are independent of the current price and, therefore, independent of historical movements. The most commonly used model is Brownian motion with a deterministic growth factor and a random term that depends on stock volatility. A typical characteristic of commodity prices is that they have a tendency to revert around a long-term average cost of generation. Therefore, prices that deviate from the long-term average cost will have a higher probability of moving towards the long-term average than away from it. The mean reversion can be due to varying renewable generation, such as in the hydropower dominated Nord Pool market in the Nordic countries, or due to mean reversion in fuel prices. Models that take this property into account are called mean-reverting models. Lucia and Schwartz [6] have studied the prices in the Nordic electricity market using one- and two-factor models. In the one factor models, the prices are assumed to follow a mean reverting process. In the two factor models, the short term variations in the prices are assumed to follow a similar process, and the long-term variations are assumed to follow arithmetic or geometric Brownian motion. The two factor models have the better fit to the data. However, Schwartz and Smith [7] argue that when considering long-term investments, the long-term factor is the decisive factor. Similarly, Pindyck [8] claims that when considering long-term commodity related investments, a geometric Brownian motion description of the price will not lead to large errors. Although using a geometric Brownian motion to model price dynamics ignores short term mean reversion, an investment in a renewable power generating unit should be regarded as a long-term investment, where the short-term mean reversion has minor influence on values and investment decisions. Especially in Nord Pool where the mean reversion in prices is driven by precipitation, prices are assumed to revert to normal levels after dry and wet years. A stochastic description of short-term deviations is more important for investments in power units with an operational flexibility such as natural gas units. Motivated by this, and due to the simple solutions obtainable for geometric Brownian motions, we assume the long-term electricity prices follow a geometric Brownian motion, where the change in price over a small time interval is written as

$$dS = \alpha S dt + \sigma S dz \qquad (1)$$

where α is the annual risk-adjusted growth rate and σ is the annual volatility. The last term, $dz = \varepsilon_t \sqrt{dt}$, is the increment of a standard Wiener process, where ε_t is a normally

distributed random continuous process with a mean of zero and a standard deviation of one. See for example [4] for a rigorous discussion about price processes.

The parameters of Eq. 1 are estimated from forward contracts with a long time to maturity, where the price is set ahead of time and, therefore, includes a risk-premium. Thus, Eq. 1 represents the risk-adjusted long-term price dynamics. An advantage of using a risk-adjusted price process is that the resulting cash flows can be discounted using the risk-free interest rate. Equation 1 says that the current long-term price level is known, but future values are log-normally distributed. Even though information arrives over time with changes in futures and forward prices of electricity, future prices are always uncertain.

We are using annual cash flow estimates in which spot prices vary each hour over a year, hence seasonal variations do not have to be taken into account in the price model. With the above price description, the risk-adjusted expected future price is found by integrating Eq. 1, since the expectation of the second term in Eq. 1, dz, is zero the expected price is given as

$$E[S_t] = S_0 e^{\alpha t} \qquad (2)$$

where S_0 is the initial price adjusted for short-term deviations.

3. The Value of Decentralized Renewable Power Generation

We assume the owner of the property with the renewable resource has available N different generators of different size - indexed i, from 1 to N. In the analysis we set a maximum capacity on the generator, even though we allow for sales back to the grid. The maximum capacity can be due to a limited space for a wind turbine, a limited space on a roof top for photovoltaics and due to limitations in water inflow for hydropower. Further, the concession to build a turbine can specify an upper limit to the developer due to bounds on the intermittent capacity a decentralized grid can handle, due to esthetic concerns or noise. The value of each generator, which depends on the amount of load that is displaced, is modeled assuming that the developer only invests in one unit. Only one unit is considered at a time because we study investments in small decentralized units, where a developer will invest in one larger unit instead of investing in two smaller units because of the reduced investment cost per kW with size. Hence, choice of unit is assumed to be between mutually exclusive projects within a size range. Since we are interested in the value of the generating units at different market prices, we need to find the net present value of the units as a function of the electricity start price. In the calculation, it is necessary to adjust for seasonal and daily correlations between the expected electricity load, power generation and spot prices.

3.1. Modeling Electricity Load, Power Generation and Electricity Prices

In a situation with hourly metering, the time correlation between electricity load, power generation and prices is important for the profitability of the investment. First, if electricity is usually generated at the same time as the electricity load is high, a large

share of the generated electricity will be valued at the end-user price, which includes grid tariffs and taxes, as opposed to the lower export price. Second, if electricity is usually generated at times when the electricity price is high, a large share of the power generation will be valued at a higher price than the annual average spot price. All three parameters have seasonal and daily variation patterns, and are correlated through the influence of varying weather. A simple approach to take into account the correlation, and in accordance with the discussion in [9], is to find the annual cash flows from available historical hourly data. In the following, at least one year of hourly data for the electricity price, climate data to estimate power generation (wind, radiation or water inflow) and the electricity load is available. If less than a year of hourly historic data is available, one must construct approximate data using available historic data and profiles or simulate the data.

The first step in the analysis is to find the hourly power generation. For renewable power, this means converting historic climate data into expected electricity generation. For wind power this means historic wind speed data, for photovoltaic units, radiation data, and for hydropower, water inflow data. Manufacturers of generating units can usually supply a power curve that gives the relationship between energy inflow and power output. Using the hourly climate data as input to the power curve gives the expected hourly power generation profile $g_{i,h}$. With time series of the hourly expected power generation and the hourly expected load, d_h, we are able to find estimates of the annual displaced electricity load and the annual exported electricity. We find the annual displaced electricity for each unit as

$$G_{Di} = \sum_{h=1}^{8760} g_{Di,h} = \sum_{h=1}^{8760} \min(d_h, g_{i,h}) \tag{3}$$

where $g_{Di,h}$ is the hourly displaced electricity load for unit i. Similarly, the exported electricity for each unit can be found as

$$G_{Ei} = \sum_{h=1}^{8760} g_{Ei,h} = \sum_{h=1}^{8760} \max(g_{i,h} - d_h, 0) \tag{4}$$

where g_{Ei} is the hourly exported electricity for unit i.

The effects on profitability from the time correlation between load, price and power generation are gathered in two scalar parameters for each project i. One parameter adjusts the average wholesale price for displaced load compared to the annual average price, and a second parameter adjusts the average price of exported electricity. The factors will vary with the capacity of the unit. For example, in a power system like the Nordic, with high electricity prices, high electricity loads due to electricity driven heating and higher wind speeds in the winter, a small unit will primarily export electricity in the summer at low prices while a larger unit will export a larger share in the winter season at a higher price.

The factor for adjusting the price for displaced electricity load is given as the ratio between the value of the displaced load on an hourly spot price and the value using the annual average price

$$K_{Di} = \frac{\sum_{h=1}^{8760} s_h g_{Di,h}}{\overline{s} G_{Di}} \tag{5}$$

where s_h is the hourly spot price and $\overline{s}$ is the average annual spot price. The corresponding factor for adjusting the price that exports receive is given with a similar formula

$$K_{Ei} = \frac{\sum_{h=1}^{8760} s_h g_{Ei,h}}{\overline{s} G_{Ei}} \tag{6}$$

If more than one year of data is available one should use the full time series.

We are now able to find the annual average received price for displaced electricity and export price as a function of the annually average wholesale price. The end-user electricity price consists of several different parts, typically the wholesale price of electricity, taxes and grid tariffs. We assume a simple general description

$$P_{Di,t} = K_{Di} S e^{\alpha t}(1+\delta) + \gamma(1+\delta) + \lambda \tag{7}$$

where K_{Di} is the adjustment factor for the average wholesale price, S is the annual average long-term market price, δ is the value added tax, λ is a supplier mark-up and γ is the grid tariff. The average electricity price relevant when exporting to the grid is assumed to be

$$P_{Ei,t} = K_{Ei} S e^{\alpha t} - \lambda \tag{8}$$

where K_{Ei} is the adjustment factor for the average effective wholesale price and the supplier mark-up, λ, is assumed to be the same as when electricity is imported.

3.2 Now-or-Never Investment Evaluation

With the given price description, the annual income from owning each power producing unit, *i*, can be calculated as

$$x_{i,t}(S) = G_{Di} P_{Di,t} + G_{Ei} P_{Ei,t} - O_i = \Phi_i + \Theta_i S e^{\alpha t} \tag{9}$$

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where O_i is the annual operation and maintenance costs. The constants in Eq. (9) are abbreviated by Φ_i and Θ_i to simplify the equation.

The present value of the investment is the sum of all expected benefits less operational costs in the project life time. It is modeled as a function of the long-term annual average electricity price the first year

$$v_i(S) = \int_0^T (\Phi_i + \Theta_i S e^{\alpha t}) e^{-rt} dt = \frac{\Phi_i}{r}(1 - e^{-rT}) + \frac{\Theta_i}{r - \alpha}(1 - e^{-(r-\alpha)T})S = \Upsilon_i + \Omega_i S \qquad (10)$$

The constants in Eq. (10) are abbreviated by Υ_i and Ω_i to simplify the equation. The net present value for each project is the present value of the benefits less the operational and investment cost

$$npv_i(S) = v_i(S) - I_i \qquad (11)$$

Only projects that maximize the net present will be considered for investment. Different projects have the highest net present value at different start prices, thus the maximal net present value is a function of the start price at the time of investment, and is given as

$$NPV(S) = \max(npv_i(S), i = 1..N) \qquad (12)$$

where $j=1..M$ projects will be a part of the upper net present value function. An investor contemplating to invest now will choose the project with the highest positive net present value at the current price. This is the static net present value approach, or the Marshallian [4, p. 145] approach, to investment decisions.

4. Investment under Uncertainty

If the owner of the property with the renewable resource has the exclusive right to invest, and if the price is expected to rise and/or there is uncertainty about future prices, there can be an added value associated with postponing the investment in a decentralized power system. The value of this option to postpone is not included in a static net present value analysis and can therefore affect the investment decision. First, if the electricity price is expected to rise, there is a positive value in postponing the investment if the discounted value of the future net present value is higher than the one today. Also, if there is uncertainty about the future price there can be a value in waiting because waiting will reveal new price information, and the developer always has the option to invest if the price moves in a favorable direction and the ability to not invest if the price is not favorable. Lastly, there can be uncertainty about which capacity is most profitable, because the optimal capacity can be a function of the start price. By waiting, the developer can get new price information and invest in the most profitable generator.

When we consider postponing the investment, we could potentially consider a strategy consisting of investing in a sequence of units. For example, first buy a small generator, and if the price goes up, a larger generator. However, in this analysis we

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assume that the units are mutually exclusive, and that there can only be one system on the site at the same time. This might be the case for wind turbines if there is limited space to site a turbine, or a developer only has concession to build one turbine. Photovoltaic systems, on the other hand, are typically modular, and capacity could be added at a later stage. However, for all types of decentralized units, installation costs and reductions in costs per kW with size can be a barrier to investment strategies that involve more than one phase.

Another consideration when a project is postponed is that also the reinvestment in a subsequent unit is postponed. We assume the most valuable investment opportunity on the occupied land is to build subsequent power generating units in perpetuity. After a generator is taken out of operation, one will usually have the option to invest in any of the units that can be considered. However, since one often will not build a small project (because the opportunity to invest in a large project is more valuable than investing in a small), and for analytic simplicity, we assume the only investment opportunity left after a project dies is to invest in the largest project available. It is also important to understand that the only decision we model is the initial, hence what happens after a project goes out of operation is just an estimate of the value at that time, and what is most important is that it is that same for both projects.

4.1 Mathematical Model Description

We have *M* projects from which to choose - the generators that maximize net present value for different electricity start prices given by Eq. (12). We further denote the value of the investment possibility in the largest project $F_M(S)$ and the investment price threshold for the largest project z_M. The value functions, which represent the expected value of the first project and all later reinvestments, have two branches as functions of the start price. At the first branch, the expected price growth during the lifetime of the investment is not large enough to expect to reinvest in the large turbine immediately. This region is from *S* equals zero to $S = e^{-\alpha T} z_M$, and the value function is the sum of the present value of the first project and the expected present value of the option to reinvest in the large project

$$V_j(S) = \Upsilon_j + \Omega_j S + e^{-rT} F_M(Se^{\alpha T}) \tag{13}$$

From the start price $S = e^{-\alpha T} z_M$, reinvestment in the large project is expected to happen immediately after the project dies; the value function is given as the discounted value in perpetuity less the investment cost for all later investments in perpetuity

$$V_j(S) = \Upsilon_j + \Omega_j S + e^{-rT}(\frac{\Phi_M}{r} + \frac{\Theta_M}{(r-\alpha)}Se^{\alpha T}) - \frac{I_M}{e^{rT}-1} \tag{14}$$

The two branches of the value functions meet tangentially at $S = e^{-\alpha T} z_M$.

To find the value of the investment opportunities and the optimal investment thresholds, we first analyze each unit or strategy individually, and then afterwards choose the unit or strategy that is the most profitable. We assume the investment opportunity in project j, $F_j(S)$, yields no cash flows up to the time the investment is undertaken. By using the Bellman's principle of optimality, with no cash flow from the investment opportunity and in continuous time, the value of the investment opportunity can be stated as [4, p. 105]

$$F_j(S_t) = \max_u (\frac{1}{1+rdt} E^*[F_j\{S_{t+dt}\} \mid S_t, u]) \qquad (15)$$

where u is the control variable, here to invest or to wait, and E^* denotes risk-adjusted expected value which must be used since we use the risk-free interest rate. By multiplying with $1+rdt$ and rearranging the equation, the investment opportunity can be written

$$rF_j(S)dt = E^*[dF_j] \qquad (16)$$

Expanding $F_j(S)$, using Ito`s lemma [4, p. 151] and taking the risk-adjusted expectations, leaves us with the following differential equation

$$\frac{1}{2}\sigma^2 S^2 F_j'' + \alpha S F_j' - rF_j = 0 \qquad (17)$$

The differential equation is written independently of time; it only depends on the current start price in the market. A solution of the differential equation is $F_j(S) = A_j S^{\beta_1}$, where A_j is a constant to be determined, and β_1 is given by the positive solution of the quadratic equation resulting from substituting the solution into the differential equation. To find the constant, A_j, and the optimal investment thresholds, z_j, we need two boundary conditions for each project [4, p. 183]. The first states that when it is optimal to invest, the investment opportunity must equal the expected net present value of the underlying project

$$F_j(z_j) = V_j(z_j) - I_j \qquad (18)$$

The second says that the value of the investment opportunity and the net present value of the underlying project must meet tangentially at the investment threshold price

$$F_j'(z_j) = V_j'(z_j) \qquad (19)$$

The value of the investment opportunity approaches the net present value of the project, and will be equal for all higher prices than the optimal investment threshold.

Now we can find optimal investment thresholds, z_j, for each project, which can be on any of the two value function branches, given in Eq. (13) and Eq. (14), for the smaller projects but only on the higher branch for the largest alternative because one expects to invest in it forever if expected price growth is positive or zero. If there is only one relevant capacity ($M=1$) the solution is completed and one will invest for all prices over z_M. With more than one mutually exclusive strategy, we will not choose a project, if another project has a higher option value. Choosing it means that opportunity to invest in the more valuable project is lost [10]. It is, therefore, optimal to wait until the price reaches a trigger level $z*$ from below

$$z* = \min_j z_j$$
$$\text{s.t. } F_j(z*) = \max_j F_j(z*) \wedge j = 1..M \tag{20}$$

This can be interpreted as waiting for start prices below the lowest price trigger, z_j, where the option to invest in that generator is worth more than the option to invest in any of the other projects. If the lowest threshold price satisfying Eq. (20) is $z* = z_M$, the solution is completed and investment is optimal in the largest project for all higher start prices, and waiting is optimal for all prices below it.

However, if $z* \leq z_M$ there can be an intermediate solution, where a smaller project is optimal for some prices and one or more larger projects are optimal for higher prices. Investment in the project, j, that is optimal for the lowest prices will then be optimal in a region from $z_{j,1}$ to $z_{j,2}$ where $z_{j,1} = z*$.

The curve that consists of the value function with the highest value, can exhibit a kink where two electricity generating units of different sizes have the same value. Around this kink there is uncertainty about which project is optimal to invest in, and therefore, the opportunity to invest in both can be worth more than investing in one of the projects. The intuition behind this can be understood by imagining a simple description of price uncertainty for a following period, where the price in the next period can go up or down. In this situation, the developer will invest in the large project if the price goes up, and in the small project if the price goes down. The discounted value of investing in the optimal project in the next period can be worth more than investing now.

There can hence be new waiting regions around the indifference point, from $z_{j,2}$ until $z_{j+1,1}$. Investment in the largest project will be optimal for all values over $z_{N,1}$. Now the solution consists of a set of one or more investment intervals, $Z_j = [z_{j,1}, z_{j,2}]$.

The value of the investment opportunity, $F_m(S)$, around each indifference point, m, is found using the same method as for individual projects. Hence, it is the solution to the differential equation in Eq. (17). Décamps, Mariotti and Villeneuve [11] have shown that the boundary conditions are also similar, but now investment can be optimal either if the price drops or grows. Both at the upper and at the lower investment price triggers, the investment opportunity must have the same value as the value function, and the value of the investment opportunity must meet the two value function tangentially at the

price triggers [11, p. 9]

$$
\begin{aligned}
F_m(z_{j,2}) &= V_j(z_{j,2}) - I_j \\
F_m{}'(z_{j,2}) &= V_j{}'(z_{j,2}) \\
F_m(z_{j+1,1}) &= V_{j+1}(z_{j+1,1}) - I_{j+1} \\
F_m{}'(z_{j+1,1}) &= V_{j+1}{}'(z_{j+1,1})
\end{aligned}
\tag{21}
$$

A solution to the differential equation that satisfies the boundary conditions is

$$
F_m(S) = B_1 S^{\beta_1} + B_2 S^{\beta_2}
\tag{22}
$$

where β_2 is the negative solution to the quadratic equation resulting from substituting Eq. (22) into Eq. (17) and B_1 and B_2 are constants to be determined. The four unknown parameters can be found from the four equations. There is no analytic solution, thus the solution must be found using numerical methods. The solution to the investment problem is now to invest in one or more investment price regions in one or more of the projects.

5. Model Parameters

In this section we present the model parameters used to model a case study of a wind turbine investment for an office building in Norway. The analysis requires price parameters, building electricity load and different wind turbine characteristics.

The Nordic countries have a well-functioning spot and financial market called Nord Pool. Since we want a representation of a long-term price that is not sensitive to short-term deviations, we base the price parameters relevant for the investment decisions on the forward contract with the longest time (three years) to maturity. The volatility parameter, σ, that represents the uncertainty in prices is found as the historic annual standard deviation of price changes of this contract, the solid line in Figure 1. Because Nord Pool only has contracts for up to three years ahead we used contracts traded between two parties, over-the-counter (OTC) contracts, to find an estimate for price growth from contracts with a longer time to delivery. In early December 2005 the 2008 contract sold at 40.9 $/MWh. OTC contracts for 2009 are traded at 41.14 $/MWh and for 2010 at 41.31 $/MWh. This corresponds to a risk-adjusted price growth of 0.5 percent. In Figure 1, the expected price growth with the upper and lower 66 percent confidence bound is plotted for the next 10 years.
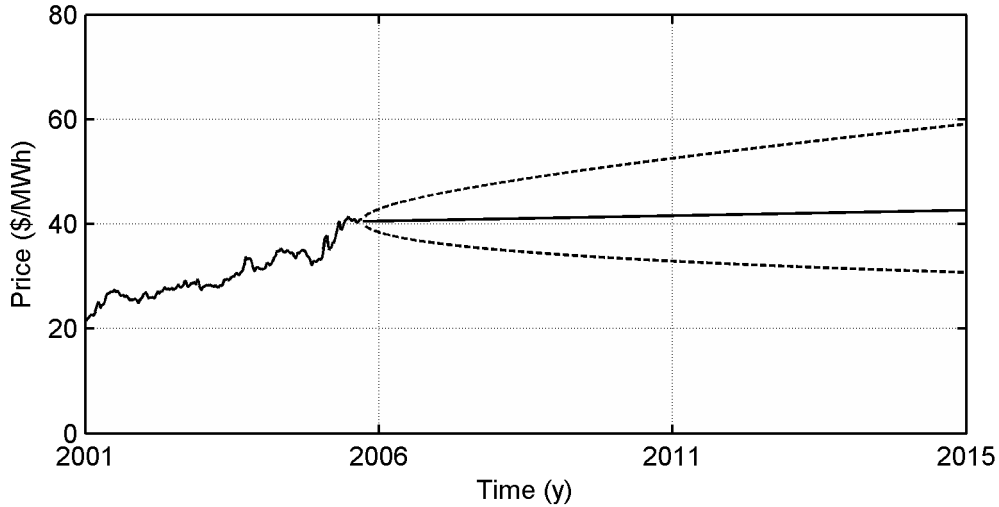
Figure 1. Historical prices of the Nord Pool three-year-ahead forward contract until late 2005 and projected prices with the upper and lower 66 percent confidence intervals until 2015

The relevant current start price is found by discounting the price forward contracts back to the current year with a price growth of 0.5 percent. The estimated price parameters, end-user price adders and the assumed risk-free nominal interest rate are presented in Table 1, and are considered representative for a Norwegian setting.

Table 1. Base case data used in the analysis

Parameter	Unit	Value
S_0	$/MWh	40.5
α	1/y	0.005
σ	1/y	0.103
r	1/y	0.05
δ		0.25
γ	$/MWh	35
λ	$/MWh	2

For the electricity load we have one year of hourly data for an office building with a maximum load 99 kW and an annual load of 293 MWh. The hourly load, in the upper panel of Figure 2, shows that there is a significant seasonal variation in consumption due to the fact that electricity is used for heating purposes, which is common in Norway. The middle panel of Figure 2 shows the hourly wind power output; there is a large variation also in the power generation. In the winter and fall the wind power output is larger. In the lower panel, Figure 2 displays the 2002 Nord Pool spot price. Because prices also are higher in winter and fall, there seems to be a positive correlation between load, generation and prices to be determined by the parameters K_{Di} and K_{Ei}.

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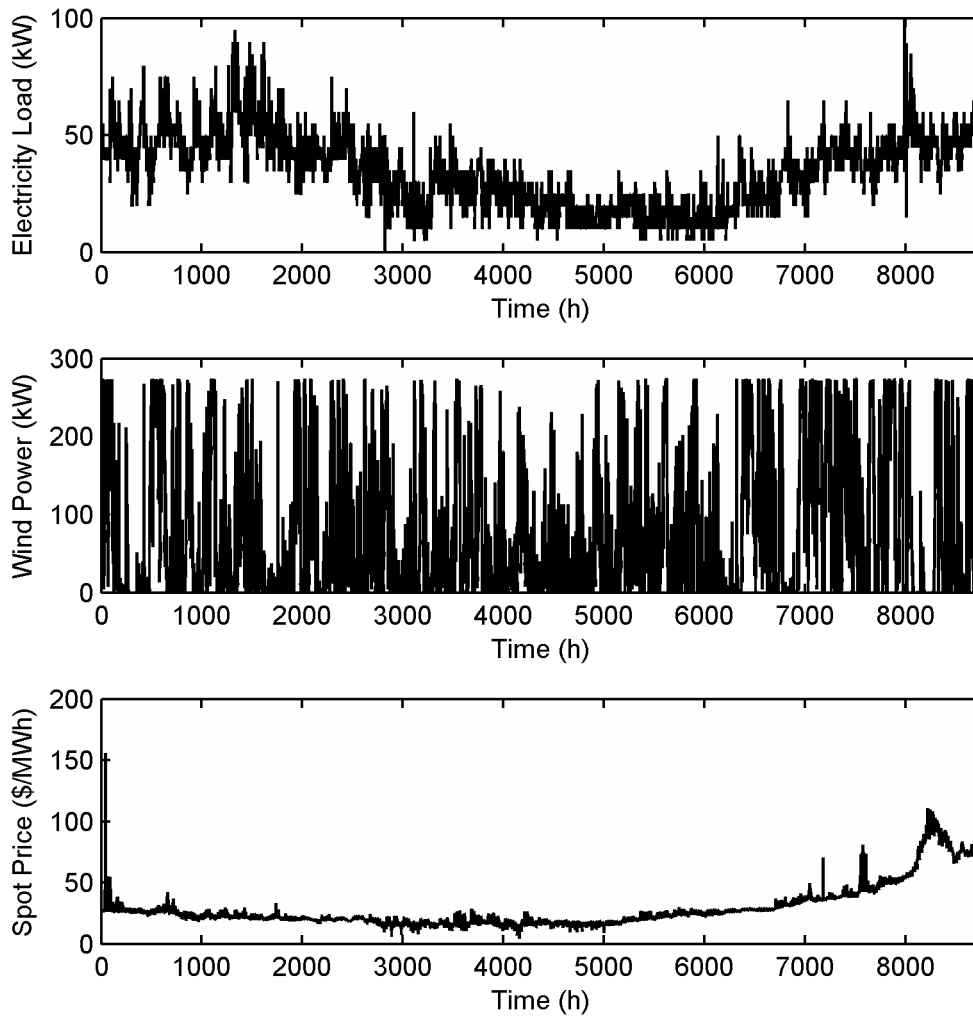
Figure 2. Office electricity load, wind power generation for the 250 kW unit, and Nord Pool spot prices in 2002

We assume the developer can choose among six different turbines with capacity from 25 to 250 kW and costs shown in Table 2. We have assumed a significant drop in investment costs per kW for wind turbines from 25 to 250 kW.

Table 2. Wind turbine data

i	C_i (kW)	I_i/C_i ($/kW)	O_i/I_i (1/y)	T (y)
1	25	2500	0.02	25
2	50	2200	0.02	25
3	100	2000	0.02	25
4	150	1900	0.02	25
5	200	1800	0.02	25
6	250	1700	0.02	25

6. Model Results

The first step in the investment analysis is to find the amount of displaced electricity load and how much electricity is exported for each turbine. Figure 3 shows the quantities of displaced and exported electricity from generation units with different capacities. From this, it can be seen that the generated power from the 25 kW turbine is used almost solely for its own load. When the size of the turbine is increased an increasing share of generation is exported.
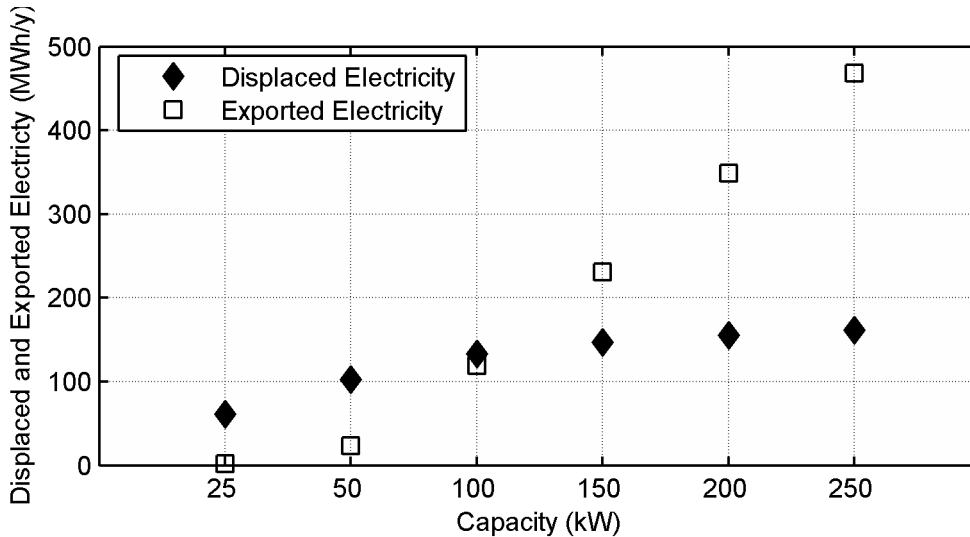
Figure 3. Annual displaced and exported electricity for the six turbines of different capacities

The correlation between load, generation and prices for the different turbines are captured by the values of K_{Di} and K_{Ei}. They are found using the data displayed in Figure 2. They show that the average prices received for displaced load and exports varies significantly with size. Displaced load receives a price that is on average 103 percent of the average price. Generation for exports shows a larger variation because the price is adjusted from 89 percent of the average price for the 25 kW to 103 percent for the 250 kW turbine. The small turbine receives a low export price because most exports occur at summer time and at times of the day when there is a low electricity load, namely at off-peak hours. As the capacity increases, electricity is also exported at peak hours because the turbine generates more electricity.

Table 3. The factors that decide the relationship between the annual average price and the average price of displaced and exported electricity

i	K_{Di}	K_{Ei}
1	1.032	0.885
2	1.041	0.958
3	1.036	1.018
4	1.034	1.026
5	1.033	1.028
6	1.032	1.029

Now, we have all the data we need to find the expected net present value of the six different turbines. The current long-term start price is estimated to be 40.5 $/MWh. The three smallest turbines, the 25 kW, the 50 kW and the 100 kW units all have positive net present values. The net present value is highest for the 50 kW turbine, as can be seen in Figure 4. In a now-or-never deterministic net present value analysis the building owner would invest in the 50 kW turbine now because it has the highest positive net present value.
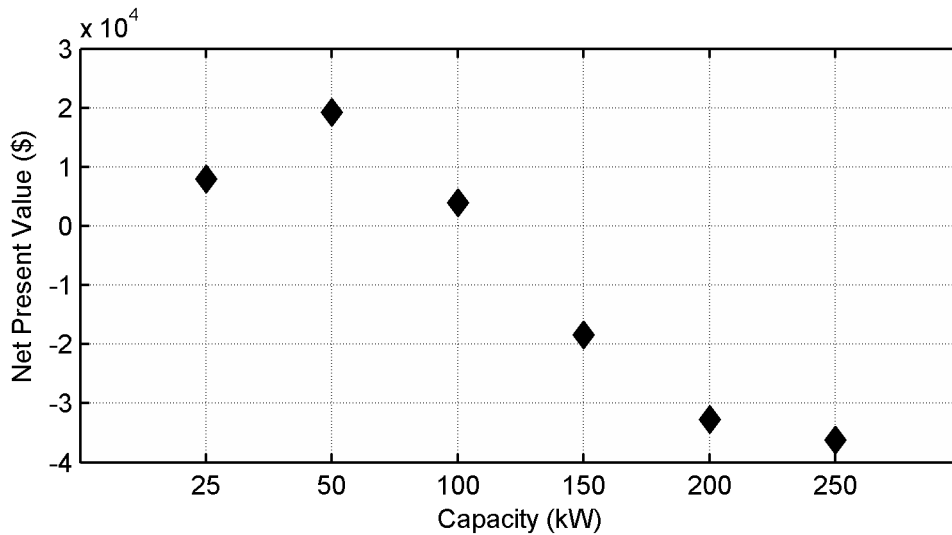

Figure 4. Static net present value analysis at current market price of 40.5 $/MWh

However, we also have the option to postpone the investment and we consider postponing the investment because we know that the electricity price can change. Therefore, we are interested in the net present value as a function of the start price. Figure 5 plots the net present value as a function of the start price for the six turbines under consideration. Each of the six linear lines in Figure 5 corresponds to the net present value of one of the six projects from Table 2. An increase in project size, results in a steeper net present value function. The 50 kW project has the net present value break-even at the lowest price, 32 $/MWh. However, the largest project has the highest net present value for high prices because the export price is high enough to recover the investment cost of the additional capacity and the largest project has the lowest investment costs per kW and produces the most electricity. Someone considering an investment on a now-or-never basis would choose the project with the highest positive net present value at the current start price. Only two turbines, the 50 kW and the 250 kW turbines, are ever optimal. For all other turbines, another turbine is worth more at all start prices.

As indicated above, to invest in the 50 kW turbine, even when it maximizes net present value, is not necessarily the optimal solution under uncertainty and price growth. It might not have sufficient return on investment to justify investment, and in addition the investment opportunity in a larger project can be worth more. At a price of 47.5 $/MWh the upper net present value exhibits a kink, where investment in the 50 kW unit maximizes net present value for lower prices and the 250 kW unit for higher prices. Therefore, there is uncertainty about in which turbine to invest in at this price. A net present value analysis that does not allow the investment to be postponed will ignore these points.

Figure 6 shows the solution when the investor has the possibility to postpone the investment. Because only the 50 kW and the 250 kW turbines maximize net present value at any prices they are the only two turbines considered. The solid lines are the expected net present value functions of the investment in the two different projects in perpetuity. Note that they are no longer linear on the lower branch because they include the option to invest in the largest project after a unit has been taken out of operation, and the option value is not a linear function of the start price. The upper dashed line is the value of the option to invest. With the base case data, it is never optimal to invest in the 50 kW turbine, because the investment opportunity of the larger turbine is more valuable for all start prices. The optimal strategy is to wait for start prices under 61 $/MWh, and invest in the 250 kW turbine for all higher prices.
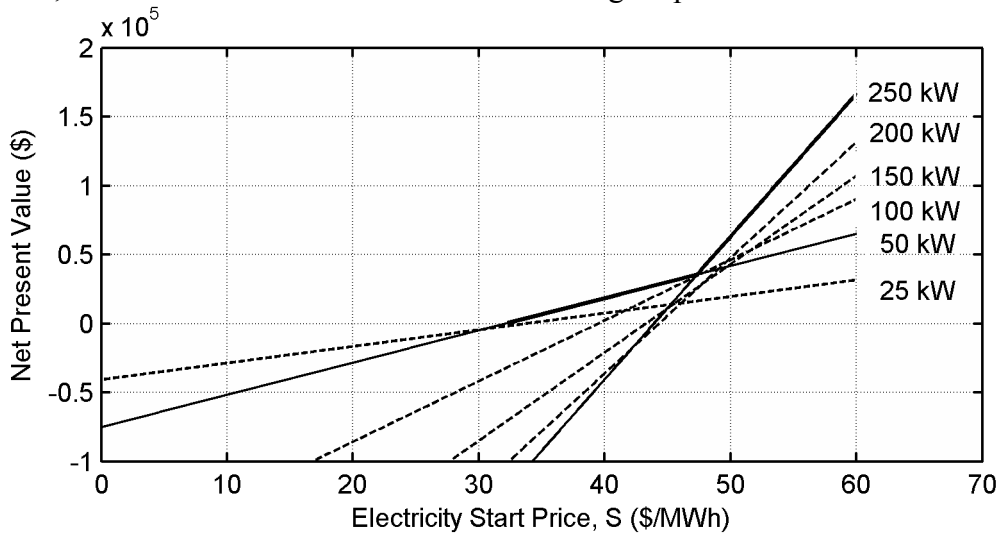
Figure 5. Net present value as a function of the long-term electricity start price, S, for the six wind turbines
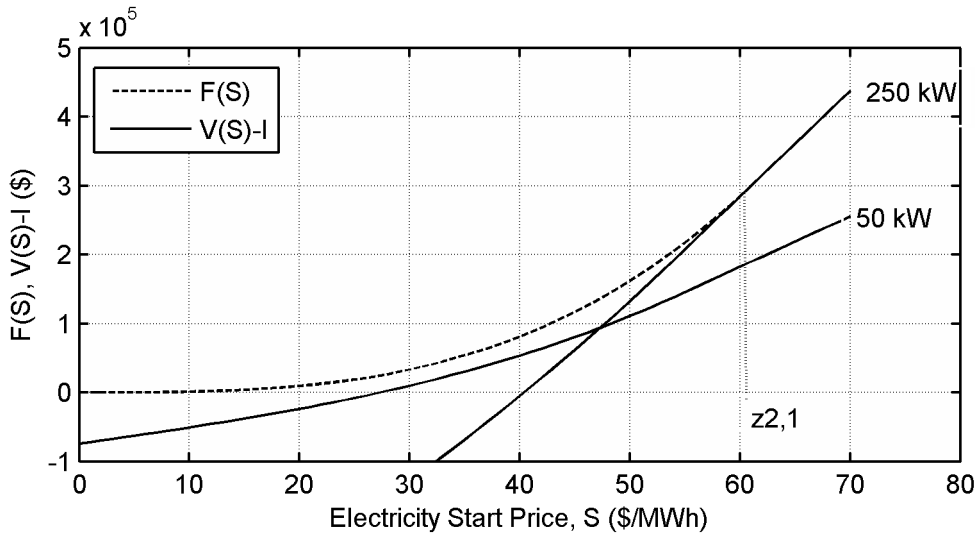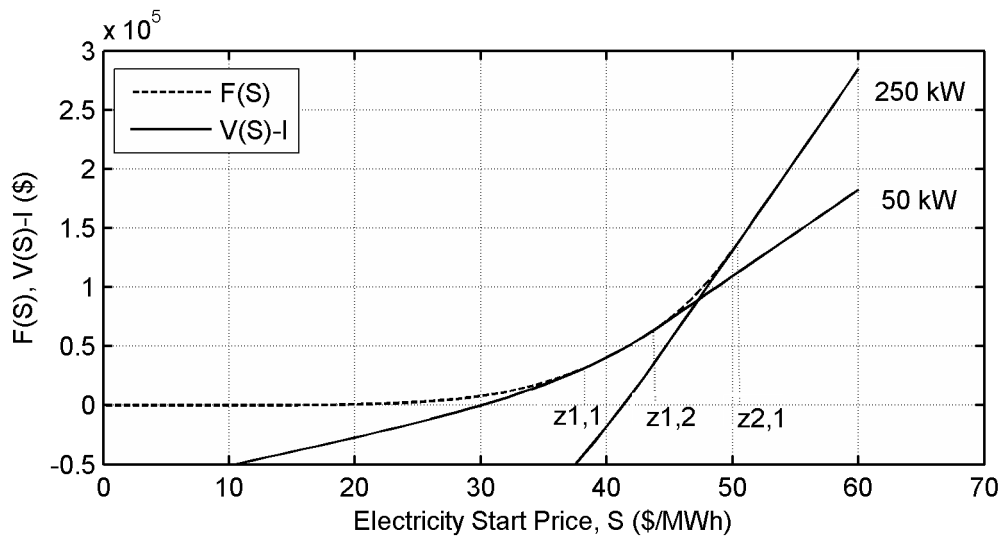

Figure 6. The value of the investment opportunity *F(S)* and the expected net present value of the 50 and 250 kW turbine after investment

Less uncertainty about the level of future prices reduces the value of the investment opportunity. This is because there is a lower probability of high prices, and therefore, a

lower value associated with waiting. Figure 7 shows the solution with an uncertainty parameter reduced from $\sigma = 0.103$ to $\sigma = 0.04$. The investment opportunity in the 250 kW unit is no longer more worth than investment in 50 kW for all start prices. Now, we have one interval from $z_{1,1} = 38.5$ \$/MWh to $z_{1,2} = 43.7$ \$/MWh where investment is optimal in the 50 kW turbine and a second interval for all prices above $z_{2,1} = 50.4$ \$/MWh where investment is optimal in the 250 kW unit. For all other start prices, it is optimal to wait for new price information.

Figure 8 shows the optimal investment intervals for the two turbines with changing values of the uncertainty parameter, σ. As expected, increased uncertainty leads to optimal investment at higher threshold prices. The intermediate waiting region gets larger and larger until only investment in the 250 kW turbine is optimal at $\sigma = 0.046$.

Figure 7. Value of the investment opportunity *F(S)* and expected net present value of the 50 and 250 kW turbine after investment with a reduced price uncertainty ($\sigma = 0.04$)
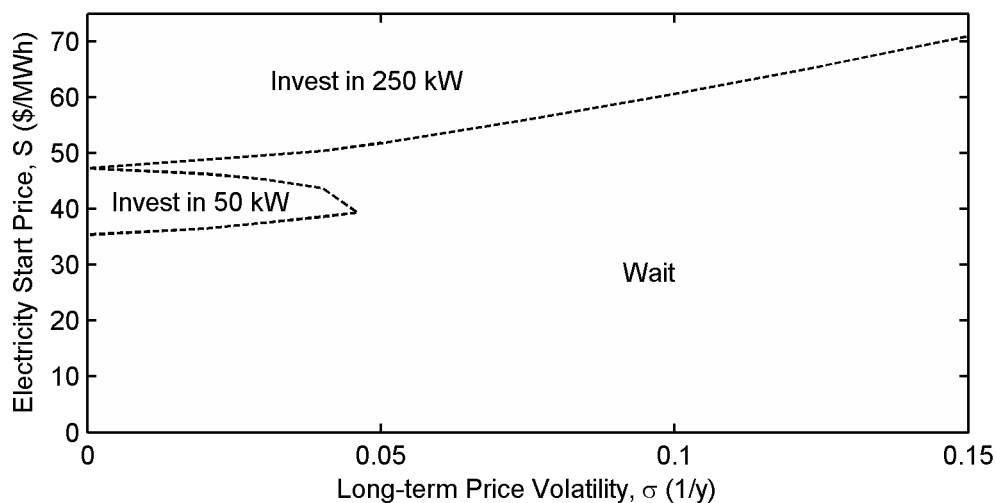
Figure 8. Investment and waiting regions as a function of price volatility and long-term electricity start price

7. Discussion

With the provided example we have presented a method for analysis of investment in decentralized renewable power generation under uncertainty, when the investor can choose between mutually exclusive capacities and chose investment timing to maximize benefits. As expected the method results in a recommendation to postpone the investment beyond the net present value break-even price because of price uncertainty. Also the optimal investment decision varies with the start price. For each capacity that is ever optimal there is a price region where investment is recommended. For the largest capacity the investment threshold is a trigger price where investment is optimal for all higher prices. The results reveal intermediate waiting regions similar to [11] and [12]. This paper does not, however, assume that the projects have an infinite lifetime. Studying a sequence of investments in perpetuity reduces the intermediate waiting region and the values at stake, because the capacity choice is not as irreversible, considering that one can choose another capacity at the end of the current projects useful life. In terms of the graphs in Figure 4 and Figure 5, the kink in the net present value functions is gentler. Only considering the value in the lifetime will be the same as assuming that one can invest only once in perpetuity. It would lead to higher investment thresholds and could fail to realize that investing in a small project can be optimal if one can invest in a larger project later. Further, the model only analyses a discrete number of capacities. This is realistic for most cases; there are usually a limited number of fairly cost effective offers to compare for investment and units do not usually come in a continuous range of capacity. The results regarding capacity choice with more sizes to choose between, would not necessarily be very different, as there still can be a kink in the net present value function where a large unit sized for exports cuts off the net present value function for a smaller unit sized to mainly satisfy the load. This indication is supported in Figure 5 by the fact that some turbines are never optimal.

We have assumed that the option to invest is perpetual, which is natural if the investor owns the property with the renewable energy resource. If the investment opportunity has a limited lifetime, the analysis is identical within the lifetime, but when the opportunity expires the decision rule is to choose the capacity that maximizes net present value, and invest in it as long as it is positive.

The method we used is a simplified method. First, we use a relatively simple model of price uncertainty, although it is justifiable for long-term projects. Second, we assume that after a project dies only the option to invest in the largest project is available. In reality, the option to invest in any project is available. Therefore, the model can fail to give accurate results if the value of the investment opportunity in the largest project is not important at the price ranges relevant for choosing between two smaller projects. If a preliminary analysis reveals such a situation, a smaller project can be used instead of the largest. Similarly if the price is expected to decline, one can compare other investment sequence. It is possible to find the accurate optimal row of investment based on the expected price, and optimize a sequence of different projects in perpetuity. However, estimates of all of the input parameters more than a lifetime ahead is bound to be uncertain and taking it into account would probably complicate the analysis more than it would improve it. When we assume that one can only invest in the large project

after the lifetime of the first, at least both strategies have the same value after they are taken out of operation, which is important for a fair comparison of the different turbines.

As we assume that the investment decision is a choice between mutually exclusive projects, we do not allow for modular investments in the model. In cases where capacity is considered to be added in many phases, one will have many different strategies to choose from. A method could be to compare some discrete strategies and compare them within this framework. Yet, transaction costs for adding capacity in many phases can be high both due to the actual construction and due to new investment analysis and market monitoring. Adding the capability to the model would increase the number of investment strategies considerably and, therefore, complicate the analysis significantly. For many applications the investment in different capacities is truly mutually exclusive (e.g. in the case of wind turbines, when there is a limited area, and building more than one plant is not possible because of the required distance between turbines). Regulation can potentially also reduce the number of installations allowed.

The results are based on one example of a customer with only one year of hourly data for consumption and wind speeds. Given these limitations however, the data sets are general enough to provide some insight into the problem. Further, the price parameters, based on Nord Pool financial data, are always only approximate. No contracts with a time to maturity over three years are sold in the market, such that good risk-adjusted price forecast for a long period is not possible.

The model does not include inflation in future investment costs and operation and maintenance cost nor income tax effects, subsidies or a turbine construction time. Including these additions to the model is straightforward, but was not done here to make the equations simple. In a real application of the model one would also model electricity generation for the different turbine alternatives more accurately. One would have a specific power curve for each turbine and analyze the wind speeds at different heights.

Some of the distributed renewable technologies are immature and reductions in investment costs are expected. We have assumed a constant investment cost over time. To allow for a reduction would complicate the model because of the time dependency and would increase the value of postponing the investment. This expected reduction in costs can be a further reason to postpone an investment.

We do not analyze uncertainty in the climatic data because we assume that their average values will not change significantly in the future, and yearly variations will even out over the lifetime. Hence, the analysis assumes the developer maximizes profits and is not scared by annual variations in the cash flow. Very often there will be publicly available climate data for a nearby location that the local data can be compared to. If the developer has good climate data there will hence not be a reason to wait for new information. Of course, if there are insufficient climatic data measurements available, making it difficult to assess their distribution accurately, such measurements are worth paying and/or waiting for. A method to analyze risk specifically is to simulate the price, power generation and load as stochastic processes, and calculate risk measures such as standard deviation of return or electricity costs and value-at-risk (the maximum simulated loss or electricity cost within a confidence level, typically 95 percent). In a risk-perspective, the cost risk is what matters for many developers, and the cost risk can be lower with renewable generation because most of the costs are initial costs, hence the price risk is less. Awerbuch [13] claims that investors often undervalue renewable generation because of the potential reductions in portfolio cost risk from renewables.

It should, however, be noted that there can be uncertainty in the regulation (political risk), for example in whether green tags that credit renewable generation or carbon taxation will be introduced, and that it can be important but difficult to quantify and incorporate in a model. Although there is uncertainty in other parameters, the price uncertainty is likely to be a dominating uncertain factor.

Among proponents of distributed generation, there is a desire to allow for net metering over a longer period, effectively letting the owner of the generator receive the higher end-user price for all generated electricity. This is the case in many states in the U.S. for example. It increase the value of the investment in renewable distributed generation and would make capacity choice simpler if, as is often the case, electricity generation that exceeds the annual load would have no value. Under such regulation one would chose the size that generates the amount closest to the annual electricity load. Then one could use this model with one alternative. But if there is an upper limit on capacity, and a larger turbine can be sized also for sales back to the grid, capacity choice is not necessarily straightforward.

8. Conclusions

Motivated by the restructuring in the electricity sector, we have presented a market-based tool for project evaluation under uncertainty for investments in decentralized renewable power generation, where the developer has the option to postpone the investment and can choose the capacity among discrete projects. Optimal investment strategies in decentralized renewable power generation depend on several factors, including electricity load, climatic data and electricity prices. We have assumed that the factor that is the most uncertain is the future electricity price, and have, therefore, included a price uncertainty description in the model. Our analysis based on data from the Nord Pool financial market, with an expected growth in the electricity price and an evident uncertainty in forward prices, suggesting that the optimal investment decision is to invest at a price considerably over the net present value break-even price. The optimal strategy is to invest in different capacities at different prices ranges. Increased price volatility increases the investment price thresholds, and can increase the value of the investment opportunity for larger projects so much that the only optimal strategy is to wait until investment in the largest project is optimal.

Acknowledgements

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PAPER II

Combined Heat and Power in Commercial Buildings:

Investment and Risk Analysis

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Combined Heat and Power in Commercial Buildings:
Investment and Risk Analysis

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Abstract

Combined heat and power (CHP) systems can generate electricity locally and recover heat to satisfy building heating loads, thereby providing energy at high efficiencies. An investment in combined heat and power is attractive if the net present value is positive. At the same time, potential developers will also consider the investment's risk characteristics. Because energy prices are volatile, a deterministic modeling framework will not be capable of evaluating the investment risk or the ability of on-site generation to respond to uncertain prices. We present a model with Monte Carlo simulation of CHP value under uncertain future wholesale electricity and natural gas prices, which are simulated as correlated mean-reverting processes. On-site generation has low start-up costs, and will operate only when expected savings exceed costs because electricity and natural gas can be purchased from the local utility. This flexibility in providing energy can be valuable under price uncertainty. The results confirm that CHP systems can reduce expected energy costs and can be particularly attractive under uncertain wholesale prices because of the ability to hedge energy costs. An increase in the price volatility increases the value of CHP, both in terms of the expected net present value and in the ability to reduce short-term energy cost uncertainty. Also, a reduction in the correlation factor between the electricity and natural gas price, and a lower mean-reversion rate increases the system's value and leads to more predictable energy costs with CHP. Savings on peak demand charges and transmission charges are important for CHP profitability, but when they are increased, the uncertainty in the energy costs and the CHP system's role as a hedge to uncertainty is dampened. The sizing of the system is closely related to the level of both the volumetric energy costs and the demand charges. Thus, simple sizing rules, such as sizing distributed generation systems to heat loads, should be avoided.

1. Introduction

Increased use of combined heat and power (CHP), the concurrent generation of heat and power, can be an important part of developing a more efficient power system than the system used today. With increasing concern about climate change and a steep global rise in the demand and price for petroleum products, the need for energy efficiency is more urgent than ever. Combined heat and power systems have the potential to improve system energy efficiency because of the proximity to heat loads, which allows for the utilization of heat that would otherwise be wasted, and because some grid losses are avoided as electricity is generated on-site [1]. This paper will address the major economic considerations for an owner of a commercial building, which is connected to both an electricity grid and a natural gas grid because owners of such buildings usually have the opportunity to invest in CHP units. The model used in this analysis will help determine the appropriate capacity of the CHP system the commercial building owner should invest in, based on the net present value and risk characteristics of the investment. With on-site generators, electricity can be bought from the grid or produced locally, and heat from the local generators can be recovered to satisfy local heat loads and will, therefore, replace the direct combustion of natural gas. In addition, the on-site generators have the potential to reduce demand charges. In the following paper, we will present a model and a case study that estimate the expected net present value and identify some economic risk characteristics of different CHP systems using Monte Carlo simulation.

Any investment has some economic risk because of uncertainty in the parameters that determine profitability. In this paper, we assume the most important uncertain parameter for a CHP-developer is the uncertainty in future wholesale energy prices. Because energy prices are uncertain, they can be a barrier to on-site generation if developers lack a good understanding of the associated risks and the systems ability to respond to uncertainty. However, combined heat and power systems can respond to uncertainty because they have flexibility in the choice of output levels and low start-up costs. We analyze the investment value of four alternative CHP systems with different sizes, using Monte Carlo simulation of the future energy prices. For each investment alternative, the net present value and the standard deviation in the simulations are calculated. Economic risk is, however, often related to shorter time horizons than the expected 20 year lifetime of CHP units, and what is important for many developers is the risk related to total energy costs. Therefore, we also calculate the first-year total costs, with and without CHP-systems, and report both the standard deviation and the highest costs within a 95 and a 99 percent confidence level.

Base case electricity price process parameters are estimated from New England ISO prices and the natural gas parameters from Henry Hub prices. To make the analysis more general, we also simulate the net present value and the first-year energy costs with changes in the electricity price process parameters and the transmission and distribution costs, all of which can change over time and are market specific.

Electricity and natural gas prices are modeled as two correlated mean-reverting stochastic processes, where the commodity prices are assumed to revert to a long-term average if the price drift away from it. We assume the building is on a time-of-use (TOU) electricity tariff and a flat natural gas tariff that varies monthly with stochastic

and seasonal variations in the wholesale prices. Further, the building electricity consumption is subject to a daily demand charge. Optimal operation of the system is found by choosing the best strategy among a number of pre-defined alternative operation levels. The alternative operation levels have different discrete targets in reducing peak demand, utility electricity purchases and in recovering heat. The presented case study shows that this flexibility in operation can be attractive, because CHP systems can adapt to uncertain prices and reduce energy cost risk. The net present value of on-site generators can increase with uncertainty because they can be programmed to operate only under favorable prices, which makes it possible to catch the upside of price uncertainty while not suffer correspondingly from the downside.

The remainder of the paper is organized as follows: the next section presents the energy price model and, pre-defines operation levels and shows how the net present value and first-year energy costs are calculated. The third presents the parameters, and section 4 presents the results. Section 5 discusses the chosen approach and section 6 concludes the analysis.

Nomenclature

Indices

i	Demand reduction level (kW)
j	Year (y)
k	Month in year
l	Day type (Week Day, Weekend Day)
m	Hour of day
s	Simulation number
t	Months from investment

Subset

H	Demand metered hours

Variables

AC	First-year total energy costs (including investment cost when CHP is installed) ($)
$G_{j,k,l,m}$	Natural gas price including a distribution charge ($/MMBtu)
$G_{W\,j,k}$	Monthly average natural gas wholesale price ($/MMBtu)
NPV	Expected net present value of investment ($)
AC	Expected first-year energy costs ($)
$P_{D\,i,k,l,m}$	Minimum generation to reduce demand by demand reduction target (kW)
$P_{M\,i,k,l,m}$	Maximum generation constrained by capacity or electricity load (kW)
$P_{Q\,i,k,l,m}$	Generation level matched to the heat load (kW)
$Q_{D\,i,k,l,m}$	Heat utilized at minimum generation level to reduce peak demand by target (kWh)
$Q_{M\,i,k,l,m}$	Heat utilized at maximum generation level (kW)

$Q_{Qi,k,l,m}$	Heat utilized at generation level matched to the heat load (kWh)
$R_{Di,k,l}$	Reductions in demand charges (kW)
$S_{j,k,l,m}$	Electricity price including volumetric transmission charges (kWh)
$S_{Wj,k}$	Monthly average electricity wholesale price ($/MWh)
$Z_{Di,j,k,l,m}$	Operational profits at minimum operation level that reduce peak demand by target ($)
$Z_{Mj,k,l,m}$	Operational profits at maximum operation level ($)
$Z_{Qj,k,l,m}$	Operational profit at generation level matched to heat load ($)
$Z_{Vi,j,k,l}$	Daily maximum volumetric profit for peak demand reducing target ($)
$Z_{j,k,l}$	Daily maximum total profit including demand reduction and volumetric profits ($)
V_{Xt}	Variance of electricity price process
V_{Yt}	Variance of natural gas price process
W_{Xt}	Stochastic process for electricity price
W_{Yt}	Stochastic process for natural gas price
X_t	Natural logarithm of the monthly wholesale electricity price ($)
Y_t	Natural logarithm of the monthly wholesale natural gas price ($)

Parameters

C	Electric capacity (kW)
D_{Gi}	Demand reduction target (kW)
$D_{Mk,l}$	Peak daily demand in demand metered hours (kW)
$L_{Ek,l,m}$	Electric load (kW)
$L_{Qk,l,m}$	Heat load (kW)
M	Maintenance Cost ($/kWh)
N	Number of simulations
$P_{\min}$	Minimum output level
T	Equipment lifetime
$\overline{X}$	Logarithm of the long-term average wholesale electricity price ($/MWh)
$\overline{Y}$	Logarithm of the long-term average natural gas wholesale price ($/MMBTU)
a_F	Annuity factor for investment cost
b_S	Stand by tariff ($/kW)
$d_{k,l}$	Daily demand charge ($/kW)
f_S	Fixed monthly electricity charge ($)
f_G	Fixed monthly natural gas tariff ($)
k_{Sk}	Monthly electricity price deterministic variation factor

k_{Gk}	Monthly natural gas deterministic variation factor
$n_{k,l}$	Number of day types in month
$p_{Sk,l,m}$	Adjustment factor to find time-of-use (TOU) prices from monthly average price
$u_{Sk,l,m}$	Electricity transmission and distribution tariff ($/MWh)
u_{Gk}	Natural gas distribution tariff ($/MWh)
α	Heat-to-power ratio
ε_{Xt}	Normally distributed variable used in electricity price process
ε_{Yt}	Normally distributed variable used in natural gas price process
μ	Electrical efficiency
γ	Efficiency of natural gas boilers
κ_X	Mean-reversion parameter for the electricity price process (1/y)
κ_Y	Mean-reversion parameter for the natural gas price process (1/y)
σ_X	Annual volatility of electricity price (1/y)
σ_Y	Annual volatility of natural gas price (1/y)
ρ	Correlation factor between electricity and natural gas

2. Model Description

2.1 Energy Wholesale Price Processes

In an investment appraisal of CHP, the future energy prices are important factors. Because of the uncertainty in future energy prices, we want to model the wholesale price of electricity and natural gas as stochastic processes. The theory of modeling stochastic prices has for the most part been developed with an application to stock prices. Commodity prices have a number of characteristics that make them different from stock prices. Stock prices have been modeled successfully using random walk models, such as geometric Brownian motion, which is the underlying process assumed in the commonly used Black-Scholes model for pricing stock options [2]. Commodity prices, however, often experience a mean-reverting effect in the price, a tendency of the prices to move back to a long-term average production cost after price deviations. The explanation for this effect is that when prices are high, producers with higher production costs will enter the market, which together with a reduced demand will put downward pressure on the price. Similarly, when the price is low, high cost producers exit the market putting upward pressure on the price. Therefore, mean-reversion has been well supported by empirical studies of energy prices [3].

Over a long time period, there will also be uncertainty about which level the prices will revert to, for example because some resources are exhaustible and due to potential technology improvements. Schwartz and Smith [4] have presented an example of a two-factor model where the short-term price variations are modeled as mean-reverting process, and the long-term price variations are modeled as a Geometric

Brownian motion. In this type of model, the price can typically be volatile in the short run, and revert around a long-term price that is less volatile. A one-factor random walk model without a mean-reversion effect must be parameterized on long-term price changes to avoid a significant probability for extremely high prices. Commodity prices are commonly modeled using the logarithm of the price to avoid the probability of negative prices.

Every commodity market is different due to the character of the traded commodity. Electricity, for example, cannot be stored and must be consumed at the same time as it is produced. Electricity that is purchased in peak hours is, therefore, expensive because it must be produced from units with few operating hours, units that typically have a low efficiency and thus low capital costs. This effect leads to a pattern of price variation with the demand variation. It can also lead to price spikes in periods with particularly high demand or supply outages. This property can be modeled as a mean-reverting process with a deterministic price pattern. In electricity markets with a reliance of intermittent renewable energy sources, such as wind power or hydropower, there can be a climate driven supply variation that creates mean-reversion in prices. The Nordic market, Nord Pool, with its high portion of hydropower shows a mean-reversion in prices due to variations in wind and precipitation. In electricity markets where natural gas is the price formative energy source, there can be a mean-reversion due to the correlations to the mean-reverting oil price. Patterns of demand and supply can also lead to seasonal and daily variation patterns in the price that are to so some extent predictable. Therefore, it can be advantageous to normalize the price with a deterministic seasonal factor to make the probability for high prices higher in peak periods.

Natural gas can be stored at a cost-effective price, which makes it cheaper to satisfy demand at peak periods and makes the price less volatile. However, natural gas prices are correlated to volatile oil prices because of substitution opportunities in some industrial processes, which will transfer volatility to the natural gas market. While storage avoids daily price variation, there can be seasonal demand patterns that storage does cannot fully smoothen.

The choice of stochastic price processes further depends on the modeling cases they are applied to. For the approach in this paper, where the value and risk of combined heat and power is modeled, it is important to capture monthly uncertainty in prices because combined heat and power units are able to respond to such price changes, and because monthly variations are important for the risk-characteristics of the investment. For models with a shorter time horizon, for example, where the goal is to optimize operation, and the building is on an electricity tariff with frequent price changes, a smaller time step should be chosen, and prices-spikes should be considered to be incorporated in the model. In this paper, it is assumed that the commercial building is on a time-of-use (TOU) electricity rate that is constant within the month, which makes it unnecessary to model short-term variations. A simple approach, which captures the major dynamics of the price processes, is to model the natural logarithms of the energy prices as two correlated mean-reverting price processes with deterministic seasonal variations. Long-term price uncertainty is not included in the model, to keep the price models simple enough to interpret the different parameters.

Under these assumptions, changes in the natural logarithm of the wholesale electricity price, X_t, can be modeled as [5]

$$\Delta X = \kappa_X(\overline{X} - X_t)\Delta t + \sigma_X \Delta W_X \tag{1}$$

where κ_x is the mean-reversion parameter, $\overline{X}$, is the logarithm of the long-term average electricity price, σ_x is electricity price volatility and $\Delta W_X = \varepsilon_{Xt}\sqrt{\Delta t}$ is an increment of a Wiener process. The price deviations are normally distributed with a standard deviation of one, $\varepsilon_{Xt} \sim N(0,1)$.

The changes in the natural logarithm of the wholesale natural gas price, Y_t, are given by a similar correlated process [5]

$$\Delta Y = \kappa_Y(\overline{Y} - Y_t)\Delta t + \rho\sigma_Y \Delta W_X + \sqrt{1-\rho^2}\sigma_Y \Delta W_Y \tag{2}$$

where κ_y is the mean-reversion parameter, $\overline{Y}$ is the logarithm of the long-term average natural gas price, σ_Y is electricity price volatility and $\Delta W_Y = \varepsilon_{Yt}\sqrt{\Delta t}$ is an increment of a Wiener process, and $\varepsilon_{Yt} \square N(0,1)$. The variance of the logarithm of the electricity price is given as [2]

$$V_{Xt} = (1 - e^{-2\kappa_X t})\frac{\sigma_X^2}{2\kappa_X} \tag{3}$$

And for the natural gas price as

$$V_{Yt} = (1 - e^{-2\kappa_Y t})\frac{\sigma_Y^2}{2\kappa_Y} \tag{4}$$

Note that the variances of this processes, increase with time and converge to a level that depends on the volatility and the mean-reversion parameter.

The actual wholesale prices are found as the product of the monthly adjustment factor, k_{Sk}, and the exponential of the natural logarithm of prices less half the variance of the electricity price

$$S_{Wj,k} = k_{Sk} e^{X_t - \frac{1}{2}V_{Xt}} \wedge k = t - 12(j-1) \tag{5}$$

where the time indices are changed from months from start date to years and months. The natural gas price is calculated in the same manner

$$G_{Wj,k} = k_{Gk} e^{Y_t - \frac{1}{2}V_{Yt}} \wedge k = t - 12(j-1) \tag{6}$$

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Now we have two correlated price processes for the electricity and the natural gas price. To estimate the price process parameters a simple approach outlined in [2] is followed. First, the seasonal parameters, k_{Sk}, and, k_{Gk}, are found as the average monthly deviation from the annual average price. Then, the mean-reversion parameters are found by regression of discrete version of the price processes to historical prices. The volatility is found from the standard errors of the regression and the correlation is simply the historical correlation factor. See for example [3] for more on estimating price process parameters.

2.2 Energy Tariff Structure

In addition to the wholesale price, a commercial building customer is charged a transmission and distribution tariff and often a demand charge. There are three main volumetric tariff structures, flat tariffs, TOU tariffs and real-time tariffs. In this work, we assume that the customer is on a TOU electricity tariff with an on-peak and an off-peak period. The difference between the on-peak and off-peak price, is calculated as the ratio between the average wholesale price and the average price in the two respective periods. We further assume that the electricity tariff includes a transmission and distribution adder, $u_{Sk,l,m}$, which is different in the on-peak and off-peak period. The volumetric electricity tariff can hence be written as

$$S_{j,k,l,m} = p_{Sk,l,m} S_{Wj,k} + u_{Sk,l,m} \qquad (7)$$

where $p_{Sk,l,m}$ is a factor to adjust the average wholesale price to the TOU periods. Also the natural gas tariff is assumed to include a distribution adder, u_{Gk}; both the natural gas wholesale price and the distribution adder are constant within the month

$$G_{j,k,l,m} = G_{Wj,k} + u_{Gk} \qquad (8)$$

In the U.S., peak demand charges are commonly based on the monthly maximum average electricity demand over thirty or fifteen minutes [6]. This charge leaves the CHP developer with an outage risk, because it cannot be guaranteed that the generators are available every peak hour of the month. In addition, it gives no incentives to run a CHP unit to reduce demand after an outage in a peak period, because the monthly demand charge is already high. In New York, the Consolidated Edison utility has developed a stand-by tariff for distributed generation with a monthly stand-by charge for a contract demand and a daily demand charge [7]. The case study in this paper is based on a simplified version of this demand tariff structure.

2.3 Alternative Operation Levels

With the given tariff structure, a commercial building with an installed CHP system can reduce energy costs by generating electricity for own consumption, using recovered heat to displace heat that is normally provided by natural gas fueled boilers, and by reducing daily demand charges. If the building electricity consumption was not subject to

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demand charges, optimal operation could be found independently every hour as the operation level that maximized hourly profits. However, with daily demand charges, the building can in addition to reducing utility purchases reduce daily demand, and reductions in the demand depends on how the units are operated in all demand metered hours. Hence, operation every hour is dependent on operation in the other hours if demand is to be reduced. Optimal operation can be estimated with an optimization program, but optimal operation depends on the energy prices, which vary in each simulation, the optimization program would have been run for every time step. Running an optimization program in every time step of a simulation program with hundreds of time steps and that must be run thousands of times to get good result distributions, would require a long unpractical computation time.

To find optimal operation, we therefore pre-define a set of different strategies, of which the CHP operator will chose the one that maximizes daily profits. First, we define a set of discrete reduction targets in daily demand, D_{Gi}, for the demand metered hours.

The set of demand reduction targets can for example be from zero kW to the capacity with steps of 10 kW. The demand reduction targets, combined with the expected load profile, are used to find the minimum operation each hour that leads to the corresponding expected demand reduction. After defining the demand reduction targets, we find optimal hourly operation for each of the demand reduction strategies. Then, the strategy that gives the highest daily profit is chosen. We define three hourly operation states

$P_{Di,k,l,m}$: *Generation at the minimum output that is compatible with the peak demand reduction target*

$P_{Mi,k,l,m}$: *Generation at the maximum output constrained by the electricity load and system capacity*

$P_{Qi,k,l,m}$: *Generation at the minimal electrical output that can satisfy the building heat load*

The three hourly operation levels are also found prior to simulation, with an optimization program or spreadsheet calculations. The minimum output level must be higher than the electricity load, $L_{Ek,l,m}$, less the new maximum demand for each demand reduction target. The operation level must also be within the allowed operation range and can be found from

$$P_{Di,k,l,m} = \min P_{Di,k,l,m}$$
$$s.t.$$
$$P_{Di,k,l,m} \geq L_{Ek,l,m} - (D_{Mk,l} - D_{Gi}) \text{ for } m \in H \qquad (9)$$
$$P_{Di,k,l,m} \in \{P_{\min},...,C\} \vee P_{Di,k,l,m} = 0$$

where $D_{Mk,l}$ is the maximum demand for each day type, $P_{\min}$, is the minimum output and, C, is the generator capacity.

The maximum hourly output, $P_{Mi,k,l,m}$, must be lower or equal to the electricity load and within the allowed operation range

$$
\begin{aligned}
&P_{Mi,k,l,m} = \max P_{Mi,k,l,m} \\
&s.t. \\
&P_{Mi,k,l,m} \le L_{Ek,l,m} \\
&P_{Mi,k,l,m} \in \{P_{\min}, ..., C\} \vee P_{Mi,k,l,m} = 0
\end{aligned}
\tag{10}
$$

The lowest electrical output where as much as possible of the building heat load, $L_{Qk,l,m}$, is satisfied by heat recovery is the electrical output level given by

$$
\begin{aligned}
&P_{Qi,k,l,m} = \max P_{Qi,k,l,m} \\
&s.t. \\
&P_{Qi,k,l,m} \le \max\left(\frac{L_{Qk,l,m}}{\alpha}, P_{\min}\right) \\
&P_{Qi,k,l,m} \le L_{Ek,l,m} \\
&P_{Qi,k,l,m} \in \{P_{\min}, ..., C\} \vee P_{Qi,k,l,m} = 0
\end{aligned}
\tag{11}
$$

For each of the three operation levels, $P_{Di,k,l,m}$, $P_{Mi,k,l,m}$ and $P_{Qi,k,l,m}$, we find the corresponding amount of heat that can be utilized for building heating needs, $Q_{Di,k,l,m}$, $Q_{Mi,k,l,m}$ and $Q_{Qi,k,l,m}$. The heat that can be utilized at the different operation levels is the minimum of the available recovered heat and the heat load

$$
\begin{aligned}
&Q_{Di,k,l,m} = \min(P_{Di,k,l,m}\alpha, L_{Qk,l,m}) \\
&Q_{Mi,k,l,m} = \min(P_{Mi,k,l,m}\alpha, L_{Qk,l,m}) \\
&Q_{Qi,k,l,m} = \min(P_{Qi,k,l,m}\alpha, L_{Qk,l,m})
\end{aligned}
\tag{12}
$$

where α is the heat-to-power ratio.

The actual demand reduction target might be infeasible to achieve because of minimum and maximum operation levels, and because of the shape of the load profile. For example if the load is 100 kW in one hour and 45 kW in all other demand metered hours, demand cannot be reduced with 70 kW if generators can only operate over 50 kW. Therefore, a variable that corrects the actual reduction in demand resulting from the various targets, $R_{Di,k,l}$, is introduced. It can be calculated as the previous maximal demand less the maximal demand with the demand reducing strategies

$$
R_{Di,k,l} = D_{Mk,l} - \max_{m \in H}(L_{Ek,l,m} - P_{Di,k,l,m})
\tag{13}
$$

2.4 Simulating Net Present Value

With the alternative pre-defined operational levels, the corresponding heat supply and the expected demand reductions, the value of every operational strategy can be calculated with Monte Carlo simulation of the wholesale prices. The value calculations are carried out in every simulation run because they depend on the simulated energy prices, and the strategy with the highest value is chosen.

First, we find the most profitable hourly operation level for each demand reducing goal, i. For each alternative operation level, the hourly volumetric profits, $Z_{Di,j,k,l,m}, Z_{Mi,j,k,l,m}$ and $Z_{Qi,j,k,l,m}$ are given as saved electricity purchased less additional natural gas purchases plus the natural gas savings due to heat recovery less operational costs

$$Z_{Di,j,k,l,m} = P_{Di,k,l,m}(S_{j,k,l,m} - G_{j,k,l,m}/\mu) + Q_{Di,k,l,m}G_{j,k,l,m}/\gamma - M$$

$$Z_{Mi,j,k,l,m} = P_{Mi,k,l,m}(S_{j,k,l,m} - G_{j,k,l,m}/\mu) + Q_{Mi,k,l,m}G_{j,k,l,m}/\gamma - M \quad (14)$$

$$Z_{Qi,j,k,l,m} = P_{Qi,k,l,m}(S_{j,k,l,m} - G_{j,k,l,m}/\mu) + Q_{Qi,k,l,m}G_{j,k,l,m}/\gamma - M$$

where μ is the electric efficiency and γ is the efficiency of the alternative method of providing heat using natural gas boilers and M is the operational costs. The daily volumetric profit, $Z_{Vj,k,l}$, for each demand reducing target, i, is the sum of the hourly profits from the most profitable operation level each hour

$$Z_{Vi,j,k,l} = \sum_{m} \max(Z_{Di,j,k,l,m}, Z_{Mi,j,k,l,m}, Z_{Qi,j,k,l,m}) \quad (15)$$

The daily profit, is the most profitable demand reduction strategy, which is the sum of savings on peak demand charges and volumetric savings

$$Z_{j,k,l} = \max_{i}(R_{Di,k,l}d_{k,l} + Z_{Vi,j,k,l}) \quad (16)$$

The net present value is the discounted daily profits multiplied by the number of days for each day type less the investment cost

$$NPV = \sum_{j} \frac{\sum_{k}\sum_{l} Z_{j,k,l}n_{k,l}}{(1+r)^{j}} - IC \quad (17)$$

where $n_{k,l}$ is the number of day types per month, I is the investment cost per kW installed capacity and r is the interest rate.

Net present value and operation will vary in every simulation run. The expected net present value is simply the average value in the simulations

$$E[NPV] = \sum_s \frac{NPV^s}{N} \quad (18)$$

where N is the total number of simulations and, NPV^s, is the net present value in simulation s.

2.5 Building Energy Cost Calculations

Total energy costs (including capital costs when CHP is installed), are calculated for the first year. The first-year energy costs in every simulation run is the sum of electricity and natural gas purchases, fixed costs, stand-by contract demand charges, daily demand charges and capital costs

$$AC = \sum_k \sum_l \sum_m n_{k,l}(L_{Ek,l,m}S_{j,k,l,m} + L_{Qk,l,m}G_{j,k,l,m}/\gamma)$$
$$+ \sum_k (f_S + f_G + \max_l(D_{Mk,l})b_S) + \sum_k \sum_l D_{Mk,l}d_{k,l}n_{k,l} + a_F IC \wedge j = 1 \quad (19)$$

where f_S is fixed monthly electricity costs, f_G is fixed monthly natural gas costs, b_S a standby charge based on maximum monthly demand and a_F, the annuity factor, is given as

$$a_F = \frac{r(1+r)^T}{((1+r)^T - 1)} \quad (20)$$

The expected first-year energy cost after the simulations is the average simulated value

$$E[AC] = \sum_s \frac{AC^s}{N} \quad (21)$$

where AC^S is the simulated value in simulation s.

3. Model Parameters

Electricity price process parameters, are estimated from New England ISO prices in the period from May 1999 to January 2003, while the natural gas price parameters were estimated from Henry Hub prices from the same period (see Table 1). The prices have been strongly correlated in the period due to the high natural gas fired electricity capacity installed in New England and because most of the peak power capacity is based on natural gas. Both the electricity and the natural gas price have a strong mean-reversion and a high volatility.

Table 1: Energy Price Process Parameters

X_0 ($/MWh)	$\overline{X}$ ($/MWh)	κ_X (1/y)	σ_X (1/y)	Y_0 ($/MWh)	$\overline{Y}$ ($/MWh)	κ_Y (1/y)	σ_Y (1/y)	ρ
3.73	3.61	3.13	0.41	1.31	1.35	1.69	0.39	0.82

Table 2 shows the energy tariffs that are used in the analysis. The electricity charges are based on a TOU rate while the natural gas charges are flat within the month. On-peak hours are from 8am to 8pm on non-holiday weekdays and off-peak the remaining days. There are monthly fixed costs in addition to the variable costs.

Table 2: Assumed energy tariffs

			On-Peak	Off-Peak	Monthly
Electricity	TOU-factors[*]	($/MWh)	1.14	0.91	-
	T&D	($/MWh)	65	45	-
	Demand Charge	($/kW)	0.4	-	-
	Standby Charge[**]	($/kW)	-	-	3
	Fixed Cost	($)	-	-	150
Natural Gas					
	Dist. Cost	($/MMBTU)	3	3	-
	Fixed Cost	($)	-	-	50

[*] To be multiplied with the monthly average wholesale prices to find TOU wholesale prices
[**] Charged monthly, based on the maximum building electricity load

Only one type of unit is considered for investment, but in systems with one, two, three or four generators of 60 kW are considered, which gives alternative installed capacities of 60 kW, 120 kW, 180 kW and 240 kW (see Table 3 for generator specifications).

Table 3: Generator Data (from [8])

| C (kW)	P_{min} (kW)	T (y)	I ($/kW)	M ($/MWh)	μ	α
60	30	20	1360	18	0.29	1.72

The building energy loads have been simulated with DOE-2, an energy load simulation program developed at Ernest Orlando Lawrence Berkeley National Laboratory, for a 7200 m^2 office building with climate data from Boston. The office building has a maximum electricity demand of 320 kW, an annual electricity consumption of 1 105 MWh and an annual heat consumption of 465 MWh. Figure 1 shows the pre-simulated electricity and heat load for the Boston office building for January and August, for week days and weekend days. The heat load is many times higher in the winter, while the electricity load is higher in the summer due to the use of electricity for space cooling. Weekend days have a lower electricity usage and most of the consumption is in the first half of the day. Additional parameters used in the analysis includes the efficiency for converting natural gas to heat, γ, through heat exchanges of 0.8 and the discount rate, r, of 8 percent.
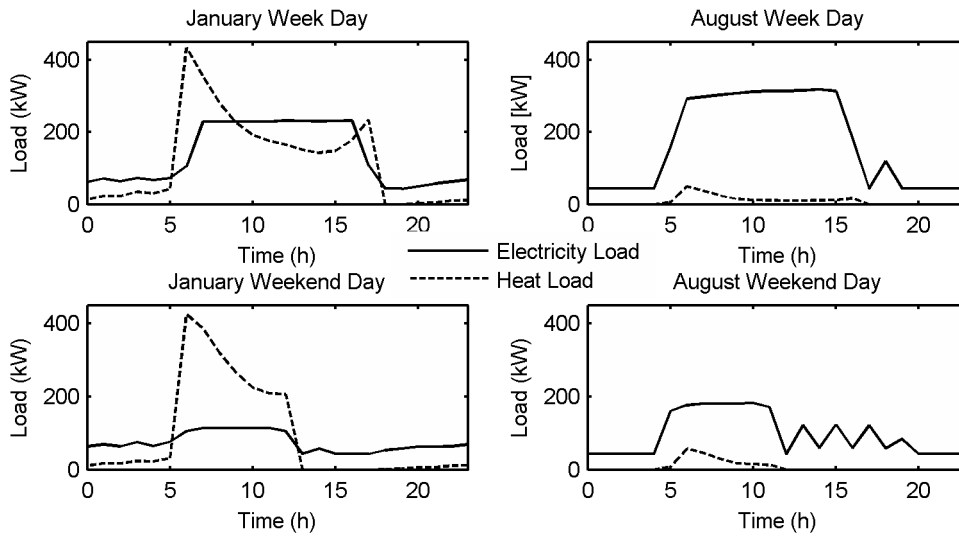
Figure 1. Pre-simulated energy loads for the Boston office

4. Simulation Results

Figure 2 shows the historical New England ISO electricity prices and the Henry Hub natural gas prices in the period from May 1999 to January 2002 and one sample of simulated monthly prices for the next twenty years. The strong correlation between the electricity and the natural gas price from the historical data is carried through in the example simulated future prices. Also, the strong tendency of the prices to revert back to a long-term average is clearly visible in the simulated paths. Note that the figure only shows one price path for each of the energy prices; in the simulation of the net present value and the first-year energy costs, 20,000 price path simulations are carried out.
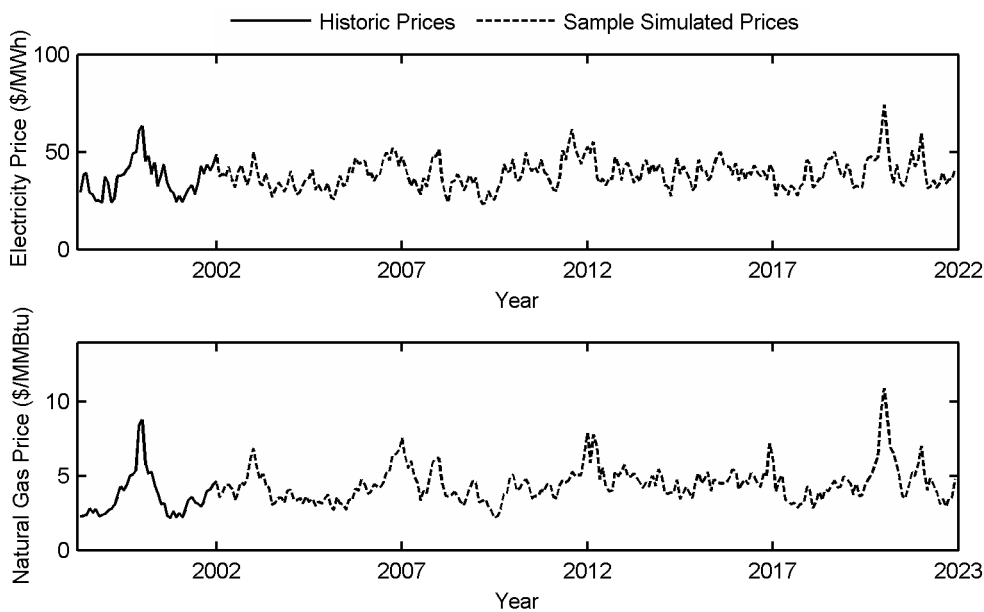
Figure 2. Historical and sample simulated electricity and natural gas prices

4.1 Base Case Results

In Figure 3, the base case results, from the simulations of the net present value, for the four considered systems can be seen. The 120 kW system has the highest expected net present value and the 240 kW system the lowest. Notice that the standard deviation of the net present value increases with capacity. None of simulation runs resulted in a negative net present value for any of the alternative systems. The explanations for the fairly low standard deviation in the net present value are that the uncertain wholesale prices are just a portion of the tariffs, that there is a high correlation between the electricity and natural gas price and the that there is a strong mean-reversion in the prices. The figure shows that CHP systems are attractive for the office building with the assumed parameters.
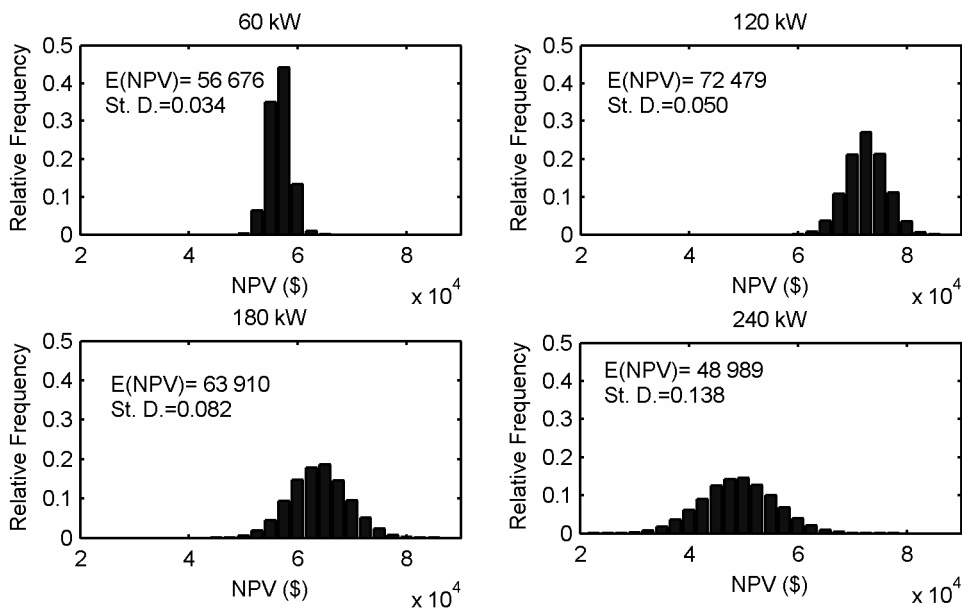

Figure 3. Simulated net present value of the four considered CHP installed capacities

Some building owners might care more about the standard deviation in the total cost than about the standard deviation of the net present value of the investment. A company might also be more concerned with cost risk over shorter periods than the 20-years expected lifetime of CHP units. Figure 4 shows the expected total energy costs and standard deviation the first year, without a CHP system installed and with the four alternative systems. The building has an expected energy cost of $ 158 935, with a standard deviation of 3.14 percent the first year. All four CHP-systems results in a lower expected first-year cost but only the 60 kW system results in a lower standard deviation. On the one-year horizon, the 240 kW system has a higher expected value than the 60 kW unit because electricity price is initially higher than the long-term average and the natural gas price is initially lower than the long-term average.

The expected costs and the standard deviation of the first-year cost does not tell the full story of the CHP associated costs risks, because two systems can have the same expected costs and standard deviation, while one can have a larger probability for a particularly high cost. Figure 5 shows the highest one-year energy costs, including the investment costs, of the four investment alternatives and for the building without CHP,

within a confidence level of 95 and 99 percent. It can be seen that all four CHP systems result in lower maximum costs within both confidence levels. The 120 kW has the lowest costs and the 240 kW the highest costs of the systems in both confidence levels.
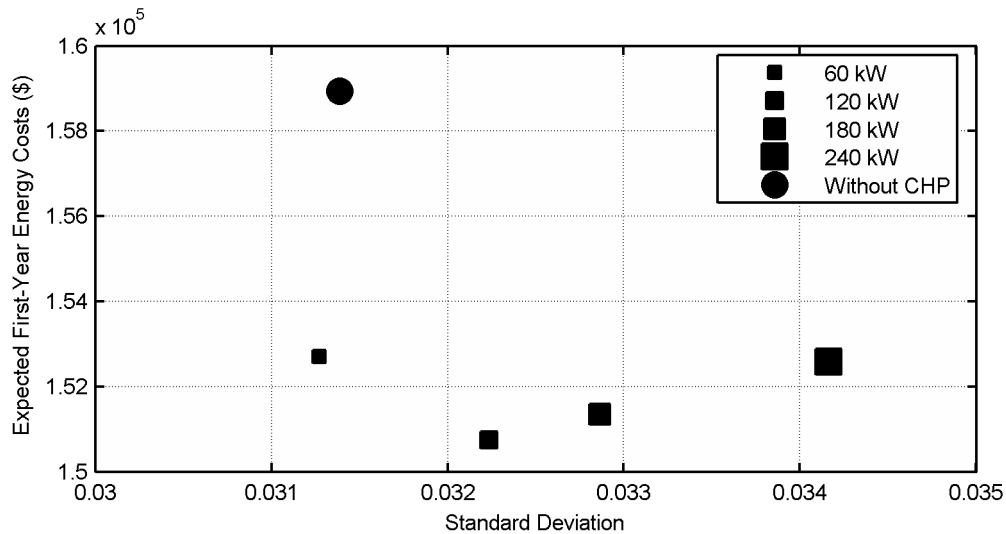
Figure 4. Simulated energy costs including capital costs for the first year with and without CHP
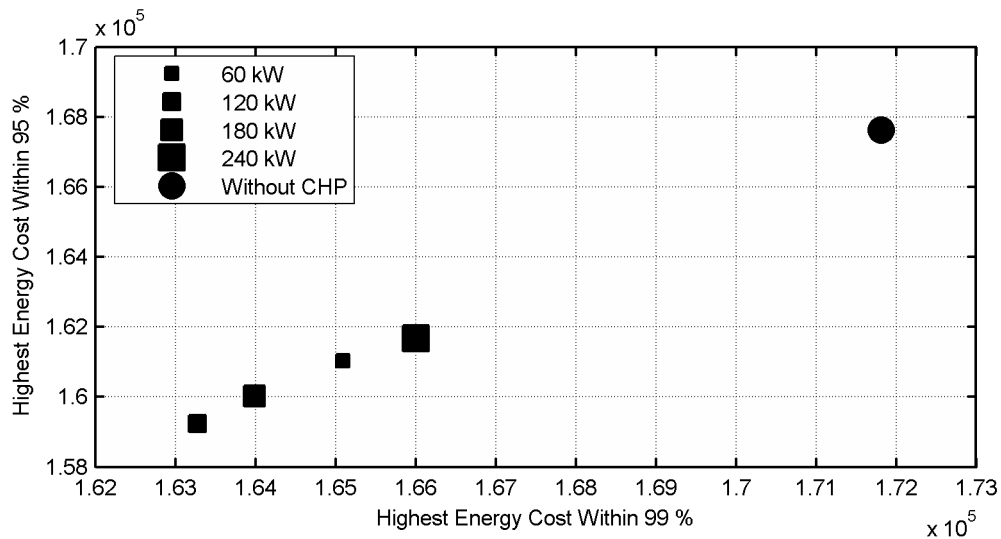

Figure 5. Highest first-year energy cost within 95 and 99 percent of simulations

4.2 Sensitivity to Uncertainty in the Electricity Price

The volatility in the electricity price is rarely constant, and it also differs between markets. Therefore, we simulate the net present value with an electricity price volatility that has been increased by a factor of 1.5 (from 0.4 to 0.6 annually). The effect of the increased price volatility is that both the expected net present value and the standard deviation are increased for all projects (see Figure 6). The increased net present value with volatility option characteristics of operation of CHP and show that operation levels are adjusted with the price levels. However, the changes in the profitability are minor, which can be explained by the fact that both the electricity and the natural gas price

process have a high mean-reversion factor. A high mean-reversion parameter means that it is unlikely that the price stays far away from the long-term average for a long period, the result being that price deviation even out over the life of the CHP units. The increase in profitability can again be explained by the operational flexibility.
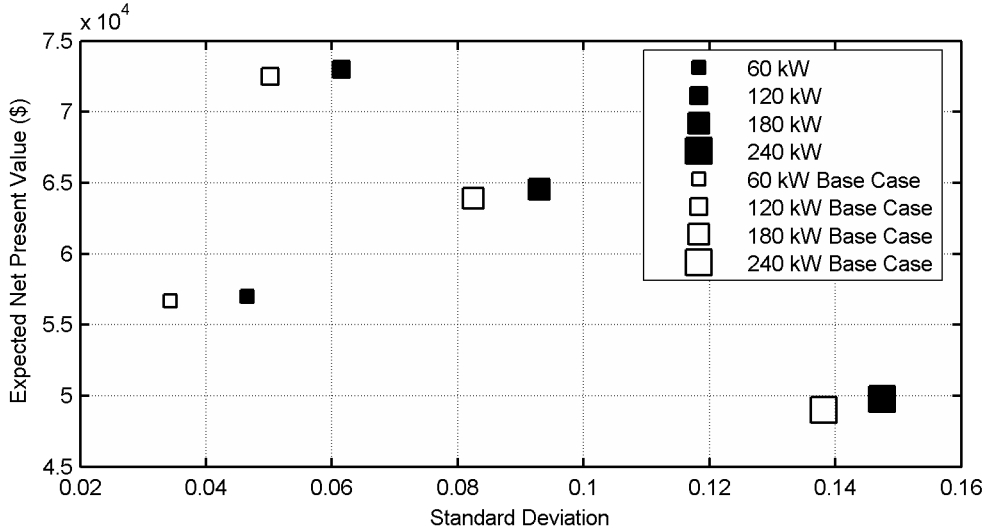
Figure 6. Expected net present value and standard deviation in simulated values with an increase in the electricity volatility of a factor of 1.5 compared to the base case

As expected, the first-year energy cost standard deviation increases with uncertainty from 3.14 to 4.49 percent (see Figure 7). With the higher electricity price volatility, all CHP systems results in a lower first-year standard deviation in energy costs. Note that with the higher price volatility, the standard deviation in energy costs is reduced with size, which means that the largest systems has the most predictable energy costs but the 120 kW unit still has the lowest expected first-year energy costs.
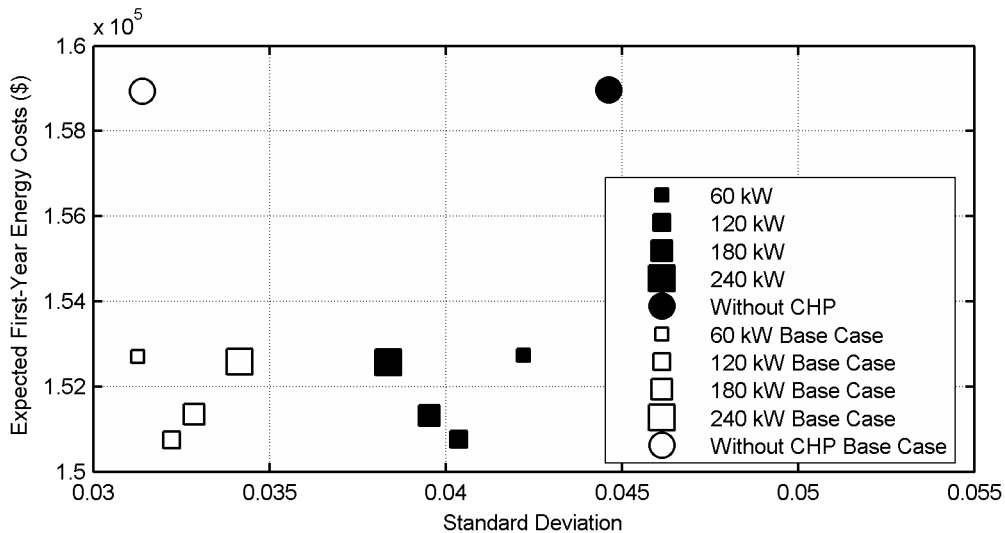
Figure 7. First-year energy costs with an 1.5 factor increase in electricity volatility from the base case
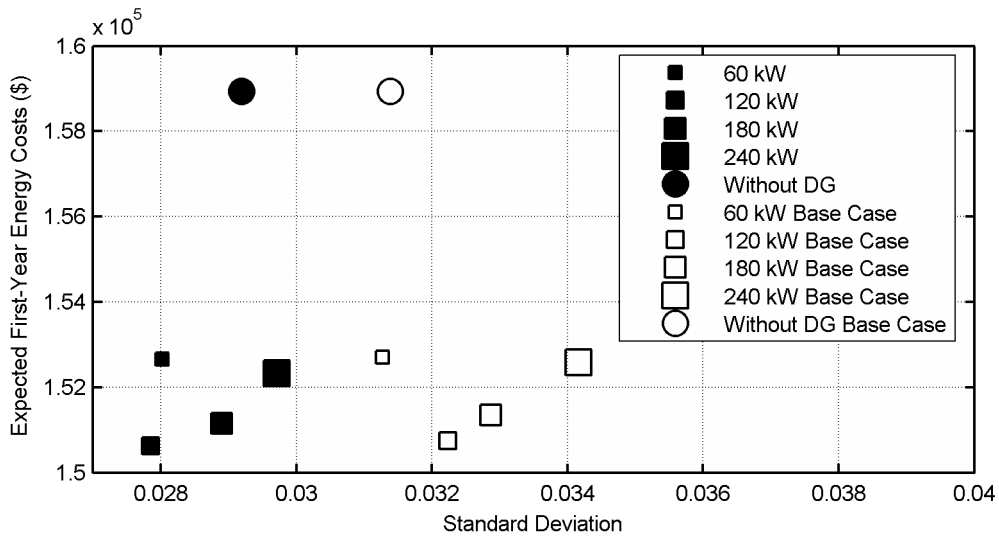
4.3 Sensitivity to the Price Correlation Factor

The New England ISO electricity prices and the Henry Hub natural gas prices have been highly correlated in the period we used to estimate the price process parameters. In the future, and in other electricity markets with a lower reliance on natural gas, the prices might be less correlated. Figure 8 shows the net present value of the four alternative systems with a halved correlation factor of 0.41, versus 0.82 previously. The figure also shows the base case solution as the hollow squares. The main change in the results is that the standard deviation is increased. This is an expected effect because natural gas fueled generators base their profitability on the spark spread, the difference between the electricity and the natural gas price, which will be more volatile when the processes are less correlated. Somewhat more surprisingly, the net present value of all projects increase, something that can be attributed to the flexibility in operation of the generators. The generators can be turned off when the profitability is low; they can catch the upside of the increased spark spread volatility while they do not suffer from the downside because they can be turned off to purchase electricity and natural gas from the grid. Also with a reduced correlation in the energy prices, the 120 kW unit is the most profitable.
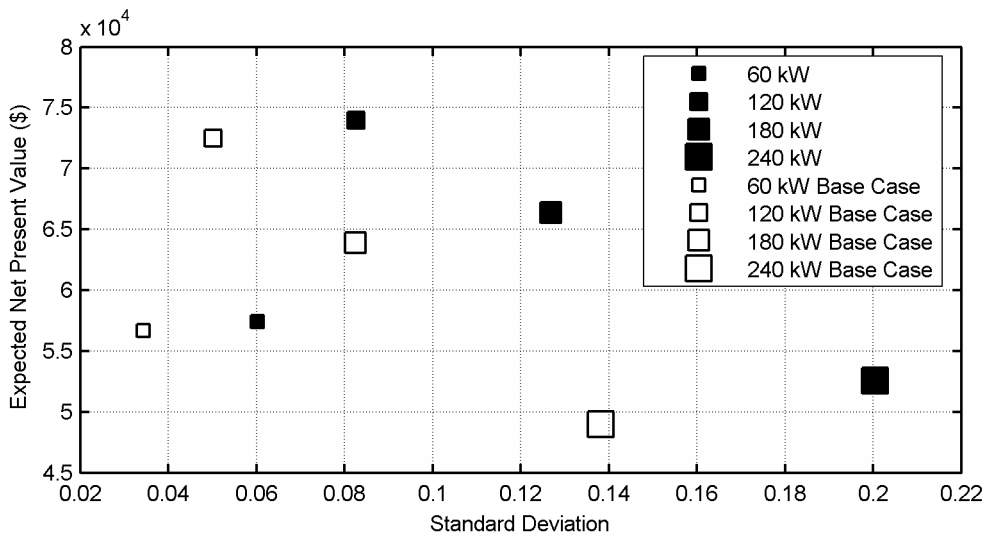
Figure 8. Net present value of the four alternative investments with a halved correlation between electricity and natural gas prices compared to the base case results

For the first-year total cost of supplying energy to the building, the effect of the reduced correlation on standard deviation is the opposite as the standard deviation of the first-year costs is reduced for all alternatives (see Figure 9). This is an expected effect, because it is now more likely that the wholesale prices move in a different direction, thereby smoothing out each others volatility's effect on cost variation. Interestingly, the three smallest systems reduce standard deviation in the first-year costs, while only the smallest system did so with the base case correlation. This result indicates that CHP units are better for hedging energy costs when the correlation between the natural gas and electricity price is lower. Also in the one-year horizon, the 120 kW unit has the lowest total building energy costs, but in this case it also has the lowest standard deviation in costs.

Figure 9. First-year energy costs including investment costs with a halved correlation factor between the electricity and natural gas price compared to the base case
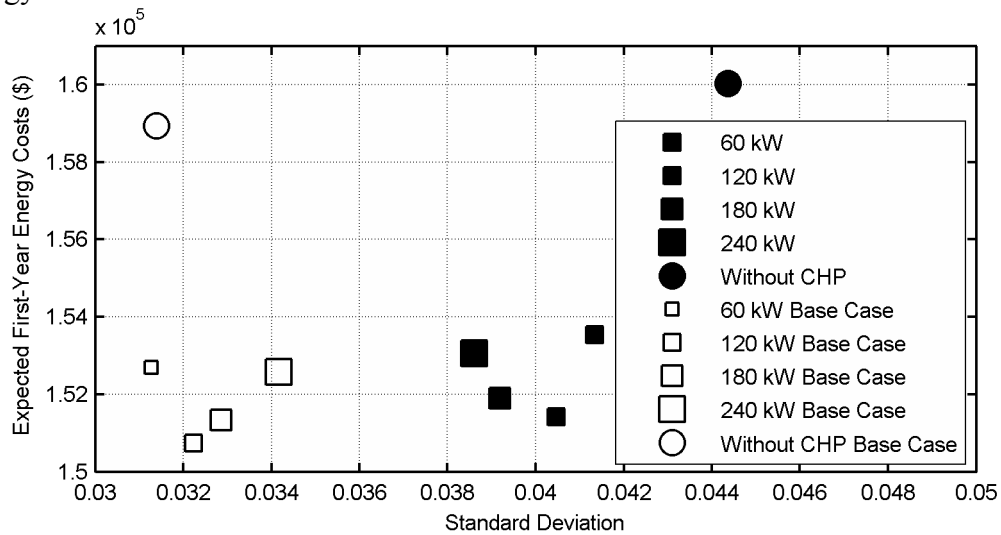
4.4 Sensitivity to the Electricity Mean-Reversion Rate

A lower mean-reversion rate implies that the price is pushed towards the long-term average price at a lower rate when it is above or below it. In Figure 10, the model is run with an electricity mean-reversion parameter for the electricity price that is reduced by a factor of 0.5, from 3.16 to 1.58. Also with a reduced mean-reversion factor the expected net present value is increased, most likely because there is a higher probability for very high prices. The standard deviation increases significantly because the prices can stay far away from the long-term average price for longer periods. Again, there is a similar shift in both net present value and standard deviation for all units, and the 120 kW unit is the most profitable.
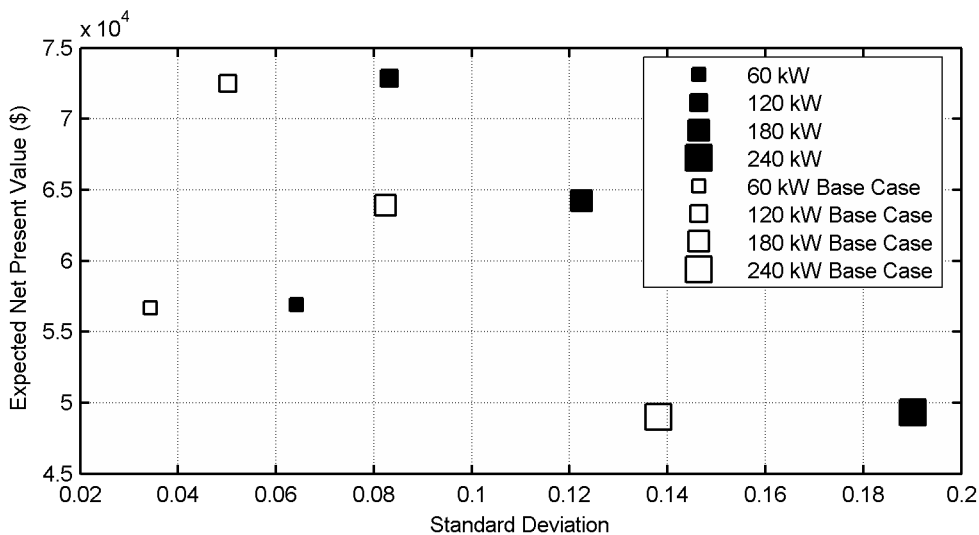
Figure 10. Simulated net present value for the four CHP systems with an electricity mean-reversion rate that has been reduced by a factor of 0.5 compared to the base case

The reduction in the mean-reversion parameter leads to an increase in the expected first-year energy costs, as seen in Figure11. This is most likely due to the fact that the electricity price is slightly higher than the long-term average initially, and the price is now less likely to fall towards the long-term average. The other main effect is that the standard deviation increases without CHP and with all CHP systems. Now, all considered systems lead to a lower standard deviation in energy costs and the standard deviation decrease with system size. Still, the 120 kW system gives the lowest expected energy costs.


Figure 11. Simulated first-year total energy costs with an electricity mean-reversion rate that has been reduced by a factor of 0.5 compared to the base case
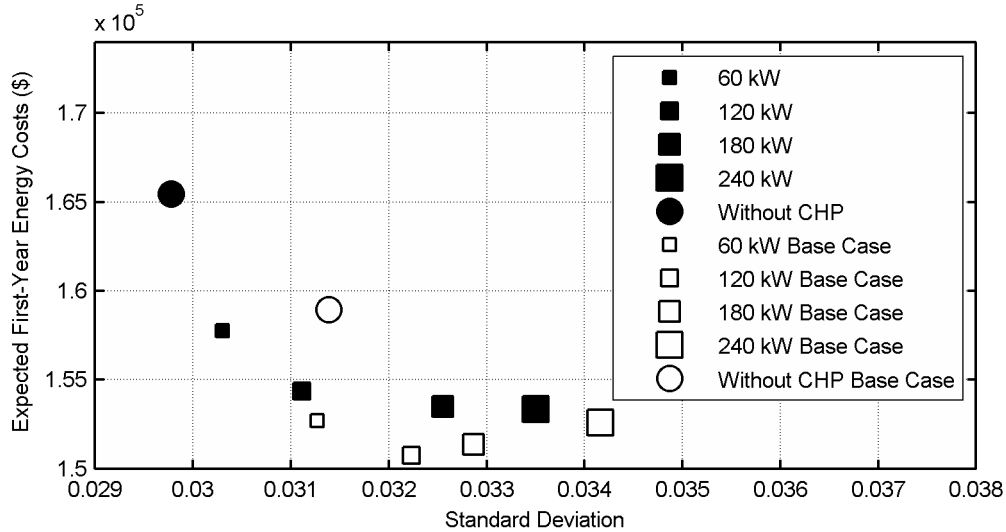
4.5 Sensitivity to Demand Charges

Demand charges can constitute a major share of a commercial building's energy costs. The level of the demand charges depends on the costs and strains on the grid system, and they are highly variable across regions; in the Boston area, the monthly demand charge in peak hours is 24 $/kW while in Atlanta there is no demand charge at all. In New York that has daily demand charges for distributed generation, it can be as high as 0.9 $/kW, depending on location and service. Units that are successful in reducing demand will have a potentially high net present value. Net present value has been simulated with a demand charge that has been increased from 0.4 $/kW to 0.5 $/kW. Figure 12 shows that the expected net present value increases significantly, and that the standard deviation is reduced for all units and to the largest extent for the largest units. With a higher demand charge the most profitable capacity has increased from 120 kW to 180 kW, and the 240 kW system has the next highest net present value. This result shows how important demand charges can be both for installed capacity and for profitability. With considerable demand charges, it is clear that the common mantra to size CHP systems to the heat load does not apply, because size depends on reductions in the demand charges. Sizing must therefore be determined by an optimization program or by analyzing alternative systems, as in this approach.

In Figure 13 the effect on first-year energy costs and standard deviation of increasing the demand charge from 0.4 to 0.5 $/kW can be seen. The costs increase the most for the alternative without CHP and for the small alternatives. The very low

reduction in first-year costs for the largest systems proves that the large systems are used effectively to reduce demand charges. All CHP systems have a higher standard deviation in first-year energy costs than without CHP, but the first-year profitability has nearly doubled for the two largest systems. An important finding from the figure is that on-site generation, and in particular larger systems, can be a hedge against increases in demand charges since the energy costs for with installed CHP systems is far less sensitive to the demand charge than without CHP.
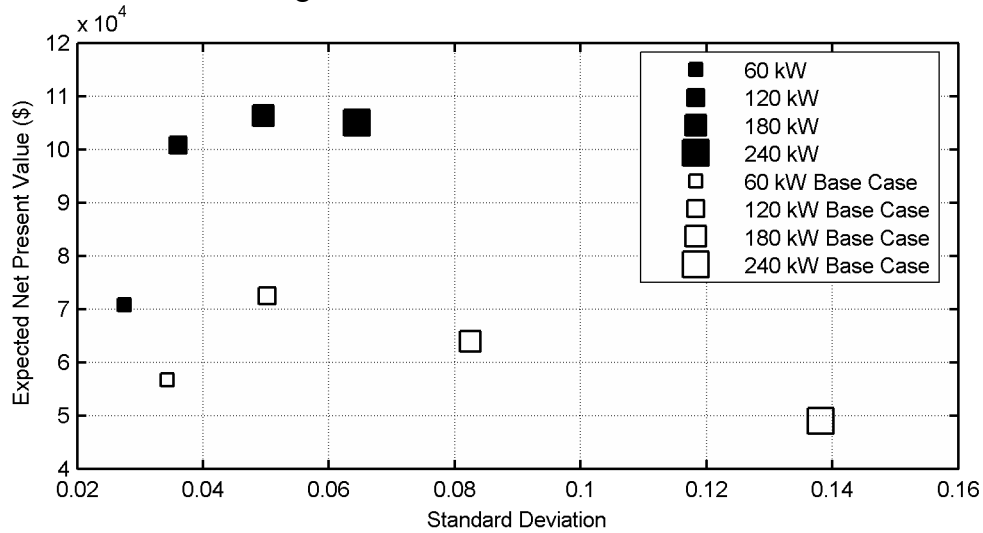
Figure 12. Expected net present value and standard deviation for a daily demand charge of 0.5 $/kW compared to the base case of 0.4 $/kW

Figure 13. Expected first-year energy costs with a demand charge of 0.5 $/kW versus 0.4 $/kW in the base case

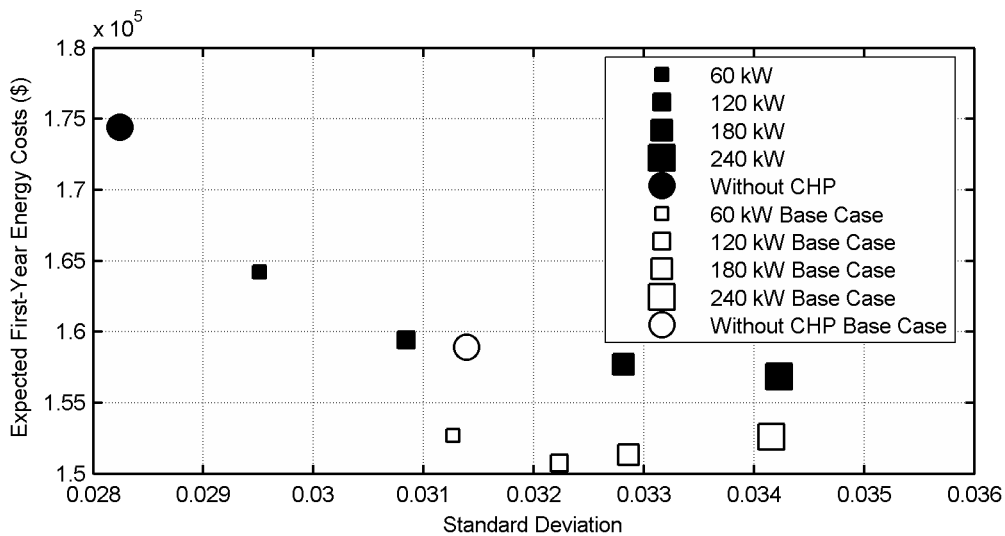*4.6 Sensitivity to Electricity Transmission and Distribution Charges*

The transmission and distribution charges do, like the demand charge, vary across regions due to the variations in the costs of building the grid and transmitting electricity. The simulated net present value with an increase in the transmission charges of a factor

21

of 1.25 is shown in Figure 14. The most profitable system is now the largest 240 kW system. The standard deviations of the net present values have decreased for all systems because the deterministic transmission and distribution charges constitute a larger share of the net present value.

The first-year energy costs also increase both with and without CHP systems installed (see Figure 15). The standard deviation in first-year energy costs decreases with the higher transmission and distribution tariff as expected. With CHP systems installed, however, the results are more ambitious, as the standard deviation decrease for the three smallest systems while it increases for the largest 240 kW system. With the increased transmission and distribution tariff, all systems have a higher standard deviation in the first-year energy costs than without CHP. But it should be noted that the expected first-year cost are from 5.7 to 10 percent lower than without CHP and the standard deviation with CHP range from 2.95 to 3.33 percent.
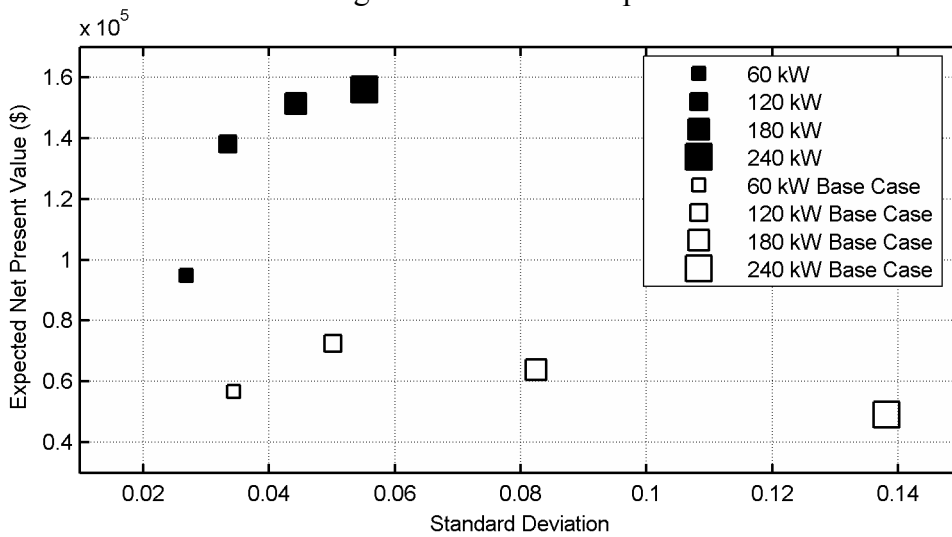
Figure 14. Expected net present value and standard deviation with an 1.25 factor increase in electricity transmission and distribution tariff compared to the base case

Figure 15. Simulated first-year energy costs with an electricity transmission and distribution tariff that has been increased by a factor of 1.25 compared to the base case

5. Discussion

In the analysis, it has been assumed that the electricity and natural gas prices follow mean-reverting processes where the levels the processes revert to are assumed to be constant. Although energy prices have been shown to fit well to mean-reverting processes, there will always be a possibility that the prices move to a higher or lower level over long periods. Including uncertainty in the level the prices revert to would make the investments more uncertain. Alternatively, a deterministic growth in the long-term price could be included if that was reflected in the market expectation. Also, price jumps and stochastic volatility could have been included to make the price processes more realistic. Further work should look at how the risk characteristics will change if energy prices are modeled with more sophisticated price models. However, the presented model captures the main characteristic of the price processes and represents an improvement compared to deterministic analyses.

Different companies will care about different risk indicators. Typically, a company cares about the probability for bankruptcy, which for instance depends on the debt level. In addition, different companies will have a different required return on their investments. Even though the analysis does not include a company specific risk analysis, the Monte Carlo model will be a good starting point for most risk analyses. Further, there is uncertainty associated with other parameters. The sensitivity analysis showed that the choice of system depends to a large extent on the level of the demand charges and the transmission and distribution costs. Including uncertainty in these costs is not a challenge in a modeling sense because it can be done with scenarios with probabilities attached to them, but estimating the parameters might be a challenge.

In the U.S., demand charges are commonly based on monthly peak demand for commercial building electricity tariffs. It is simple to modify the model to include monthly demand metering, but without perfectly reliable CHP units this would come with uncertainty in the system's ability to reduce the demand charges. Under such conditions, the system availability could be modeled with a Monte Carlo simulation integrated with the price models.

In areas with cooling loads, adding absorption chillers to the on-site generators can be profitable. Including absorption chillers in potential system configurations, would also make the system more flexible because recovered heat can be used for both heating and cooling at times with both a space cooling and a hot water load. Absorption cooling can be included in the model in a way similar to heating, with alternative operational decisions, but it would make the model significantly larger as there would be many more operating states to consider. Previous work has focused on the ability of renewable energy sources to reduce cost uncertainty [9]. The presented model could also be expanded to include renewable energy sources by using a set of production profiles each month, such as an average, a low and a high power generation day. Although renewable resources can reduce the volumetric costs very successfully, and to some extent the demand charges, they would not reduce natural gas costs unless thermal renewable systems are installed. Thus, there will still be energy cost uncertainty for buildings with renewable energy sources, even though a large share of the costs are capital costs, which can be made predictable with fixed interest rates. Analyzing the effect of including renewable energy resources is nonetheless an interesting research topic for future work.

6. Conclusion

We have presented a Monte Carlo simulation model for evaluation of investments in CHP systems, for commercial buildings, with stochastic electricity and natural gas prices. The energy prices have been modeled as mean-reverting processes, where the prices are assumed to be pushed back towards a long-term average if they drift away from it. The model has been applied to four alternative CHP system investments, with capacities of 60, 120, 180 and 240 kW, for a Boston office building with pre-simulated energy loads. The building was assumed to be on a TOU-tariff structure with a standby contract demand charge and daily demand charges based on the maximum daily demand. The price model parameters were estimated with New England ISO prices and Henry Hub natural gas prices, which were volatile, highly correlated and had a strong mean-reversion in the data period. Under this wholesale energy price environment and with the assumed tariff structure, CHP systems are attractive investments. The net present value of the investment is positive for all considered systems, but the 120 kW system has the highest net present value. Standard deviation in the net present value increases with the size of the CHP system. Only the 60 kW system results in a lower standard deviation in the total first-year costs, but all systems have lower maximum one-year costs within 95 and 99 percent of the simulations. The sensitivity analysis shows that the value of CHP increases with a lower correlation factor, a lower mean-reversion factor and with increasing uncertainty in the electricity price. The reason for this, is that the operational flexibility in the CHP units makes it possible to operate the systems only when the price conditions are favorable, which means they will catch the upside of the increased uncertainty but not suffer correspondingly from the downside because electricity and natural gas can be bought from the market. In a more uncertain energy cost environment, the trend seems to be that the CHP systems result in lower first-year energy cost volatility. These results indicate that potential developers of CHP in commercial buildings should not be frightened by uncertainty in energy wholesale prices. Rather, high price uncertainty can be a reason to invest in CHP to hedge the annual energy costs. In addition, it should be noted that in this case, and generally for U.S. tariffs, the wholesale prices are a minor constituent of the electricity tariff. Both higher demand charges and transmission and distribution charges, which are modeled as constants, lead to larger systems being optimal than with the base case parameters. This shows that the tariff structure can play an important role in finding the optimal size of the systems.

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PAPER III

Optimizing Distributed Generation Systems for

Commercial Buildings

Karl Magnus Maribu

Optimizing Distributed Generation Systems for Commercial Buildings

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Abstract

Important factors for distributed generation profitability are identified using a mixed integer linear model with simulated load data for a healthcare and an office building in California. Under the assumed time-of-use (TOU) electricity prices, with monthly peak demand charges, the installed distributed generation system's ability to reduce demand charges can be a critical factor for profitability. Systems with lower reliability than promised can infer large losses to the developer, which makes demand charges a potential barrier to wide spread distributed generation adoption. In a variety of natural gas and electricity price scenarios, the optimal decision is to install distributed generation units with heat recovery and absorption chillers. The benefit maximizing solution reduces a building's carbon emissions in most price scenarios. The introduction of a carbon tax can reduce emissions further. In competition with natural gas-fueled equipment, both the break-even cost and the installed capacity of photovoltaics is reduced in both buildings. The healthcare building has the highest return on capital. High discount rates favor small base load generation systems with heat recovery.

1. Introduction

Technological progress for small power producing units and an increased focus on efficient and renewable power production can force a change where distributed generation (DG) becomes an important part of the future energy system. The focus in this paper is on the economic potential of distributed generation in commercial buildings. Customers with electricity, heating and cooling loads can invest in generating units to satisfy part of their loads. Many technologies can be used on-site, including gas turbines, reciprocating engines, fuel cells, wind turbines and photovoltaics. All technologies installed locally have the potential to reduce grid losses and costly grid investments [1]. Renewable technologies have the highest potential to reduce carbon emissions, but also, natural gas-based units with heat recovery can serve end-use loads at a higher efficiency than a central system, and thus, reduce emissions. Also, absorption cooling can offset expensive peak load electricity and reduce the peak load in systems with summer cooling peaks. This work tries to identify the decisive factors for investment profitability, preferred technology type and potential barriers to distributed generation development in commercial buildings.

The model, presented in this paper, finds the optimal combination of distributed generation units given a building's energy load profiles, energy prices and available technologies. The model is used as a framework for analyzing how two commercial buildings, an office and a healthcare building, can install optimal generation portfolios under different economic and policy scenarios. It is assumed that the building currently satisfy heat loads by natural gas combustion and cooling loads by a central electrical cooling system. It is also assumed that the customers have access to both a natural gas distribution system and a location for both natural gas-based systems and photovoltaics. Alternative technologies have different characteristics such as capacity, investment cost, efficiency, operation cost, operation flexibility and expected lifetime. The investment alternatives are interrelated because the available electricity, heating and cooling loads are dependent on the installed equipment. It is a well-accepted rule to invest in the alternative that maximizes net present value. However, because the alternative technologies have different expected lifetimes the net present value cannot be compared directly. Therefore, the model maximizes equivalent net annual benefit of the investment over a given time horizon.

Many factors affect the optimal solution, and potentially particularly important factors are the electricity and natural gas price forecasts. Some selected price scenarios and their effect on the solution is presented. For example, the paper tries to answer at which investment costs photovoltaic systems (which are an immature technology with expected future reductions in investment cost) can compete with buying electricity from the grid and with natural gas fueled equipment. Further, building emissions, corresponding to a range of carbon taxes, are compared to emissions without distributed generation. This analysis assumes time-of-use (TOU) prices where peak demand charges, which are charged based on the maximum monthly building electricity load in TOU-periods, can constitute a considerable amount of the energy bill. A generator's ability to reduce demand charges, therefore, depends on its reliability. A natural question to answer is how sensitive the investment decision is to the systems ability to reduce demand charges. Various developers of distributed generation will have different

expectations for return on capital and the sensitivity to the assumed discount rate shows how the optimal systems vary.

The second section of the paper presents the investment model, and the third section presents the model parameters and the scenarios used. In the fourth section, the results from solving the model in the scenarios for the healthcare and the office building are given. The fifth section concludes the analysis and suggests some areas for further work in modeling the economic attractiveness of distributed generation in commercial buildings.

Nomenclature

Indices

i	Distributed generation (DG) unit
j	Time period
k	Season (Winter, Spring, Summer, Fall)
l	Day type (Weekday, Weekend day, Peak day)
m	Hour of day
t	Time-of-use period (Off-peak, Part-peak, Peak, All)

Subsets

NG	Natural gas-based units of i
PV	Photovoltaic units of i

Variables

B_j	Annual benefits
EV	Equivalent net annual benefits
O_j	Annual operational costs
$P_{i,j,k,l,m}$	Electricity production from unit
$P_{C\,j,k,l,m}$	Displaced electricity purchases from absorption cooling
$P_{D\,j,k,l,m}$	Expected reduction in electricity load for monthly demand charges
$P_{E\,j,k,l,m}$	Electricity production from all units
$P_{Q\,j,k,l,m}$	Recovered heat that satisfies building heat load
$R_{D\,j,k,t}$	Expected reduction in peak demand

Integer Variables

x_i	Number of purchased units of DG equipment
$y_{i,j,k,l,m}$	Number of units running at each time step

Parameters

C_i	Capacity
$D_{k,t}$	Maximum load in time-of-use periods
G_{0k}	Initial wholesale natural gas price
$G_{R\,j,k}$	Retail natural gas price

3

$G_{W\,j,k}$	Wholesale natural gas price
H	Study horizon
I_i	Investment cost
$L_{E\,k,l,m}$	Electricity-only load
$L_{C\,k,l,m}$	Cooling load in electricity units (assuming central electric cooling system)
$L_{Q\,k,l,m}$	Heat load
$N_{D\,k,l}$	Number of day types in each season
N_M	Months in season
N_Y	Number of years in each forecast period
$O_{F\,i}$	Annual fixed operational costs
$O_{V\,i}$	Variable operational costs
$S_{0\,k,l,m}$	Initial wholesale electricity price
$S_{R\,j,k,l,m}$	Retail electricity price
$S_{W\,j,k,l,m}$	Wholesale electricity price
T_i	Lifetime
U_S	Electricity price adder for transmission and distribution
U_G	Natural gas price adder for distribution
$V_{k,m}$	Solar production as ratio of capacity
a_i	Annuity factors for investment costs
a_H	Annuity factor for discounted cash flows
$d_{k,t}$	Demand charges
f_j	Discount factor
r	Discount rate
α_S	Annual growth in electricity price
α_G	Annual growth in natural gas price
β_C	Coefficient of performance (COP) for absorption cooling process
β_E	COP for central electric chillers
β_G	COP for natural gas-based heating
β_Q	COP for heat exchanger
$\gamma_{Q\,i}$	Heat-to-power ratio
$\gamma_{C\,i}$	Heat-to-power ratio for cooling (zero if absorption chillers are not installed)
θ_i	Generator's ability to reduce demand charges
θ_C	Absorption chiller's ability to reduce demand charges
λ	Minimum generator operation level (percentage of capacity)
μ_i	Electric efficiency

2. Investment Model

The objective of the investment model is to maximize the net economic benefit of installing distributed generation equipment. Since different units have different lifetimes, the model's objective function is the net equivalent annual benefit over a study horizon. Economic benefits of distributed generation in commercial buildings come from serving local electricity, heat and cooling loads. Buildings with distributed generation can serve electricity loads by purchasing electricity from the grid or by generating on-site. It is assumed the buildings in the study have installed gas boilers to serve building heat loads, thus heating loads can be met by direct combustion of natural gas or by waste heat from combined heat and power units. Further, it is assumed that the buildings have a central electric chilling system. Cooling loads can, therefore, be met by electricity purchases from the grid or by absorption chillers that utilize recovered heat to provide cooling.

There are a number of potential DG technologies. These include reciprocating engines, gas turbines, fuel cells, photovoltaic power and wind turbines. Thermal technologies can be equipped with or without a heat exchanger and an absorption chiller. In addition, units come in a variety of sizes and have different characteristics such as electrical efficiency, investment cost, operational costs, heat rates and lifetime. In the analysis, it is assumed that electricity cannot be exported, therefore, the local load that on-site generators can serve is limited; the energy loads vary significantly throughout the day and natural gas-based units have a limited operation range. Because of these characteristics, the benefit maximizing DG system can be a combination of units (e.g. a combination of base load and peak-load units). Hence, finding the optimal system is an optimization problem. Since units come only with discrete capacities, the problem is implemented as a mixed integer linear program. A price forecast period of 20 years is used and modeled as four five-year periods. To represent variation in prices and building loads, four seasons with three day types with hourly data are used. The winter season is November, December and January, spring February to April, summer May to July, and fall August to October. Day types are weekdays, weekends days and peak days. Peak days have the average hourly load of the monthly three non-holiday weekdays with the highest electricity load. Weekdays have the average hourly load of the remaining non-holiday weekdays. Weekend days have similarly the hourly average loads of weekend days of the months in each season.

Three load types are modeled: electricity-only, cooling and heat load. Electricity-only load is the electricity load less the electricity that is used for cooling, while cooling is the electric cooling load when the central cooling system is used, and the heat load is the sum of space and water heat load.

2.1 Mathematical Model Formulation

The investment model maximizes the equivalent net annual benefits of installing distributed generation equipment in a building. The equivalent net annual benefit, EV, is a function of annual benefits, B_j, operating costs, O_j, investment costs, I_i, capacity of installed equipment, C_i, and annuity factors

$$EV = a_H (\sum_j f_j (B_j - O_j)) - \sum_i a_i x_i C_i I_i \qquad (1)$$

where x_i is an integer variable that decides the number of units to invest in. The annuity factors are calculated from

$$a_H = \frac{r(1+r)^H}{((1+r)^H - 1))}, \qquad a_i = \frac{r(1+r)^{T_i}}{((1+r)^{T_i} - 1))} \tag{2}$$

The discount factor is the sum of the annual discount factors within each period

$$f_j = \sum_{u=v}^{u=w} \frac{1}{(1+r)^u} \tag{3}$$

where r is the discount rate and the summation is from the first year in the period, $v = 1 + N_Y(j-1)$, to the last year in the period, $v = j \cdot N_Y$. Benefits of installing distributed generation come from reduced electricity purchases due to local electricity generation, $P_{Ej,k,l,m}$, reduced electricity purchases due to utilization of waste heat to meet cooling loads, $P_{Cj,k,l,m}$, reduction in monthly peak demand, $R_{Dj,k,t}$, and reduced natural gas purchases due to the utilization of waste heat, $P_{Qj,k,l,m}$, and can be written as

$$B_j = \sum_k \sum_l \sum_m N_{Dk,l}(P_{Ej,k,l,m}S_{Rj,k,l,m} + P_{Cj,k,l,m}S_{Rj,k,l,m} + \frac{1}{\beta_G}P_{Qj,k,l,m}G_{Rj,k}) + \sum_k \sum_t N_M R_{Dj,k,t}d_{k,t} \tag{4}$$

where $N_{Dk,l}$ is the number of day types in every season, $S_{Rj,k,l,m}$ is the retail electricity price, $G_{Rj,k}$ is the retail natural gas price, N_M is the number of months per season, $d_{k,t}$ is the peak demand charge and, β_G is the coefficient of performance (COP) of natural gas combustion to heating. The operational cost is the sum of natural gas purchases for running on-site generators and variable and fixed operation and maintenance costs, O_{Vi} and O_{Fi} and is given as

$$O_j = \sum_i \sum_k \sum_l \sum_m N_{Dk,l}P_{i,j,k,l,m}(\frac{1}{\mu_i}G_{Rj,k} + O_{Vi}) + \sum_i x_i O_{Fi} \tag{5}$$

where $P_{i,j,k,l,m}$ is individual generator electrical output level and, μ_i is generator electrical efficiency.

The wholesale electricity prices have seasonal and daily variations and an annual growth. The electricity retail price is a function of the expected annual growth, α_S, the initial wholesale price, $S_{0k,l,m}$, and a utility adder, U_S, which includes transmission costs and a utility profit

$$S_{Rj,k,l,m} = (1+\alpha_E)^{(j-1)N_Y}S_{0k,l,m} + U_S = S_{Wj,k,l,m} + U_S \tag{6}$$

where $S_{Wj,k,l,m}$ is the electricity wholesale price. The natural gas retail price is assumed to have a seasonal pattern, but no variation within the month. It is a function of the annual expected price growth, α_G, the initial wholesale price, G_{0k}, and a utility adder, U_G, which includes transportation costs and profits

$$G_{Rj,k} = (1+\alpha_G)^{(j-1)N_Y} G_{0k} + U_G = G_{Wj,k} + U_G \tag{7}$$

where $G_{Wj,k}$ is the effective wholesale natural gas price.

Reductions in utility electricity purchases each hour is the sum of generation over all units

$$P_{Ej,k,l,m} = \sum_i P_{i,j,k,l,m}$$

In each time step, natural gas-fueled generators must operate between the minimum output level, λ, and the generator capacity or be turned off

$$y_{i,j,k,l,m} \le x_i \quad for \ i \ in \ NG \tag{8}$$

$$P_{i,j,k,l,m} \le y_{i,j,k,l,m} C_i \quad for \ i \ in \ NG \tag{9}$$

$$P_{i,j,k,l,m} \ge y_{i,j,k,l,m} \lambda C_i \quad for \ i \ in \ NG \tag{10}$$

where the integer variable, $y_{i,j,k,l,m}$, determines if and how many of the units should operate in each hour. Both locally generated electricity and absorption cooling can serve cooling loads, when there is both a central cooling system and absorption chillers installed. The sum of generation that satisfies own electricity load and the absorption cooling, $P_{Cj,k,l,m}$, must be less than the sum of the electricity load, $L_{Ek,l,m}$, and the cooling load, $L_{Ck,l,m}$,

$$P_{Ej,k,l,m} + P_{Cj,k,l,m} \le L_{Ek,l,m} + L_{Ck,l,m} \tag{11}$$

The system cannot offset more cooling from absorption chillers than the building cooling load

$$P_{Cj,k,l,m} \le L_{Ck,l,m} \tag{12}$$

The system cannot offset more heat, $P_{Qj,k,l,m}$, than the building heat load, $L_{Qk,l,m}$

$$P_{Qj,k,l,m} \le L_{Qk,l,m} \tag{13}$$

Photovoltaic generation is determined by the time varying solar radiation, $V_{k,m}$

$$P_{i,j,k,l,m} \leq V_{k,m} C_i \ \ for \ i \ in \ PV \tag{14}$$

Waste heat utilization is constrained by concurrent production of electricity due to heat-to-power production ratios

$$\frac{1}{\beta_Q} P_{Q\,j,k,l,m} + \frac{\beta_E}{\beta_C} P_{C\,j,k,l,m} \leq \sum_i \gamma_{Qi} P_{i,j,k,l,m} \tag{15}$$

where β_Q is the COP of the heat exchangers, β_E is central chiller COP, β_C is the absorption cooling COP and γ_{Qi} is the heat-to-power ratio. Waste heat can be utilized for cooling only if absorption chillers are installed

$$\frac{\beta_E}{\beta_C} P_{C\,j,k,l,m} \leq \sum_i \gamma_{Ci} P_{i,j,k,l,m} \tag{16}$$

where γ_C is the same heat-to-power ratio, however, it is zero if absorption cooling equipment is not installed.

Since generators are not perfectly reliable, an expectation of reductions in peak demand is included over the time-of-use periods. Finding accurate expectations of reduced demand would depend on individual generator reliability and the load duration curve. Ability to reduce peak demand would further be reduced for each kW reduction because each kW reduction would require continuous generation a longer period, and in reality operational decisions could be changed within the billing period in the case of an outage at a peak hour. To account for this in a simple way in a deterministic model, one single expectation of generator ability to reduce demand charges is used for each generator. The expected reduction in hourly load, $P_{D\,j,k,l,m}$, which can be assumed used to reduce monthly demand charges is the sum over the product of each generator's ability to reduce demand and the production over all units, added the product of the absorption chillers' ability to reduce demand

$$P_{D\,j,k,l,m} = \sum_i \theta_i P_{i,j,k,l,m} + \theta_C P_{C\,j,k,l,m} \tag{17}$$

Expected reduction in monthly demand charges, $R_{D\,j,k,t}$ for each TOU-period must be less than the initial peak demand, $D_{k,t}$, less the expected peak demand with distributed generation

$$R_{D\,j,k,t} \leq D_{k,t} - (L_{E\,k,l,m} + L_{C\,k,l,m} - P_{D\,j,k,l,m}) \wedge k \in t \wedge l \in t \wedge m \in t \tag{18}$$

Here, the indexes for month, k, for day type, l, and hour, m, must be a part of the time-of-use periods, t.

All decision variables must be non-negative

$$x_i, y_{i,j,k,l,m}, P_{i,j,k,l,m}, P_{E j,k,l,m}, P_{Q j,k,l,m}, P_{C j,k,l,m}, P_{D j,k,l,m} \geq 0 \; \textit{for all} \; i,j,k,l,m \; (19)$$

The presented model is a modified and re-implemented version of the Distributed Energy Resource Customer Adoption Model (DER-CAM) developed at Ernest Orlando Lawrence Berkeley National Laboratory [2]. The model differs from previously published models because it maximizes benefits instead of minimizing costs, which gives better control over solution accuracy as a percentage of annual net benefits. It further includes a price forecast and it is, therefore, based on a seasonal load description instead of a monthly one, to make it possible to solve the model in a reasonable time. This version also includes a minimum operation level constraint and a parameter to reduce expectations in demand reductions. The model is implemented in GAMS, and a GAMS-MATLAB interface proposed by Ferris [3] was used for solving the model.

3. Scenario Design and Model Parameters

3.1 Building Energy Loads

Two building types are used in the analysis: a healthcare and an office building. Data is generated with DOE-2, a building simulation program developed at Ernest Orlando Lawrence Berkeley National Laboratory, using standard building types. Climate data is from San Francisco, California. Table 1 shows that the buildings have different load profiles. The healthcare building has a far higher electricity load and higher cooling and heat load. The office building has the highest peak electricity load, but it is twice as large as the healthcare building, which means that it has lower energy intensity.

Table 1. Energy load characteristics for buildings used in analysis

	Building Type	
Property	Healthcare	Office
Size (m^2)	8 333	16 666
Maximum electricity load (kW)	526.4	583.8
Annual electricity load (MWh)	2 928.3	1 821.9
Annual cooling load (MWh)	294.1	201.0
Annual heat load (MWh)	1 340.3	423.2

3.2 Model Parameters

Table 2 shows the model parameters used in the analysis. The real before-tax discount rate used is 7.5 percent. Heat exchangers and boilers are both assumed to have a coefficient of performance (COP) of 0.8, absorption chillers 0.65 and electric chillers 4. Absorption cooling units have an expected reduction of monthly demand charges of 80 percent. The minimum production level is 50 percent of rated capacity. The solar production data is generated using PVWATTS [4].

Table 2. Model parameters

Parameter	r	β_Q	β_C	β_G	β_E	N_Y	H	λ	θ_C
Value	0.075	0.8	0.52	0.8	4	5	20	0.5	0.8

3.3 Technology Data

Table 3 presents technology cost and performance data for the units that are allowed for investment in the analysis. Ten different units are considered: one photovoltaic module and nine natural gas-fueled units. Natural gas-fired reciprocating engines come in three capacities and three versions. They can be installed to produce electricity only, they can be equipped with heat exchangers, and they can be equipped with absorption chillers. In the latter case, they will also need a heat exchanger, effectively making them able to recover heat to serve both heat and cooling loads. The data shows a slightly decreasing investment cost per kW capacity. Adding heat exchangers and absorption chillers adds significantly to the costs. For natural gas-fired technologies, data for reciprocating units are used. Electric efficiency is higher for the larger units. All natural gas-fueled units have an 80 percent probability of reducing monthly peak demand, while photovoltaics have a 50 percent expected reduction compared to the average production profile due to variations in radiation. Also, absorption chillers are assumed to have an 80 percent probability of reducing monthly peak demand, θ_C, is assumed to be 80 percent. The minimum operation, λ, of all units are 50 percent of capacity.

Table 3. Technology data, from [5] and [6]

i	Technology	Type[*]	C_i kW	T_i y	I_i \$/kW	O_{Fi} \$/kW	O_{Vi} \$/MWh	μ_i[**]	γ_{Qi}	γ_{Ci}	θ_i
	Natural gas engines										
1		NG	60	20	991	0	18	0.287	-	-	0.8
2		NG	100	20	1030	0	18	0.300	-	-	0.8
3		NG	300	20	790	0	13	0.310	-	-	0.8
4		CHP	60	20	1362	0	18	0.287	2.16	-	0.8
5		CHP	100	20	1350	0	18	0.300	2.05	-	0.8
6		CHP	300	20	1160	0	13	0.310	1.85	-	0.8
7		CHP-C	60	20	1851	18.9	18	0.287	2.16	2.16	0.8
8		CHP-C	100	20	1774	16.5	18	0.300	2.05	2.05	0.8
9		CHP-C	300	20	1465	12.1	13	0.310	1.85	1.85	0.8
	Photovoltaics										
10		PV	50	30	7600	12	-	-	-	-	0.5

*NG-natural gas fueled electricity production, CHP - combined heat and power, CHP-C - combined heat, power and cooling
** Efficiency based on higher heating value (HHV)

Other technology alternatives could have been considered both in terms of size and type. It is important to mention that microturbines represent a promising technology. They have the potential to increase efficiency and reduce emissions, but are currently not cost competitive with reciprocating engines. However, as they have lower emissions, they are sometimes the only option to use under emission standard regulations. They can also be installed in packaged units, where many units share the same heat recovery system, which reduce the investment cost. Fuel cells are another upcoming technology that in

the future could serve buildings represented in this study. For larger buildings, natural gas turbines would be an alternative. Different natural gas technologies will in any case have similar characteristics as a gas engine.

3.4 Electricity and Natural Gas Price Scenarios

Electricity and natural gas price forecasts are important for the profitability of distributed generation. For natural gas-based generation it is the spark spread, the difference between electricity and natural gas price, which determines profitability. For renewable generation, only the absolute value of the electricity price matters.

The electricity prices in this work are based on Pacific Gas and Electricity [7] rates in 2005. The volumetric part of the rate is reduced by 15 percent, as currently high prices are assumed to be short-term deviations after to the California energy crisis [8]. California Electricity Commission's [9] forecast for the wholesale price of electricity is used to estimate the wholesale price and utility adder on the base case rates. For natural gas, we use Pacific Gas and Electricity [7] historic prices to estimate a transport and supplier adder for the base case. For finding an approximate base case price forecasts, information from the Energy Information Administration [10] and the California Energy Commission [9] has been used. For both electricity and natural gas, we construct a low, base and high price scenario (see Table 4). Together that leaves nine different combinations of electricity and natural gas prices. Electricity and natural gas prices are usually correlated. Hence, the probability of the natural gas price going down while electricity prices go up is lower than the probability that they move in the same direction. But, no attempt to attach probabilities to the different scenarios is made. The purpose is solely to illustrate the effect of different energy price developments.

Table 4. Natural gas and electricity price scenarios

Scenario Name	Natural Gas Price Scenario	Electricity Price Scenario	G_0 ($/MWh)	S_0 ($/MWh)	U_G ($/MWh)	U_S ($/MWh)	α_G (1/y)	α_S (1/y)
L-L	Low	Low	13.6	28	10.9	49.3	0	0
L-B	Low	Base	13.6	30	10.9	49.3	0	0.015
L-H	Low	High	13.6	32	10.9	49.3	0	0.03
B-L	Base	Low	15.4	28	10.9	49.3	0.015	0
B-B	Base	Base	15.4	30	10.9	49.3	0.015	0.015
B-H	Base	High	15.4	32	10.9	49.3	0.015	0.03
H-L	High	Low	17.1	28	10.9	49.3	0.03	0
H-B	High	Base	17.1	30	10.9	49.3	0.03	0.015
H-H	High	High	17.1	32	10.9	49.3	0.03	0.03

Table 5 shows the TOU data used in the analysis from 2005 PG&E data (PG&E 2005). Two TOU periods exist in the winter from November to April: a part-peak period from 8 am to 9 pm on non-holiday weekdays and off-peak at all other times. In summer, from May to October, there are three time periods: on-peak from 12 pm to 6 pm non-holiday weekdays, part-peak from 8 am to 12 pm and from 6 pm to 11 pm on non-holiday weekdays and off-peak period all other times. Demand charges are charged per kW maximum load in the same TOU periods. In addition, there is a demand charge for the maximum demand over all periods as seen in Table 5.

Table 5. Base case time-of-use (TOU) electricity price data first period

	Season	Unit	Peak	Part-peak	Off-peak	All
			TOU-Period			
Volumetric charges						
	Winter	$/MWh	-	73.92	60.38	-
	Summer	$/MWh	97.73	68.1	60.59	-
Demand charges						
	Winter	$/kW	-	3.69	-	3.18
	Summer	$/kW	13.51	3.75	-	3.18

3.5 Carbon Tax Scenarios

A carbon tax can potentially change the optimal DG system and operation of the installed units. The model is solved for the two buildings with a carbon tax from 0 to 500 $/ton, with increments of 100. The emissions from the building energy use are calculated assuming that electricity bought on the grid is produced by a central gas-fired power plant with an efficiency of 45 percent and grid losses of 9 percent, comparable to average losses in U.S. grid system [1]. Emissions are assumed to be directly proportional to the amount of natural gas that is consumed, which is assumed to be 0.05312 kg/kWh [6]. The electricity price increases with the product of central power emissions and the carbon tax, hence, carbon emission costs are passed on to consumers.

3.6 Photovoltaics Investment Cost Scenarios

Optimal DG systems under potential reductions in investment costs for photovoltaics, which can be due to technological improvements or subsidies, are analyzed. The model is first solved assuming the developer considers only photovoltaic units, and then solved for photovoltaics in competition with natural gas-fired technologies for photovoltaics costs ranging from 1.6 $/W to 2.4 $/W, with a step of 0.2 $/W.

3.7 Sensitivity to the Ability to Reduce Peak Demand

Demand charges are based on the maximum monthly demand in the different TOU periods. Hence, the system's ability to reduce demand charges depends on equipment reliability and variation in renewable production. This is a risk for a distributed generation developer. The model is solved for both buildings with natural gas units and absorption chiller ability to reduce demand charges varying from 100 to zero percent with a step of 10 percent.

3.8 Sensitivity to the Discount Rate

Choice of interest rate will not only determine the level of the annual benefits, but it may also change the optimal system. A risky project is usually discounted with a higher discount rate. However, for various reasons, different businesses use different discount rates for projects with similar risk characteristics. Therefore, the model is solved with real before-tax discount rates ranging from 5 to 20 percent.

4. Results

4.1 Base Case Results

Figure 1 shows how the DG equipment produce electricity, heat and cooling in the reference solution for the healthcare building on a peak summer day during the first period. The base case solution for the healthcare building is to install a single 300 kW unit with a heat exchanger and absorption cooling. At off-peak hours the electricity production is at the minimum level because low heat and cooling loads limit production with heat recovery, and the spark spread is not sufficiently large to make it profitable to produce electricity without waste heat utilization. At peak hours, and in some of the part peak hours, the system produces at full capacity. Recovered heat is used for both serving the heat and the cooling load. Notice that recovered heat for the heat load is reduced as the electricity load is on its highest; all recovered heat is used for absorption cooling to offset demand charges at peak hours.
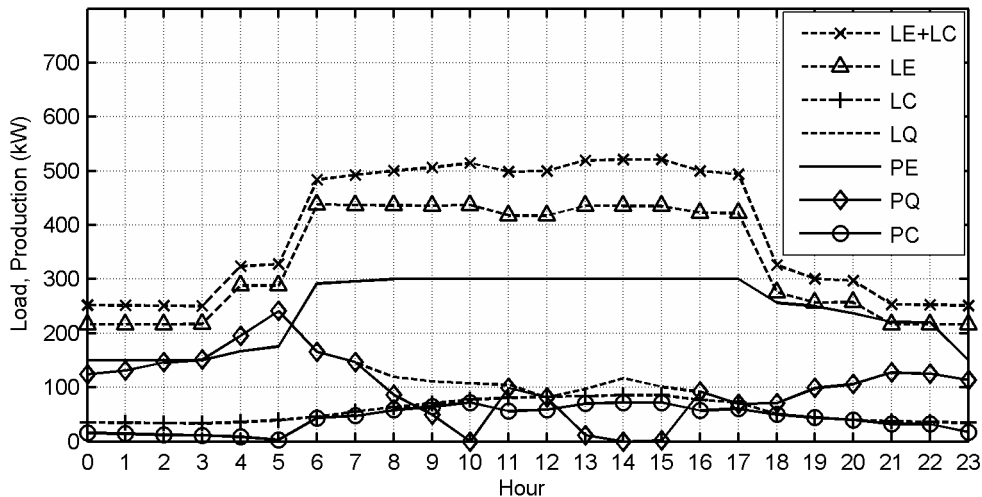
Figure 1. Total electricity load, electricity only load and electricity, cooling and heat production for the healthcare building, first period, summer and peak day for base case solution

For the office building, the base case solution is to install a 300 kW unit with heat recovery and absorption cooling in combination with a unit with only electricity production. Figure 2 shows how the two units operate during a peak summer day in the first period. The more efficient 300 kW unit operates between 5 am and 7 pm, and the 60 kW unit operates from 7 am to 6 pm. At 5 pm, the larger unit is turned off because the total electricity load drops under the minimum production level. This illustrates that the smaller unit both has the potential to serve as a peak power unit and as a unit that generate at hours when the load that is too low for the large unit to generate because of minimum operation constraint. The way the 60 kW unit increases its output as the electric load increases confirms that it operates to reduce demand charges.
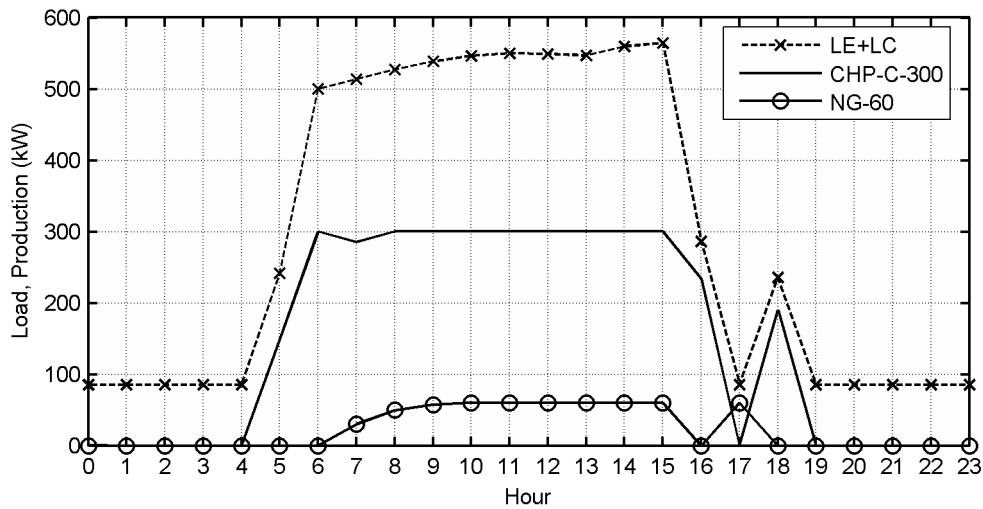
Figure. 2. Total electricity load and production scheduling for different units for the office building, first period, summer and peak day for base case solution

That the healthcare building has a higher annual electrical load than the office building is reflected in the benefits of the installed equipment, since the generators in the healthcare building reduce electricity purchases more than in the office building (see Table 6). The reduction in demand charges is similar in the two buildings, but is a larger share of the benefits for the office building. The healthcare building has the highest net annual benefit.

Table 6. Breakdown of annual benefits and costs in base case solution

	Building Type	
Equivalent Annual Benefits and Costs ($)	Healthcare	Office
Reduced Electricity Purchases	183 430	110 809
Reduced Demand Charges	46 381	54 438
Reduced Natural Gas Purchases	46 041	14 267
Total Benefits	*275 852*	*179 514*
Increased Natural Gas Purchases	169 363	91 400
Fixed Operation and Maintenance Costs	3 630	3 630
Variable Operation and Maintenance Costs	24 819	13 613
Investment Costs	43 112	48 944
Total Costs	*240 924*	*157 587*
Equivalent Net Annual Benefits	*34 928*	*21 927*

4.2 Electricity and Natural Gas Price Scenarios

The optimal installed equipment for all nine price scenarios can be seen in Table 7. Units with heat recovery and absorption cooling are installed in all scenarios. The 300 kW unit with heat recovery and absorption cooling is installed in all scenarios in both buildings, except in the high natural gas and low electricity price scenario in the healthcare building. A low natural gas price, a high electricity price, or a combination of both, lead to a high installed capacity. Additional capacity comes from smaller units

without any heat recovery in all cases. Installed capacity is similar in the two buildings, which have a similar peak electricity load.

**Table 7.** Installed units in different price scenarios

Building Type	Installed Unit	Price Scenario: Natural Gas - Electricity								
		L-L	*L-B*	*L-H*	*B-L*	*B-B*	*B-H*	*H-L*	*H-B*	*H-H*
Healthcare	NG-60 (kW)	-	-	60	-	-	-	-	-	-
Peak El. Load	NG-100 (kW)	-	100	100	-	-	100	-	-	-
526 kW	NG-300 (kW)	-	-	-	-	-	-	300	-	-
	CHP-100 (kW)	-	-	-	-	-	-	100	-	-
	CHP-C-300 (kW)	300	300	300	300	300	300	-	300	300
	Total (kW):	*300*	*400*	*460*	*300*	*300*	*400*	*400*	*300*	*300*
Office	NG-60 (kW)	60	-	60	-	60	-	-	-	60
Peak El. Load	NG-100 (kW)	-	100	100	-	-	100	-	-	-
583 kW	CHP-C-300 (kW)	300	300	300	300	300	300	300	300	300
	Total (kW):	*360*	*400*	*460*	*300*	*360*	*400*	*300*	*300*	*360*

Net annual benefits vary significantly in the nine scenarios. Benefits for the healthcare building varies more than for the office building, as seen in Figure 3. Further, the additional installed capacity in some of the scenarios does not add much to the annual benefits as the base case solution is very close to optimal in all nine scenarios, for both buildings. This is because most of the costs are operational and not investment costs for natural gas-based DG units. The units have operational flexibility and can adjust production levels to the price conditions in the different price scenarios.

Base load central power generation has a higher electric efficiency than on-site generation and central electric chillers have a high COP. But central generation does not utilize the heat production from electric generators like DG with heat recovery and absorption cooling, and the electricity must be transmitted to the end-user with an energy loss. Hence, installing on-site generation can, but does not necessarily, reduce carbon emissions. In this analysis, DG is compared to a central power plant with 45 percent efficiency and 9 percent energy loss from the power plants to end-use. Figure 4 shows how the building's carbon emissions vary assuming central electricity generation at 40.5 percent efficiency including grid losses. Emission reductions are largest with a low electricity price, in the low and base case natural gas price scenarios, because for high electricity prices, when the difference between the prices is large enough, less efficient and more polluting operation is profitable. For the high natural gas price, it can be seen that the relationship is not the same because, in this case, a higher electricity price makes more efficient operation profitable. The healthcare building is most effective in reducing carbon emissions and reduces emissions in all price scenarios. Emissions in the office building are reduced in all scenarios except in the scenario with a low natural gas price combined with a base case or high electricity price.
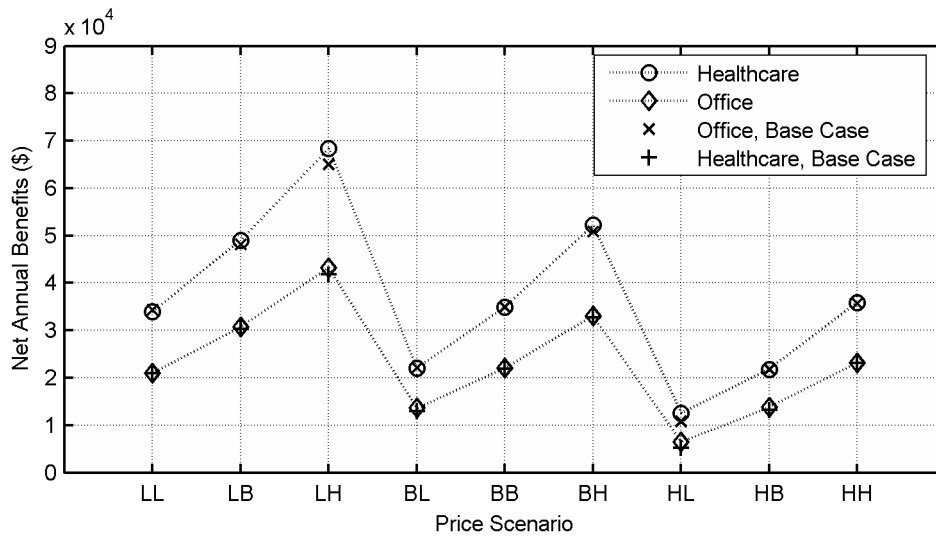
Figure. 3. Net annual benefits under the price scenarios for optimal and reference solution
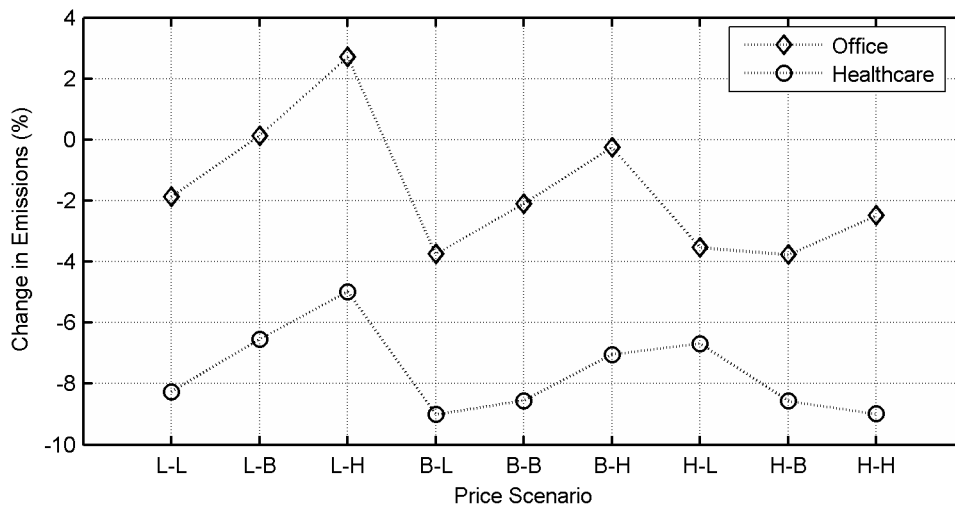

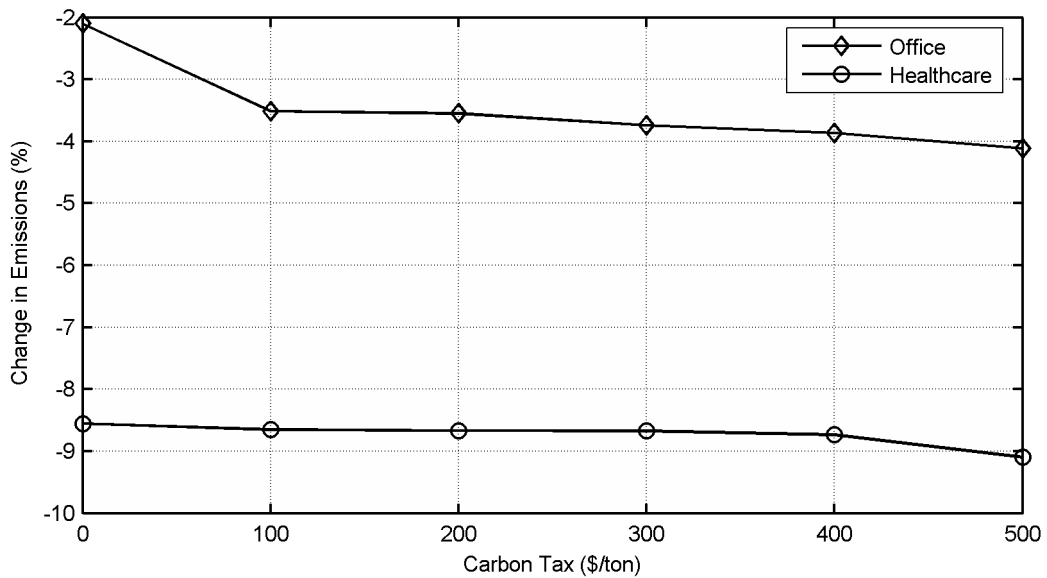**Figure. 4.** Changes in building carbon emissions in price scenarios

4.3 Carbon Tax Scenarios

Figure 5 illustrates the effect of the carbon tax on optimal installed capacity. The 300 kW unit with heat recovery and absorption cooling seems to be robust to a carbon tax up to 500 $/ton in the two buildings. Only the 60 kW unit without heat recovery in the office building is phased out. It unit is phased out because it cannot generate electricity at higher efficiencies than the assumed central system.

The base case installed generators reduce emissions for all levels off the carbon tax (see Figure 6). Both buildings reduce emissions as the carbon tax increases. The healthcare building is most efficient in reducing emissions by reducing emissions from 8.5 to 9 percent. Most emission reductions comes from phasing out the inefficient unit from the office building, but the price signal from the carbon tax also marginally changes operation of the 300 kW units to be more efficient at higher tax levels.

16
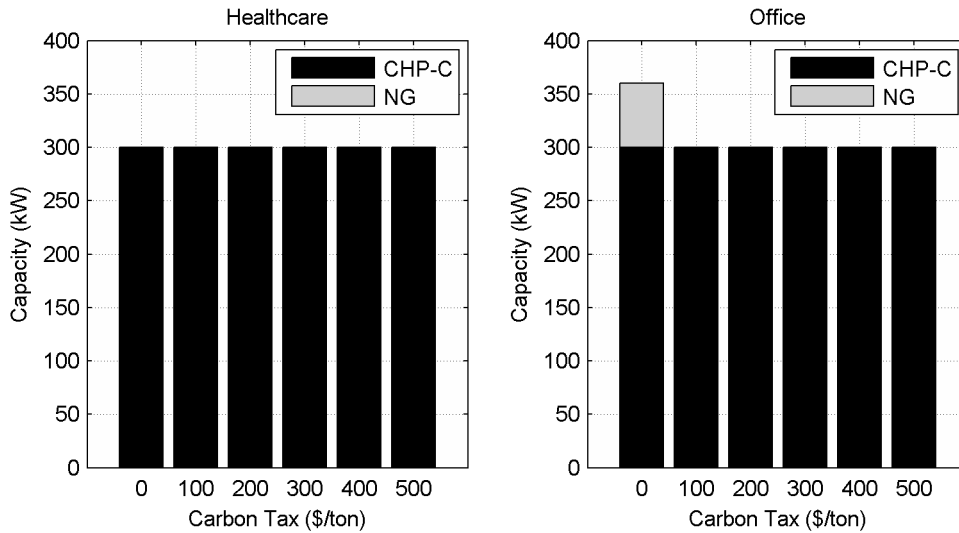
**Figure 5.** Installed capacity under different carbon tax scenarios

Figure 6. Relative changes in system carbon emissions under carbon tax scenarios

4.4 Photovoltaic Cost Scenarios

In Figure 7, it can be seen that photovoltaic systems have a break-even investment cost of approximately 2.4 $/W in the two buildings when only photovoltaic systems are considered for investment. At around 1.8 $/W for the office building and 2 $/W for the healthcare building highest capacity is installed When photovoltaic systems are considered in competition with natural gas-based technologies they have a lower break-even cost and a lower optimal PV capacity.

Even for very low investment costs, the optimal system is a combination of photovoltaics and natural gas-based units. Natural gas-based units are invested in combination with photovoltaics most likely because they are more suited for reducing

demand charges, due to variation in solar radiation and low radiation in the morning and afternoon. In the healthcare building, the 300 kW unit with absorption cooling is optimal in all photovoltaics cost scenarios. In the office building, the small electricity-only unit is phased out when the photovoltaic cost drops. When the photovoltaic cost is at its lowest, the optimal system no longer includes absorption cooling, but rather an electricity-only unit and a small combined heat and power unit.
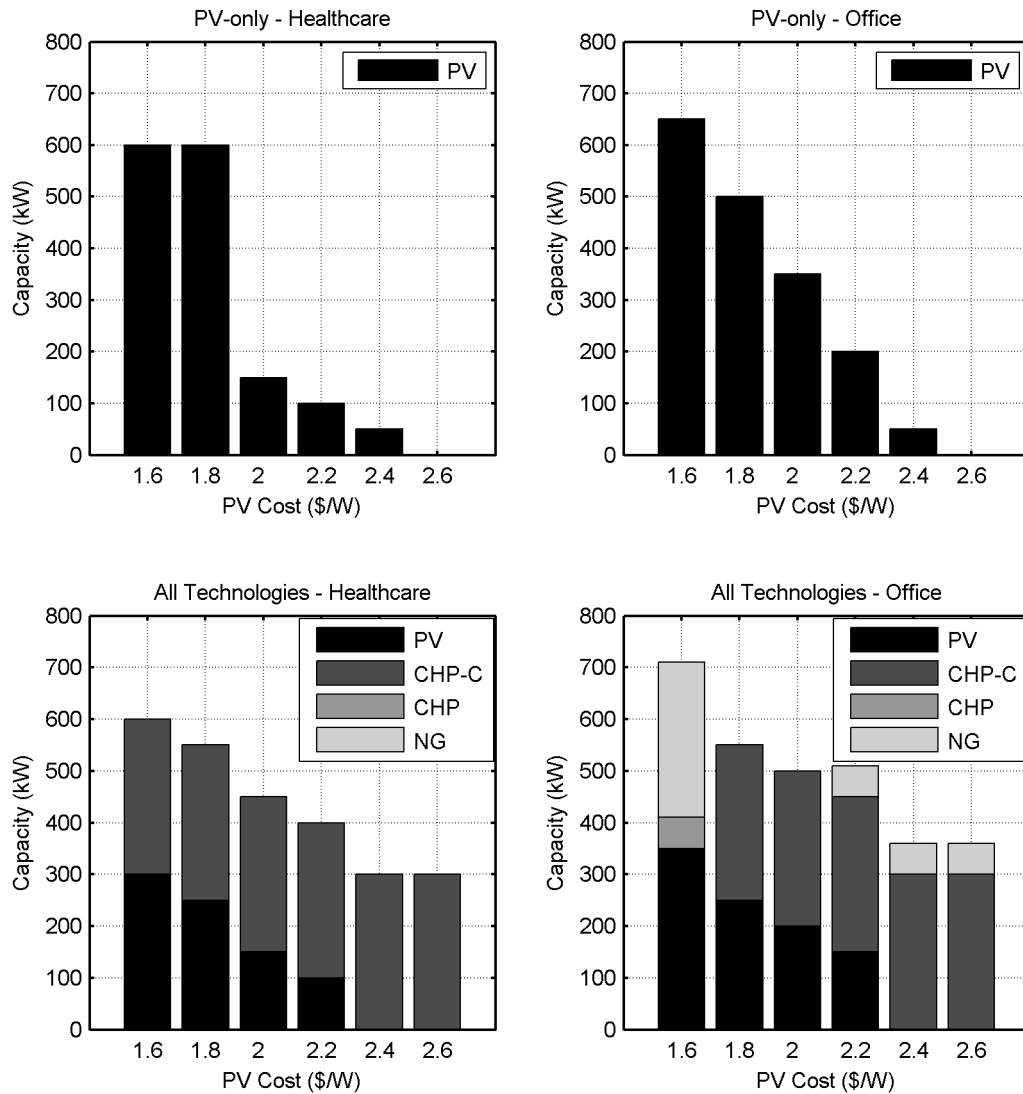

Figure 7. Optimal DG portfolio with only photovoltaics systems and for photovoltaics in competition with gas-fired technologies

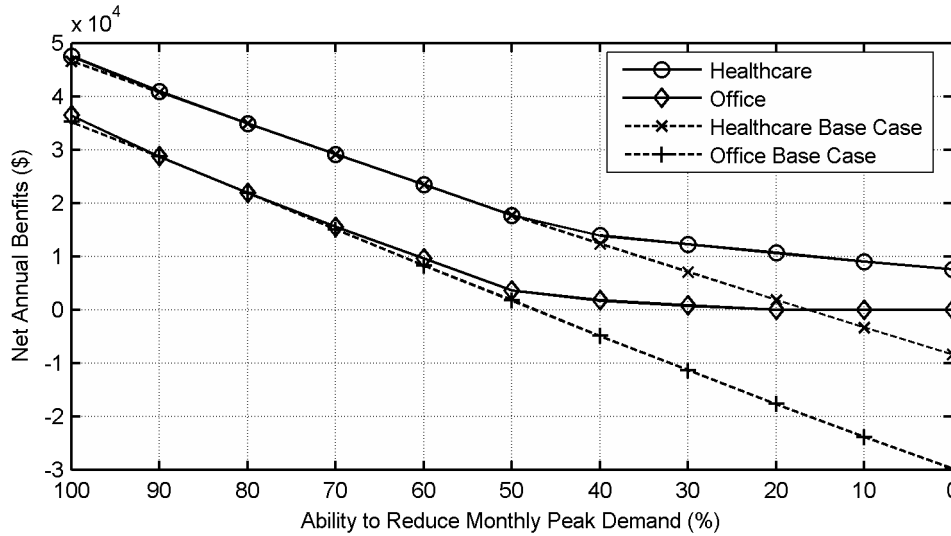*4.5 Sensitivity to the Ability to Reduce Peak Demand*

Figure 8 shows the sensitivity in the optimal solution to the systems' ability to reduce demand charges. Without an ability to reduce demand charges, the investment in distributed generation in the office building would not have been profitable. Reduction in demand charges is a very important factor for the profitability of the investment in distributed generation under assumed TOU-rates. The size of the system is reduced dramatically in both buildings as their ability to reduce demand charges is reduced.

Figure 9 shows the net annual benefits at different system abilities to reduce demand charges. It confirms the importance of demand charges for profitability. If the generators ability to reduced demand charges is half of the potential reduction, the net annual benefit in the office building is reduced to around a seventh. With the base case assumption, that the ability to reduce demand charges is 80 percent of the maximal with perfect reliability, there is a possibility of loosing 30,000 dollars each year if the system is unable to reduce demand charges in the office building. The installed system in the healthcare building is less sensitive to demand charges, but the base case assumption can infer losses if the system proves less reliable than assumed.

In a system with a large penetration of distributed generation, the cumulative stress on the grid from buildings with DG would probably be low even with outages because there is no systematic pattern in the outages. Further, in a building with DG that has already had an hour with a high level of electricity purchases, there will not be an incentive to reduce demand the rest of the month. Daily demand charges, instead of monthly, would reduce this risk, as would real time pricing without demand charges.
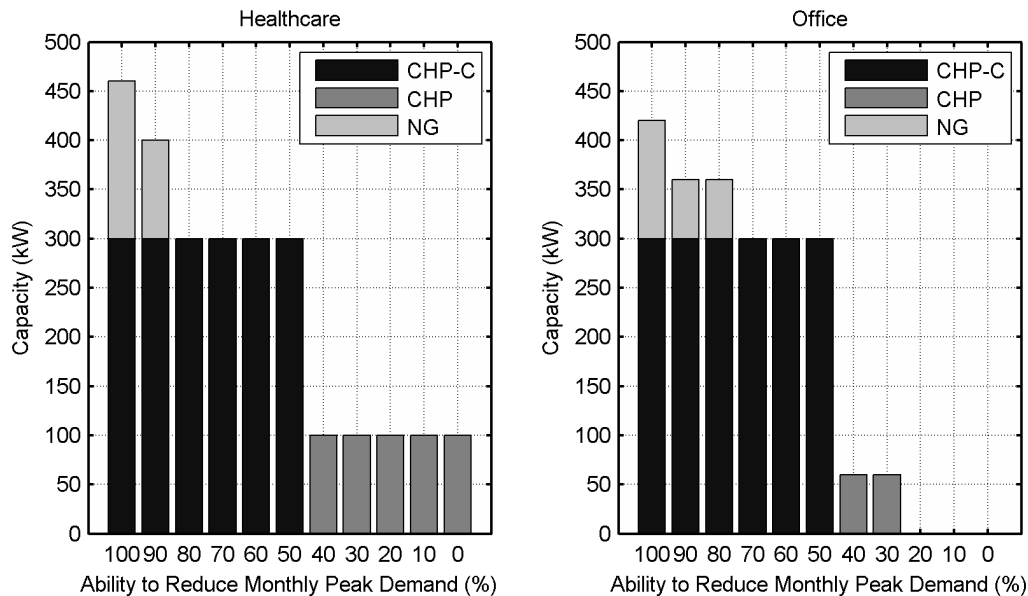
Figure 8. Installed capacity for different system abilities to reduce peak monthly demand
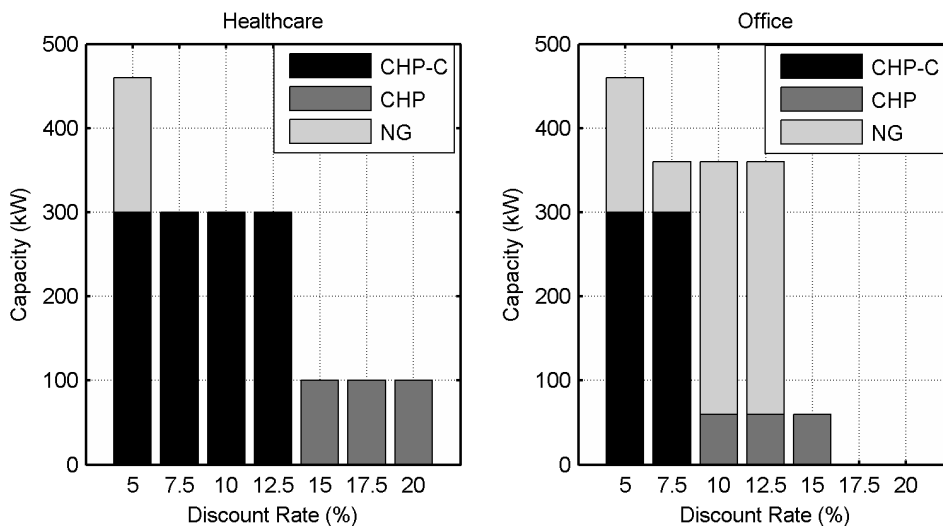
Figure 9. Net annual benefits with different system ability to reduce demand charges

4.6 Sensitivity to the Discount Rate

As can be seen in Figure 10, the optimal system depends on the chosen discount rate. A low discount rate leads to investments in large systems with a combination of units with and without heat recovery. For the highest discount rate of 20 percent, the healthcare building installs a 100 kW unit with heat recovery. The highest discount rate at which investment is optimal in the office building is 15 percent; the system is a 60 kW combined heat and power unit.

Figure 11 shows the net annual benefits for different discount rates. The investment is marginally profitable for the office building at 15 percent while the healthcare building still has considerable positive cash flow at 20 percent, the highest interest rate considered.

Figure 10. Installed capacity with different discount rates
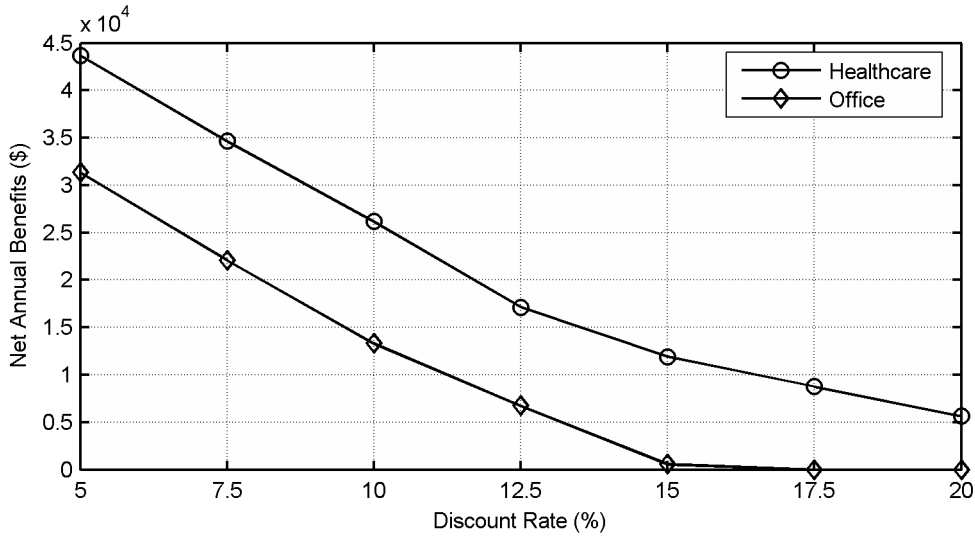
Figure 11. Net annual benefits with different discount rates

5. Conclusions and Further Work

The paper has identified some major economic and regulatory issues with private adoption of DG by applying a mixed integer linear program to simulated data for a healthcare and an office building, using climate and energy price data from San Francisco, California. The model was solved with nine price scenarios. Systems with heat recovery are optimal in all scenarios, and additional absorption cooling is optimal in all scenarios for the healthcare building and in all, except the one with a high natural gas and a low electricity price, for the office building. In scenarios with a large spark spread, engines without heat recovery and absorption cooling are added, which results in higher carbon emissions. The healthcare building is most efficient in reducing emissions.

The only change in the optimal capacity for scenarios with a carbon tax from 100 to 500 $/ton, is that a small natural gas unit, solely used for electricity generation, is phased out from the office building. The office building reduces emissions from 2.5 percent, without a carbon tax, to 5 percent, with a carbon tax of 500 $/ton, assuming the purchased electricity is delivered to the building at 40.5 percent efficiency. The healthcare building's emission reductions are larger, ranging from 8.5 to 9 percent under a carbon tax.

If only photovoltaic systems are considered, small photovoltaic systems are profitable from a modular investment cost of 2.4 $/W. Larger systems are installed from investment costs around 1.8 to 2 $/W. In the office building, higher capacities are profitable at higher investment costs than in the healthcare building. This is because demand charges can be reduced to a larger extent since the office electricity load is fairly coincident with photovoltaic production. If photovoltaic systems are considered in competition with natural gas fired generators, the break-even investment cost is lowered to 2.2 $/W. For all costs from 1.6 to 2.2 $/W, smaller systems are now installed in combination with natural gas fueled generators with heat recovery and absorption cooling.

Distributed generation is profitable for the healthcare building with real discount rates up to highest used in the analysis of 20 percent. Comparatively, the office building's investment is profitable only up to a discount rate of 15 percent. For high discount rates, the optimal decision is to install base load units with heat recovery and without absorption cooling.

The electric generator's ability to reduce demand charges seems to be a very important factor to the profitability of the systems. In scenarios where the natural gas-fueled generator's ability to reduce demand charges varied from 100 to zero percent, the optimal capacity in the healthcare building varied from 460 kW to 100 kW. In the office building, the optimal capacity changed from 420 kW to zero. Further, the base case solution is very sensitive to the actual ability to reduce demand charges. This is particularly true for the office building, where there is a potential for large annual losses if the system is less reliable than promised. Demand charges should be constructed to reflect system costs and should give correct incentives to DG adoption and operation. This might not be the case with monthly demand charges since they were constructed for buildings without DG and similar utility electricity consumption profiles most days. After an outage at a peak hour, the DG user has no incentive to operate even though it might reduce system costs.

Uncertainty in peak demand reductions are not very well analyzed in a framework of a mixed integer model with average load profiles. A systems ability to reduce demand charges depends on the each unit's reliability and the combination of installed units. Additionally, the decision maker will have the opportunity to change the operational strategy in the case of an outage early in a metering period. Simulation models that allow for random outages and dynamic decision making can be better for analyzing reductions of demand charge and the effect on profitability in a more realistic way. The approach proposed by Firestone and Marnay [11] is an example of a simulation approach to model the interaction of demand charges and reliability.

There are several potential improvements in the presented approach. For example, this model with average load data does not capture situations where there might be net cooling and heating days within the same month. Including separate cooling and heating days in the model would be more realistic. Using average days further limit the potential to value systems under real-time pricing. However, mixed integer optimization programs can be hard to solve, and improving time resolution can increase time to find a solution considerably.

Comparing emissions from local generation with central emissions can be challenging because choosing what kind of production on-site generation replaces is not straightforward. Rather than using an average central efficiency, another approach could be to use a time varying efficiency on central generation, where the systems marginal unit's efficiency is used in each time step.

Assuming deterministic prices can further undervalue DG because generators can produce at favorable prices and shut down at unfavorable prices. Also, the cost risk reducing potential of distributed generation is not well analyzed in a deterministic optimization framework. Two systems can have similar expected benefits but different risk characteristics. A simulation approach could be appropriate for analyzing DG energy cost hedging potential.

Acknowledgments

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Paper IV

Distributed Energy Resources Market Diffusion Model

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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 programs. 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 program scenario, in which more research improves DER performance and stronger technology outreach program 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.

Keywords: Distributed generation, technology market diffusion, research valuation

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.

Section 2 presents the approach in more detail and gives further explanation of the external modeling tools used in the analysis. The third section explains the intuition and mathematical detail of DER-MaDiM. Section 4 presents the data used in the model, while section 5 presents results of both the DER-CAM runs and the predicted market diffusion from DER-MaDiM. Section 6 concludes the analysis and suggests future improvements in the modeling approach.

Nomenclature

Indices

i	Results type (capacities, energy consumption, private savings)
j	Census division
k	Building type
l	Building size
m	Time period

Variables

|	
$A_{E\,j,k,l,m}$	Annual existing floorspace that adopts DG
$A_{N\,j,k,l,m}$	Annual net new floorspace that adopts DG
$A_{T\,j,k,l,m}$	Annual total floorspace that adopts DG
$F_{D\,j,k,l,m}$	Total floorspace with DG
$F_{N\,j,k,l,m}$	Net new floorspace with economic potential to install DG
$F_{T\,j,k,l,m}$	Total floorspace with economic potential to install DG
$R_{A\,i,j,k,l,m}$	Annual change in result metrics
$R_{T\,i,j,k,l,m}$	Cumulative result metrics over time
X_m	Fraction of commercial building floorspace with potential and installed systems

Parameters

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

2. Modeling Approach and External Modeling Tools

The goal of the work is to predict the likely adoption of distributed generation in the U.S. 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 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 for present and future years and run of the Distributed Energy Resources Customer Adoption Model (DER-CAM) to estimate the economic attractiveness of DG in a given building type, region, and in a set of the forecast years and use linear interpolation to estimate annual results

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
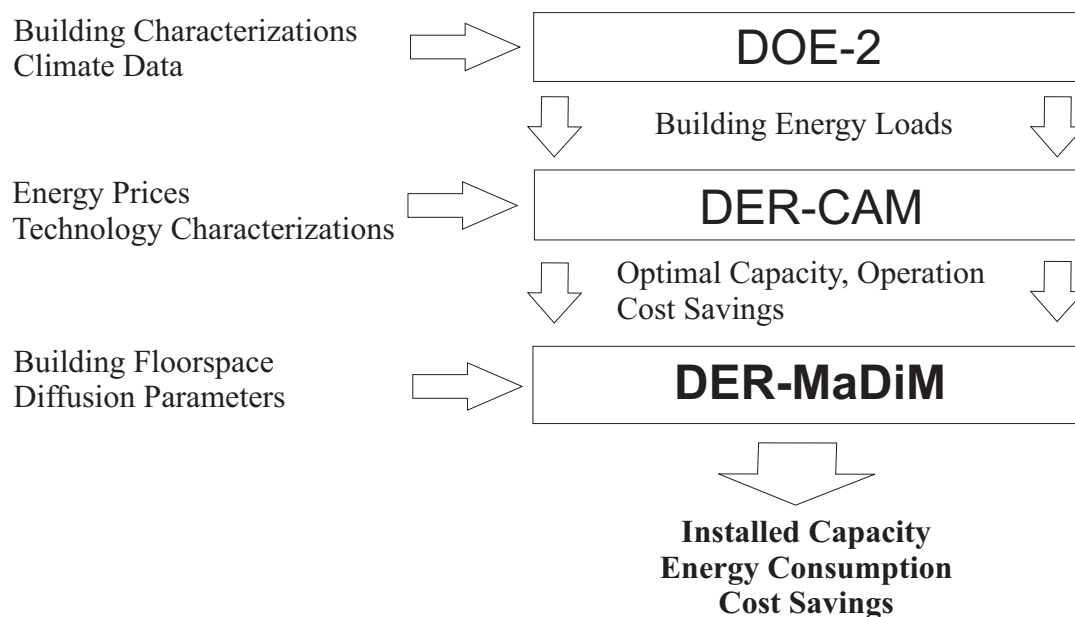
Figure 1. Overview of the modeling approach

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 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 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. The DOE-2 simulation requires the following input data given in Table 1.

Table 1. Major input needed to simulate building energy loads with DOE-2

Building Descriptions	Envelope Descriptions	Operational Characteristics	Equipment Characteristics
Building Type	*Vintage*	*Average Hot Water Intensity*	*Vintage*
Location	*Construction*	*Peak Lightning Intensity*	*System Type*
Size	*Insulation*	*Peak Gas Cooking Load*	*Plant Type*
Nr. of Floors	*Window to Wall Ratio*	*Hours of Operation*	
	Window Pane Type	*Control Strategies*	
	Shading Coefficient	*Thermostat Set Points*	

Basic input data such as building size are obtained from the Commercial Building Energy Consumption Survey (CBECS) 1999 building characteristic data [3], 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. [4].

2.2 Distributed Energy Resources Customer Adoption Model

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 total energy costs 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. DER-CAM output includes the optimal DG system and an hourly operating schedule, as well as the resulting costs, fuel consumptions, and carbon emissions. Figure 2 shows a high-level schematic of DER-CAM.
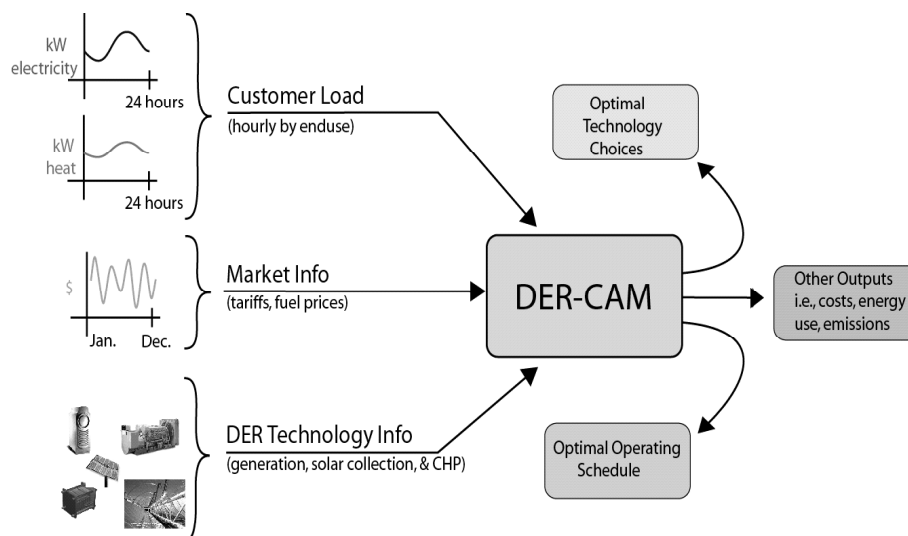
Figure 2. DER-CAM schematic

3. Mathematical Description of DER-MaDiM

While the previous section found optimal DG systems, optimal DG operation and expected building cost reductions, this section tries to model the actual market diffusion of the technologies. 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]. Epidemic models explain the introduction of new technologies with the means knowledge of the technology 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 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 customer characteristics as an explanatory factor on why some firms adopt new technologies before others. Customer characteristics, such as building energy profiles and local tariff structures, 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 modeled 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 gets 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 increase 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

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

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 DG 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 DG, $F_{Nj,k,l,m}$,

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

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 DG economic potential have DG 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 DG. Total annual floorspace that adopts DG 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 DG is floorspace with DG 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 DG is total floorspace with DG divided by floorspace with potential in U.S. commercial building sector

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

The different result metrics (see Table 2) 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 DG

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

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 U.S. 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

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

4. Model Data

Table 2 is a description of the indices used in the study. All 9 U.S. census divisions are modeled and five building types in two sizes. Results are reported over nine dimensions.

Table 2. Description of indices used in DER-MaDiM

	Result Dimensions	Census Division	Building Type	Building Size
	i	j	k	l
1	Total installed capacity	New England	Healthcare	Small
2	Total installed capacity, reciprocating engines	Middle Atlantic	Lodging	Large
3	Total installed capacity, microturbines	East North Central	Mercantile	
4	Installed capacity, electricity generation only	West North Central	Education	
5	Installed capacity with heat exchangers	South Atlantic	Office	
6	Installed capacity with absorption cooling	East South Central		
7	Change in electricity purchases	West South Central		
8	Change in natural gas purchases	Mountain		
9	Annual private cost savings	Pacific		

Table 3 displays how four cities are assumed to represent the whole U.S., in terms of climate and energy rates.

Table 3. Mapping of four selected cities to U.S. Census regions and divisions

Region	Census Division	City
Northeast	New England	Boston
	Middle Atlantic	Boston
Midwest	East North Central	Chicago
	West North Central	Chicago
South	South Atlantic	Atlanta
	East South Central	Atlanta
	West South Central	Atlanta
West	Mountain	San Francisco
	Pacific	San Francisco

4.1 Building Data

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.
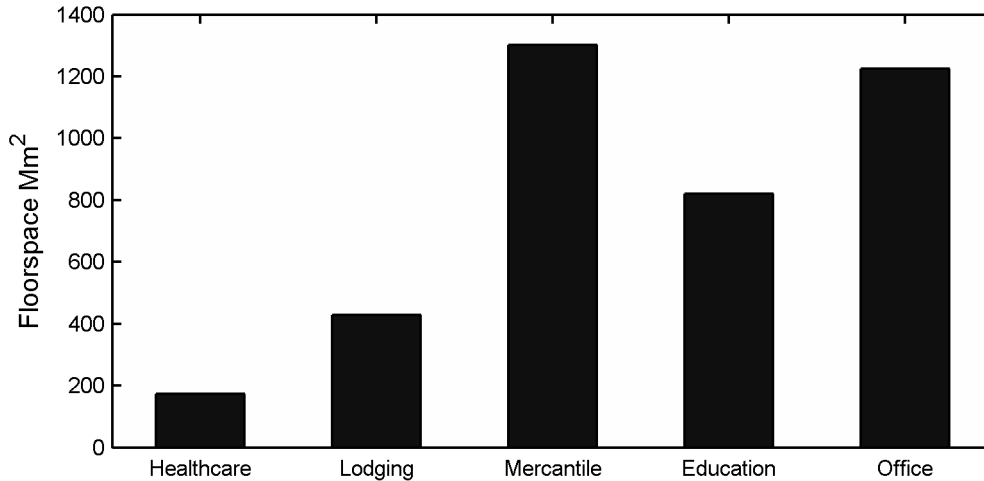
Figure 3. Total U.S. floorspace of the different building types [9]

Table 4 displays the size distribution of U.S. commercial floorspace in the five building types. Notice that healthcare buildings have most floorspace in the largest categories while mercantile buildings have a particularly small share of large buildings. The remaining building types have more even size distributions.

Table 4. Percent of commercial floorspace in building CBECS size bins [3]

Size (m²)	93-465	465-930	930-2,325	2,325-4,650	4,650-9,300	9,300-18,600	18,600-46,500	> 46,500
Median (m²)	*233*	*698*	*1,628*	*3,488*	*6,975*	*13,950*	*32,550*	*60,450*
Education	3.5	4.6	9.1	18.6	22.1	15.3	13.5	13.5*
Healthcare	6.6	5.7*	4.7	9.6	9.2	11.0	26.4	26.8
Lodging	2.2*	6.3	9.6	25.3	16.8	11.7	17.6	10.6*
Mercantile	8.9	10.1	20.5	9.6	14.4	17.0	4.1	15.4
Office	10.1	8.8	12.3	9.9	16.2	14.3	13.0	15.5

*Assumed value. Data withheld because the relative standard error was greater than 50 percent, or fewer than 20 buildings were sampled

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 [3] 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.

Table 5 presents the peak load by building type and size and the selected range of building size for candidate small-scale DG. Small-scale DG is in the range of the smallest DG 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 300-2,000 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 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 5 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.

Table 5. Commercial building size distribution with corresponding building peak load for Boston [3]

Size (m^2)	93-465	465-930	930-2,325	2,325-4,650	4,650-9,300	9,300-18,600	18,600-46,500	> 46,500
Median (m^2)	*233*	*698*	*1,628*	*3,488*	*6,975*	*13,950*	*32,550*	*60,450*
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
Education	11.5	34.5	80.5	172.5	**345**	690	**1610**	2990
Office	10.75	32.25	75.25	161.25	**322.5**	645	**1505**	2795

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. For buildings with a lower peak, DG system incurs a 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 DG site. For buildings with a peak load over 2 MW, gas turbines can be a strong competitor to reciprocating engines and microturbines. In addition, some large buildings already have DG systems installed. At the same time, there is a potential market in some buildings where the investments in large gas turbines does not provide a sufficient return. Table 6 shows the percentage of buildings that are assumed to have DG potential by the size of the peak load.

Table 6. Percentage of buildings assumed to have DG potential

|	Existing Buildings	New Buildings
Below DG Attractive Size Range (< 300 kW)	16	18
DG Attractive Size Range (300 – 2,000 kW)	80	90
Over DG Attractive Size Range (> 2,000 kW)	32	36

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 bin 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 7. 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.

Table 7. Electricity (EL) load, natural gas (NG) load and fuel-to-electricity (F/E) ratio

		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	11934	3629	15705	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	17188	4967	21504	1681	2867	3847	16028	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	17270	5486	23758	1954	3406	4345	18038	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	2293	5300	559	2577	1081	4457
Total NG Load	GJ	7731	12776	3324	14404	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

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 have the average load profile for remaining non-holiday weekdays and weekend days have the average load profile for weekend days and holidays. In Figure 4, the weekday profiles for the large San Francisco office building can be seen. Most of the seasonal variation is in cooling and heating. In Chicago there is typically no cooling load in the winter, as can be seen in Figure 5. Notice also the difference in the space heating profiles between the healthcare and the office building. The healthcare building keeps the same temperature during the whole day, and therefore needs more heating during night time hours.
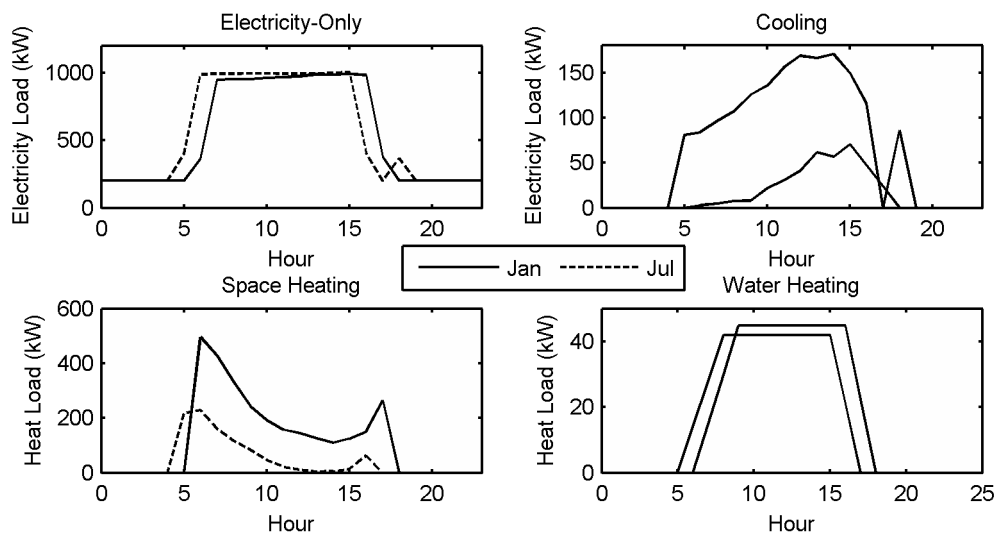
Figure 4. January and July energy loads for the large San Francisco office building
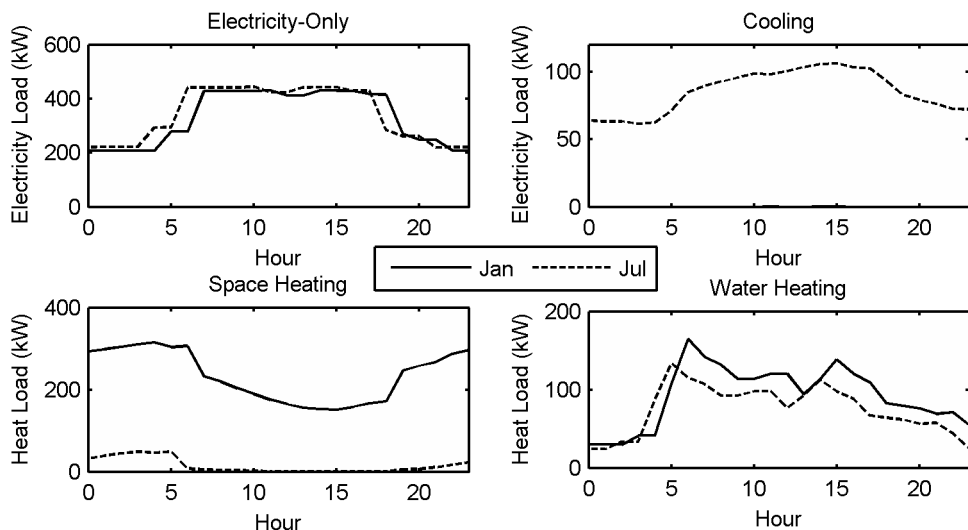
Figure 5. January and July energy loads for the small Chicago healthcare building

4.2 Distributed Generation Technology

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 [5] with additional data provided from work done at the LBNL [6]. 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 8. 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 8. 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

4.3 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 U.S. electricity rates [7]. 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. The monthly fee is a fixed charge each month. Table 9 shows the 2004 electricity rates for all four cities.

Table 9. Assumed 2005 electricity rates for the commercial buildings [7]

	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

The 2004 natural gas rates for the regions containing the four cities of consideration were obtained from the AEO2005 Reference Case [8], and are shown in Table 10. 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 the higher quantities and more consistent rates of prime power DER rather than typical commercial building consumption. The AEO2005 [8] 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 Table10.

Table 10. AEO2005 natural gas rates in 2004 ($/kWh, HHV3) [8]

	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

The AEO2005 Reference Case [8] 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 [7] to estimate rates for 2012 and 2022 are shown in Table 11. 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 DG service is less than that for standard (i.e. heating, cooking) service because DG 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 11 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 DG profitability depends on the difference between natural gas and electricity prices, implying that falling prices do not necessarily mean less favorable DG market conditions.

Table 11. Scaling factors for 2012 and 2022 electricity and natural gas prices [8]

	Electricity		Natural Gas		Natural gas (DG)	
	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

4.4 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.

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[3] HHV refers to higher heating value. 1 kWh of natural gas contains 3,412 Btu.

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 12. 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 12. 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

4.5 Technology Diffusion Parameters

Table 13 summarizes the parameters that determine the spread of DG knowledge and adoption as a function of percentage annual savings on the energy bill. 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.

Table 13. 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

Figure 6 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.
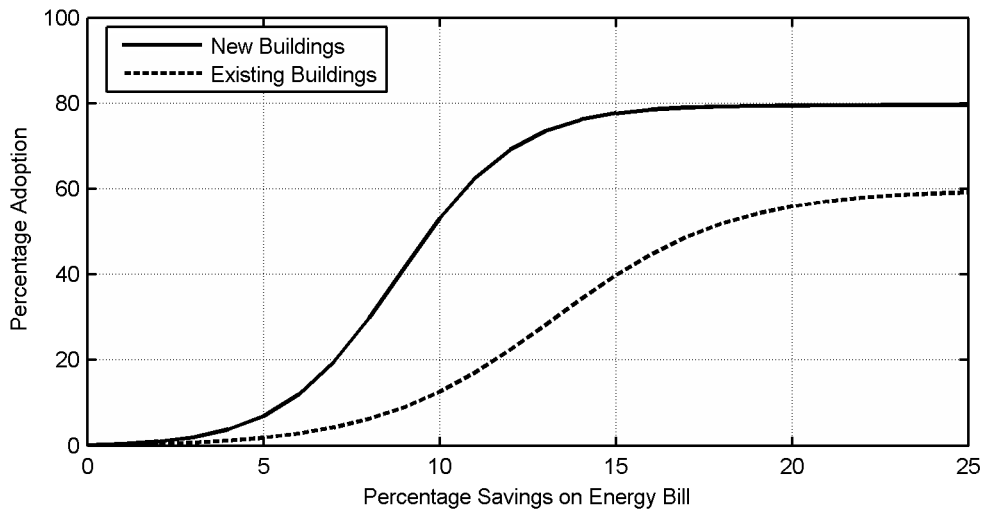
Figure 6. Adoption curves for new and existing buildings where owners has DG knowledge

5. Results

5.1 Optimal Distributed Generation Systems for the Modeled Buildings

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 14 displays the optimal DG capacity found with DER-CAM for the 160 runs. DG systems are in general largest in San Francisco and in Boston while there in Atlanta is no optimal DG capacity in any of the cases. Table 15 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 Table 7 and Table 15 suggests that the most important indicator of DG profitability in the U.S. 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 DG installations. That peak electricity load seems more important than energy load profiles can mean that DG 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 14.** 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

Table 15. 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

5.2 Predicted DG Market Diffusion

Figure 7 shows the modeled 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.
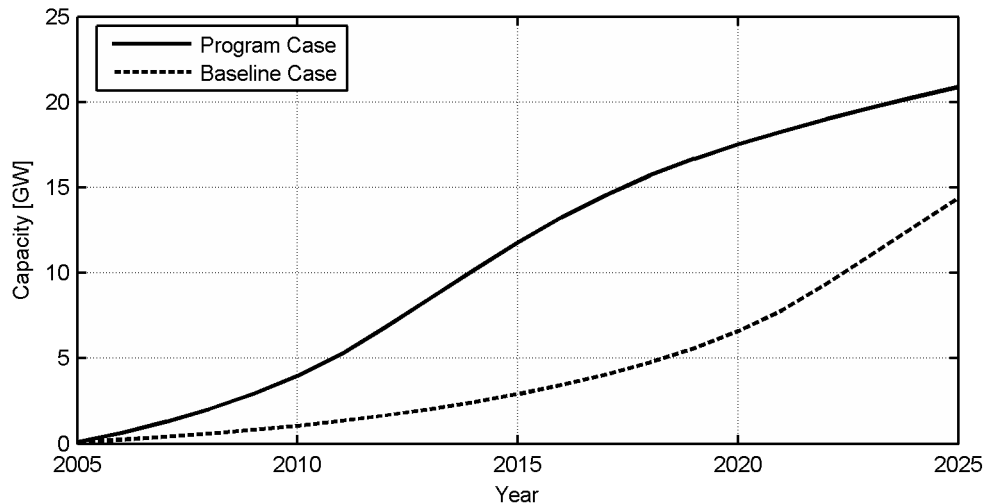
Figure 7. Cumulative installed DG capacity in U.S. commercial sector in Baseline and Program cases

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 8). 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.
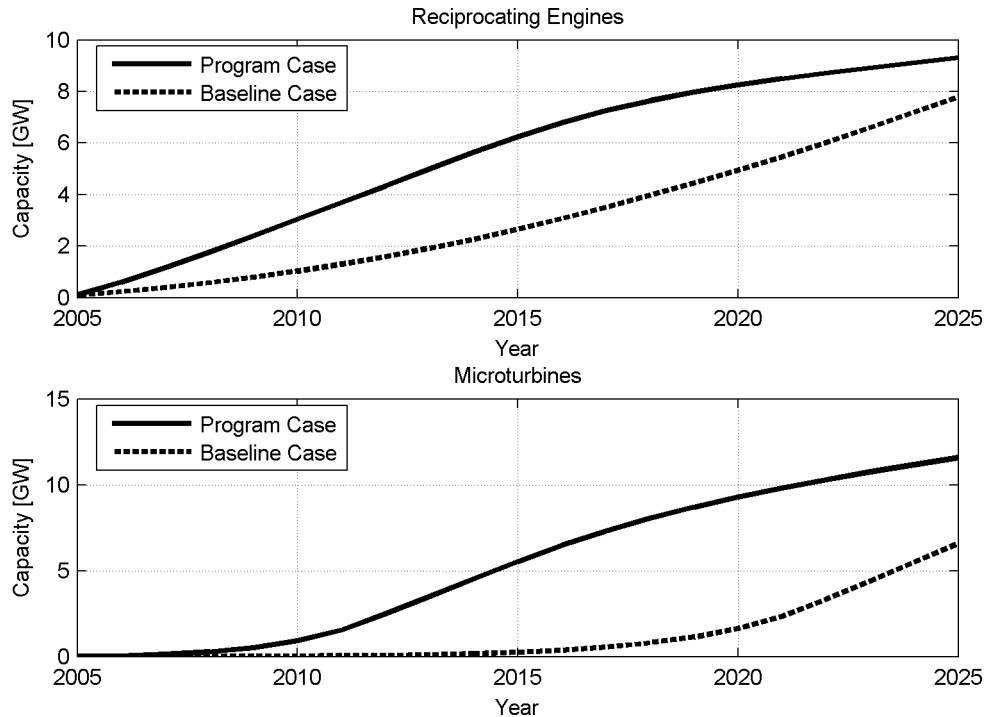
Figure 8. Cumulative installed capacity of reciprocating engines and microturbines in the Program and Baseline cases

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 9 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.

Figure 10 displays ratio of net changes in electricity purchases to net changes in building natural gas purchases. This ratio can be viewed upon as an efficiency metric, which can be compared to the central efficiency for delivery to the end-used. Combined heat and power 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, 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.
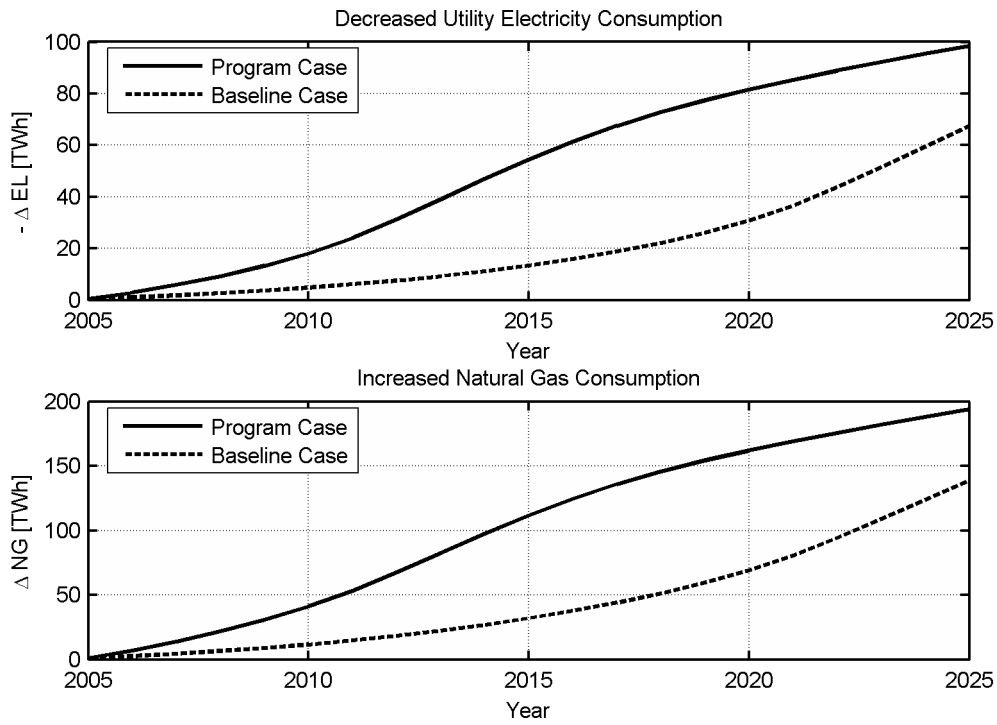
Figure 9. Electricity produced on-site and increased natural gas consumption
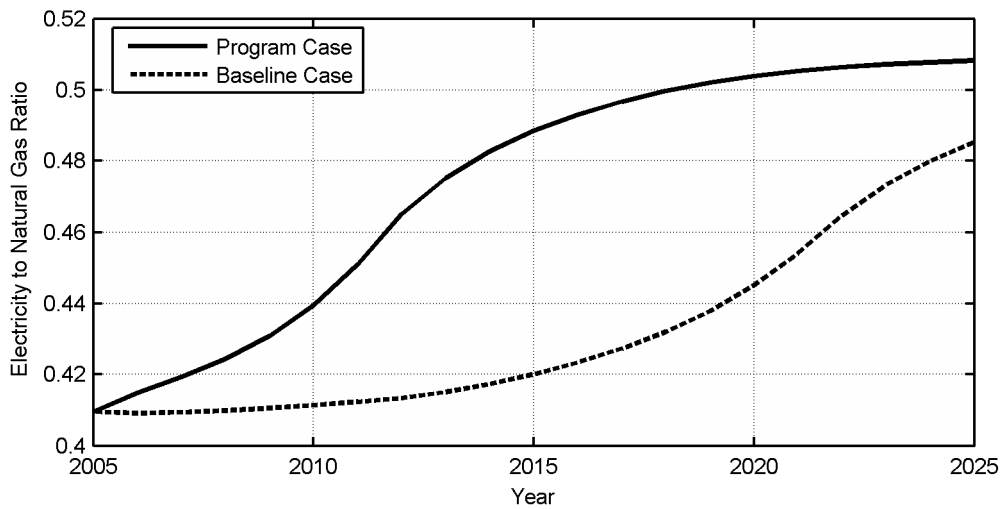
**Figure 10.** On-site electricity generation to increased natural gas consumption ratio

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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 11. 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.
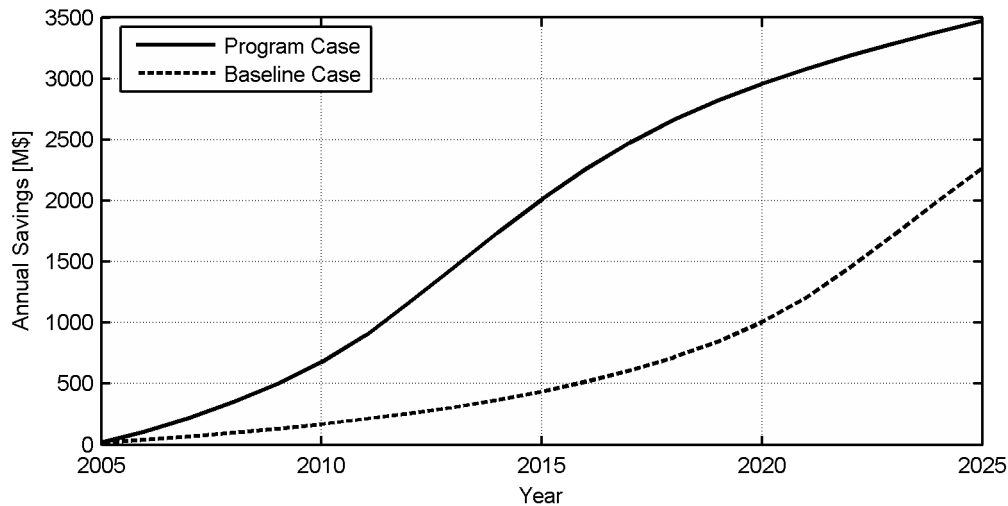
Figure 11. Annual private cost savings from DG in Program and Baseline cases

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 12, 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.

In the Program case, most DG is expected in office buildings followed by mercantile buildings (see Figure 13). 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.
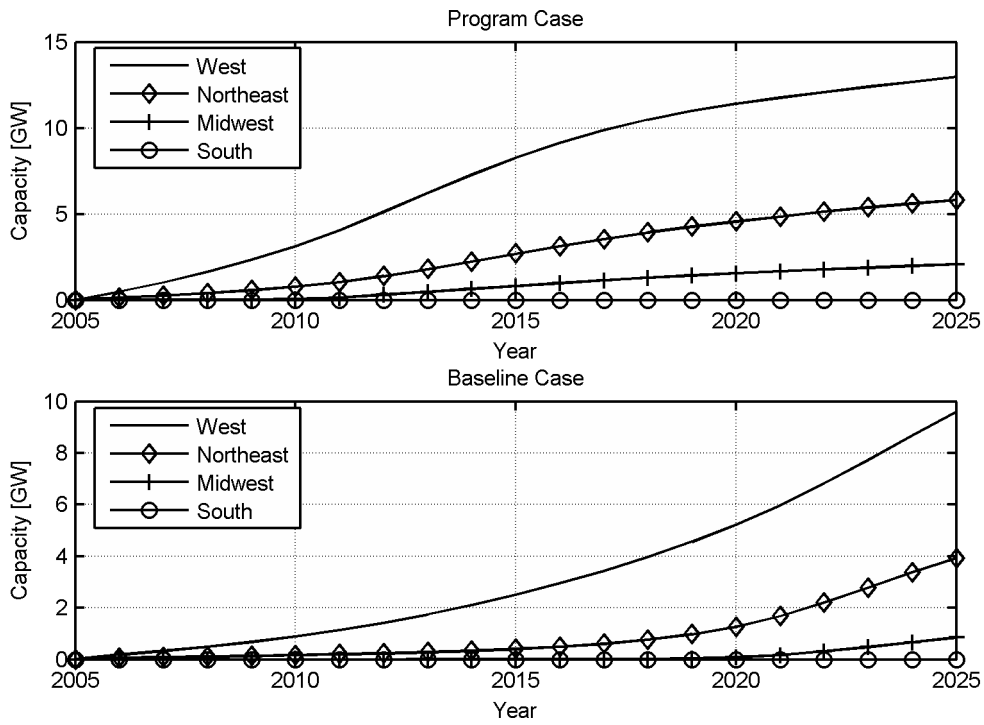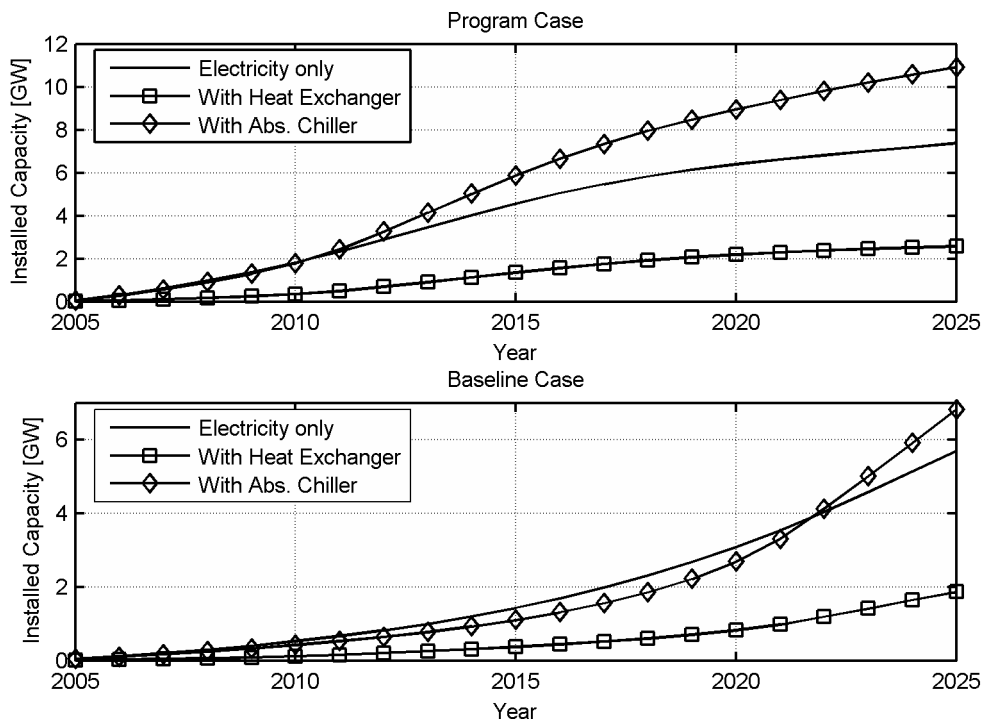
Figure 12. Cumulative installed DG capacity in Census regions in the forecast period in Program and Baseline cases
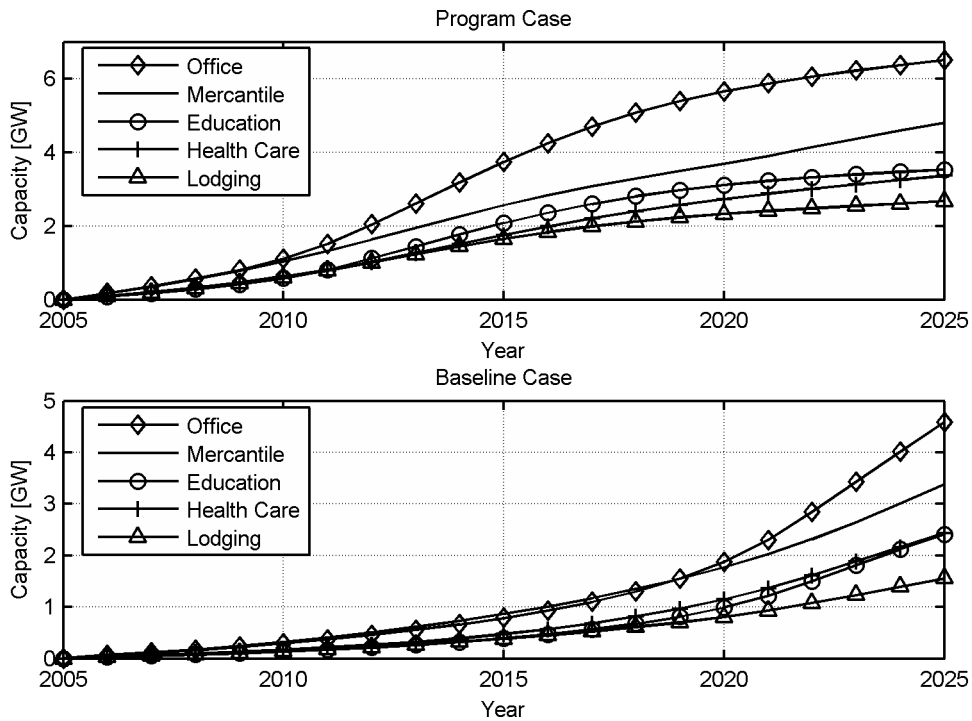

Figure 13. Cumulative installed DG capacity for building types in Program and Baseline Cases

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 14. 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 8). 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 9).

The sensitivity in installed capacity to the outreach parameter, α, for the Program and Baseline cases has been tested. The outreach parameter has the capability of increasing DG knowledge and thereby the fraction of building owners in the market who will invest according to the adoption curve given in Figure 6. Figure 15 displays that, according to the model, increasing DG knowledge can increase installed capacity significantly. Notice that both for the Baseline and the Program cases the marginal effect of the parameters decreases for high values since the difference between a value of 10 and 20 percent is small. Also, the end of the horizon the difference in a 10 and a 20 percent value is reduced to practically nothing, because the word-of mouth process takes over when large fractions of the commercial floorspace has DG systems installed. This indicates that outreach programs can be particularly important during the introduction of a technology and that they can be reduced when capacity has increased.

Figure 14. Cumulative installed capacity with electricity generation only, heat recovery and absorption cooling
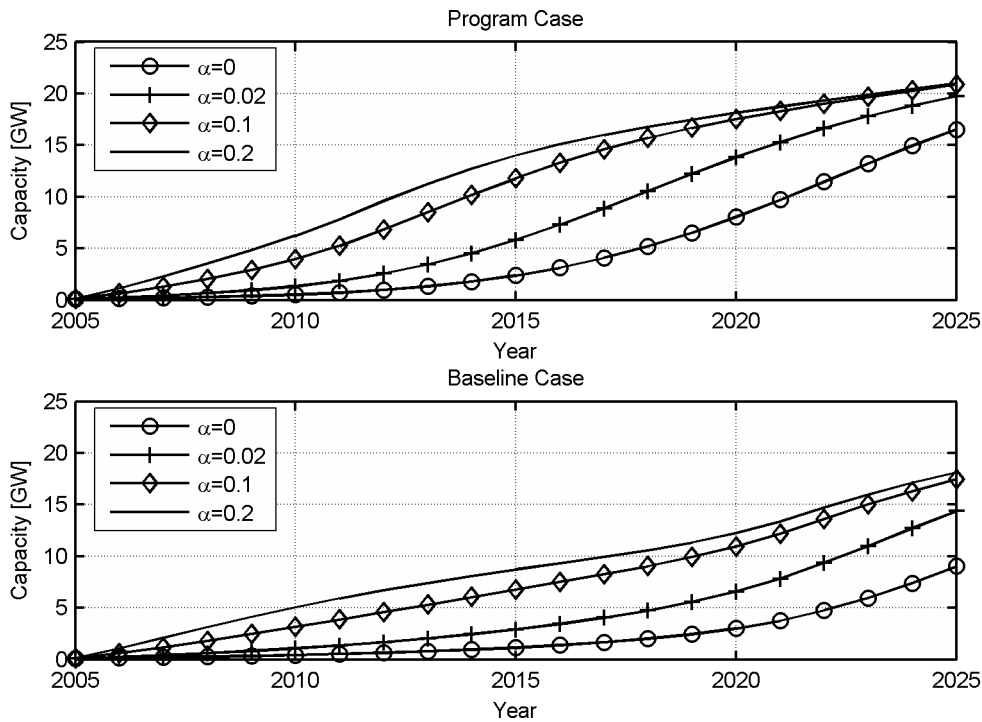
Figure 15. Sensitivity of installed capacity to the outreach parameter α

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 modeling 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

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

Acknowledgements

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