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Modeling of Customer Adoption of Distributed Energy Resources

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California Energy Commission

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Preface

The electricity industry may well be standing at the technological threshold to a new era built of the most fundamental change in power system engineering and organization since the original, small, isolated power networks of the nascent industry first began to be interconnected. The technical challenges, risks, and rewards of this new era are all major and sobering. We hereby step across the threshold and accept the consequences.

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Acronyms

BUG	back-up utility generator
CARB	California Air Resources Board
CAISO	California Independent System Operator
CEC	California Energy Commission
CERTS	Consortium for Electric Reliability Technology Solutions
CHP	combined heat and power
CO	carbon monoxide
CPUC	California Public Utilities Commission
DER	Distributed Energy Resources
DER-CAM	Distributed Energy Resources Customer Adoption Model
DG	distributed generation
DOE	U.S. Department of Energy
DRP-CAISO	Demand Relief Program-CAISO
DRP	demand response program
EPA	U.S. Environmental Protection Agency
EPRI	Electric Power Research Institute
EOB	Electricity Oversight Board
ESP	electric service provider
ER	electricity revenue
FC	fuel cell
FCV	fuel-cell vehicle
GAMS	General Algebraic Modeling Systems
GENCO	generating company
HC	hydrocarbon
HVAC	heating, ventilation, and air conditioning
IDER	integration of distributed energy resources
IEM	imbalance energy market (of CAISO)
IERN	imbalance energy revenue neutrality
IFC	International Fuel Cell
MAISY	market analysis and information system
μGrid	microgrid
NEM	Net Energy Metering
NEMS	National Energy Modeling System
NOx	nitrogen oxide
O&M	operation and maintenance
OEM	original equipment manufacturer
OIR	Order Instituting Ratemaking
PAFC	phosphoric-acid fuel cell
PEM	proton-exchange-membrane fuel cell
PLACE^{3}S	Planning for Community Energy, Economic and Environmental Sustainability
PM	particulate matter
PM-10	particulate matter of10 μm or smaller
PPM	parts per million
PQR	power quality and reliability

PV	photovoltaic
PX	California Power Exchange
PXRN	Power Exchange Revenue Neutral
RECLAIM	REegional CLean Air Incentives Market
RSMEANS	R.S. Means Company annual handbook of cost estimates
SAS	statistical analysis software
SCAQMD	South Coast Air Quality Management District
SCE	Southern California Edison
SCR	selective catalytic reduction
SDG&E	San Diego Gas and Electric
SNCR	selective non-catalytic reduction
SOFC	solid-oxide fuel cell
SOx	sulfur oxide
TAG	Technical Assessment Guide
TOU	time of use
UDC	utility distribution company
VMT	vehicle miles traveled

Acknowledgments

The work described in this report was coordinated by the Consortium for Electric Reliability Technology Solutions and funded by the Assistant Secretary of Energy Efficiency and Renewable Energy, Office of Power Technologies, U.S. Department of Energy and Renewable Energy under Contract No. DE-AC03-76SF00098 and by the California Energy Commission, Public Interest Energy Research Program, under Work for Others Contract No. BAG99-396(00).

The authors would like to recognize the contribution of the following prior participants in distributed energy resources research at Berkeley Lab: Raquel Blanco, Cornelia P. Kawann, Julie G. Osborn, and F. Javier Rubio. Also, we are particularly grateful for helpful input from colleagues and reviewers, and from our program manager for this work, Mark Rawson of the California Energy Commission.

Executive Summary

This report describes work completed for the California Energy Commission (CEC) on the continued development and application of the Distributed Energy Resources Customer Adoption Model (DER-CAM). This work was performed at Ernest Orlando Lawrence Berkeley National Laboratory (Berkeley Lab) between July 2000 and June 2001 under the Consortium for Electric Reliability Technology Solutions (CERTS) Distributed Energy Resources Integration (DERI) project.

Our research on distributed energy resources (DER) builds on the concept of the *microgrid* (µGrid), a semiautonomous grouping of electricity-generating sources and end-use sinks that are placed and operated for the benefit of its members. Although a µGrid can operate independent of the *macrogrid* (the utility power network), the µGrid is usually interconnected, purchasing energy and ancillary services from the macrogrid. Groups of customers can be aggregated into µGrids by pooling their electrical and other loads, and the most cost-effective combination of generation resources for a particular µGrid can be found.

In this study, DER-CAM, an economic model of customer DER adoption implemented in the General Algebraic Modeling System (GAMS) optimization software is used, to find the cost-minimizing combination of on-site generation customers (individual businesses and a µGrid) in a specified test year. DER-CAM s objective is to minimize the cost of supplying electricity to a specific customer by optimizing the installation of distributed generation and the self-generation of part or all of its electricity. Currently, the model only considers electrical loads, but combined heat and power (CHP) analysis capability is being developed under the second year of CEC funding.

The key accomplishments of this year s work were the acquisition of increasingly accurate data on DER technologies, including the development of methods for forecasting cost reductions for these technologies, and the creation of a credible example California µGrid for use in this study and in future work. The work performed during this year demonstrates the viability of DER-CAM and of our approach to analyzing adoption of DER.

Analysis Method and Creation of Example Microgrid

The µGrid created for this study, Microgrid Oaks, is a hypothetical San Diego strip mall of eight commercial buildings: a supermarket (grocery), an office, three restaurants (fast food, sit-down, and deli), a department store, a retail store, and a warehouse store. Metered end-use electricity load data for commercial buildings were obtained from Southern California Edison (SCE) and used to create the load shapes for the businesses in Microgrid Oaks. Appropriate fuel and electricity costs for San Diego were applied for the test year, 2000.

DER-CAM was run for Microgrid Oaks as a whole and the eight businesses individually under 13 different scenarios. In the base-case scenario, the customer is free to install DER and purchase electricity at the California Independent System Operator (CAISO)

imbalance energy market (IEM) price plus an adder that guarantees revenue neutrality for the utility distribution company (UDC) (This is the Imbalance Energy Revenue Neutrality or IERN case). The variations on the base case cover changes in economic or regulatory conditions — relaxation of constraints on operating hours for diesel-fueled back-up generators, opportunities for customers to sell self-generated energy to the macrogrid before meeting their own loads, and changes in energy or related prices or in subsidies for particular DER technologies. The scenarios are defined specifically in Table ES-1 below.

Our study assumed that Microgrid Oaks wishes to install distributed generation to minimize the cost of electricity consumed on site. DER-CAM determined the technologies and capacity that the µGrid would likely to install given the mall s configuration and economic data in the year 2000 and predicted when customers would be self-generating and/or transacting with the grid and whether it would be worthwhile for customers to disconnect entirely from the grid.

The results of this analysis describe the most cost-effective combination of on-site generation for the µGrid during the year 2000 and an elementary operating schedule that would optimize the customer s benefit from DER operation. The model outputs include estimates for such items as total electricity bill, on-site electricity generation, and electricity purchases in each hour. Results were generated for the individual customers in Microgrid Oaks so that their individual optimal generation strategies can be studied and the benefits of µGrid aggregation can be compared to individual customer DER adoption can be assessed. In addition, the apparent effect of their different individual characteristics, notably load shape and capacity factor, on results provides insights into the Grid characteristics that might affect their economics and operations.

The key inputs to the model are the customer s load profile; the customer s electricity purchasing technology option; the capital, operation and maintenance (O&M), and fuel costs of the various available DER technologies; and the basic physical characteristics of alternative generating technologies. The market prices used in most scenarios are the 2000 CAISO IEM prices (augmented by an adder as noted above), which were highly volatile at times and extremely high in the latter part of the year when California s restructured market began unraveling. These prices were used both because they reflect recent market information and because they were expected to produce interesting results, especially generator operating schedules.

With these inputs, the model determines:

- The optimal, cost-minimizing capacity of each technology to be installed;
- When and how much of the installed capacity will be running; and
- The total cost of supplying electricity.

DER equipment data were collected from diverse sources to establish reasonable cost and performance parameters for about 30 DER options currently available for installation. This data set includes information on two microturbines, a commercial fuel cell, small wind and photovoltaic (PV) systems, and a wide range of reciprocating engines that burn diesel and natural gas fuel. Installation costs for these technologies were estimated using a standard engineering handbook. A data set representing possible equivalent data for 2010 was also developed, with emphasis on forecasting of fuel- cell costs for that year. Consequently, the 2010 data set includes two additional fuel-cell technologies and a fuel-cell vehicle. Costs for these technologies were estimated using a combination of experience curves and literature review.

The analyses described in this report are not intended to be thorough financial or engineering evaluations of whether on-site generation makes sense for the particular customers and µGrid studied, nor are they intended to provide market assessments or forecasts of DER penetration. The goal is simply to look at economic fundamentals and see what DER technologies may be attractive to µGrids, in what combinations they might be installed, and how they might be operated a decade or so in the future.

Analysis Results and Conclusions

Table ES- 1 summarizes the DER capacity installed by the individual grocery store and by the µGrid, according to the results DER-CAM s analysis. Although the details of the generating equipment adopted by each of the businesses in Microgrid Oaks acting individually vary quite significantly based on each business s electrical loads, the results for the grocery illustrate the pattern of capacity adoption by individual customers. In general, we find that if customers join together to form a µGrid, the pattern of technologies adopted is more stable than if customers act separately. For example, the µGrid usually selects two natural gas or diesel back-up generators, but customers acting on their own select a wide variety of technologies. Intuitively, this pattern seems plausible because the µGrid, as a larger customer, can pool its resources and capitalize on the economies of scale inherent in many DER technologies, including reciprocating engine generators. Microgrid Oaks purchases larger units than do businesses acting individually; the 500-kW natural gas generator is particularly common in Microgrid Oaks choices under different scenarios, and the 500-kW diesel generator is common in the relaxed-diesel-constraint cases.

Table ES- 1. Technologies Adopted (Grocery and µGrid)

Scenario	Grocery (Dangerway)	µGrid (Microgrid Oaks)
PXRN 1999	None	None
Low Natural Gas Prices	3 75-kW microturbines	2 500-kW natural gas generators, and 1 75-kW microturbine
IERN 2000	3 75-kW microturbines	2 500-kW natural gas generators, and 1 75-kW microturbine
IERN 2010	1 250-kW PEM fuel cell	4 250-kW PEM fuel cells
High DiscoER	3 75-kW microturbines	1 500-kW natural gas generators, and 8 75-kW microturbines
Diesel 1,052 Hours	1 55-kW natural gas generator and 1 500-kW diesel generator	1 500-kW natural gas generators, and 2 500-kW diesel generators
75% PV Subsidy	2 100-kW PV Systems, 2 55-kW natural gas generators, and 1 75-kW microturbine	9 100-kW PV Systems, 1 500-kW natural gas generator, and 3 75-kW microturbines
50% PV Subsidy	3 75-kW microturbines	2 500-kW natural gas generators, and 1 75-kW microturbine

Notes:

PXRN 1999 is a case based on 1999 power exchange electricity prices, with a revenue-neutral adder to compensate distribution companies for commodity non-energy costs. Year 2000 CAISO IEM prices are used in all other cases.

Low Natural Gas Prices is a case where the cost of commodity natural gas is halved relative to the base case.

IERN 2000 and IERN 2010 are year 2000 and year 2010 cases based on the imbalance energy market in 2000, year 2000 and year 2010 technology costs, and a revenue-neutral adder to compensate distribution companies for non-energy costs.

High DiscoER is a case based on a doubled revenue-neutral adder.

Diesel 1,052 Hours is a case where the environmental permit restriction on diesel generators is eased to allow 1,052 hours per year of operation.

75% PV Subsidy is a case where the turnkey costs of PV systems are subsidized by 75%.

50% PV Subsidy is a case where the turnkey costs of PV systems are subsidized by 50%.

We see from Figure ES- 1 that installation of DER generation capacity results in significant electricity bill savings over the do-nothing-IERN scenario. Note that customers in the do-nothing scenario are buying electricity at the 2000 CAISO imbalance energy price, not under tariffed rates. As discussed previously, customers acting together as Microgrid Oaks are able to realize greater savings because they can take advantage of economies of scale. In particular, customers with higher load factors (i.e., flatter loads) are able to achieve greater percentage cost savings because they need not install additional capacity or purchase from the IEM to meet peaking loads that are not economic to self-provide. Figure ES- 2 indicates that this relationship is a strong one. Customers are not allowed to sell to the macrogrid in any of these cases. When sales to the macrogrid are possible, DER-CAM results show customers making massive investments in DER, often to the point of hundreds of generators being installed, a reflection of the unusual circumstances prevalent in 2000, which are a key driver in all results presented here. Note that using 1999 PX prices in place of CAISO 200 IEM prices eliminates all adoption of DER. The exceptional 2000 prices present an excellent opportunity to exercise the model although we hope that the results represent a boundary case.

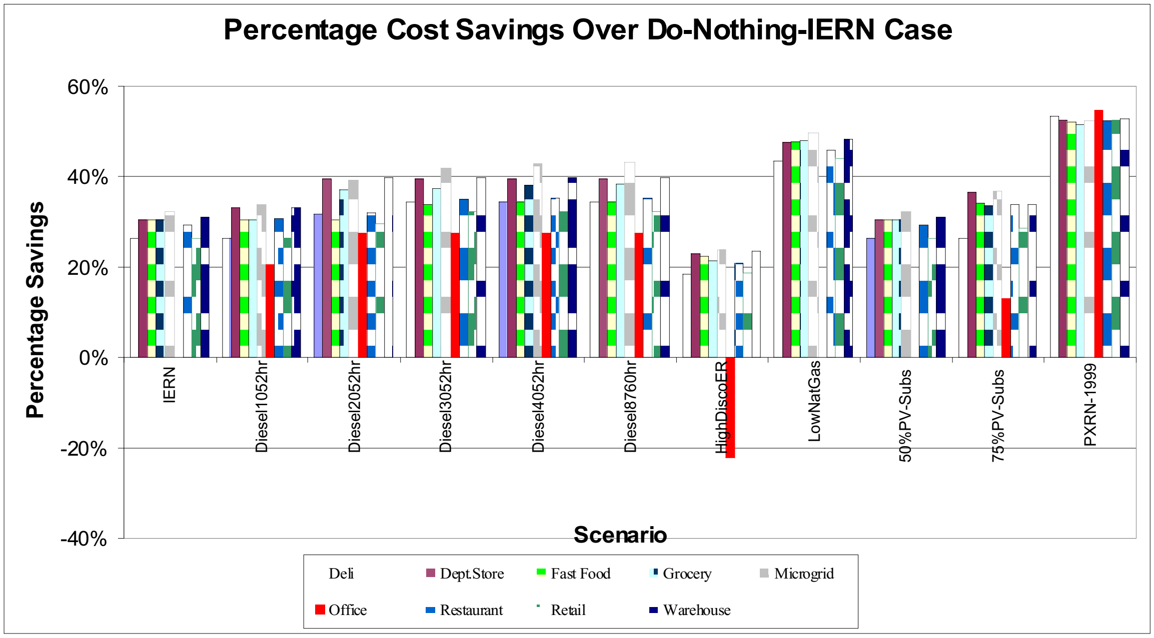

Figure ES- 1. Savings Per Scenario/Activity Over Do-Nothing-IERN Case

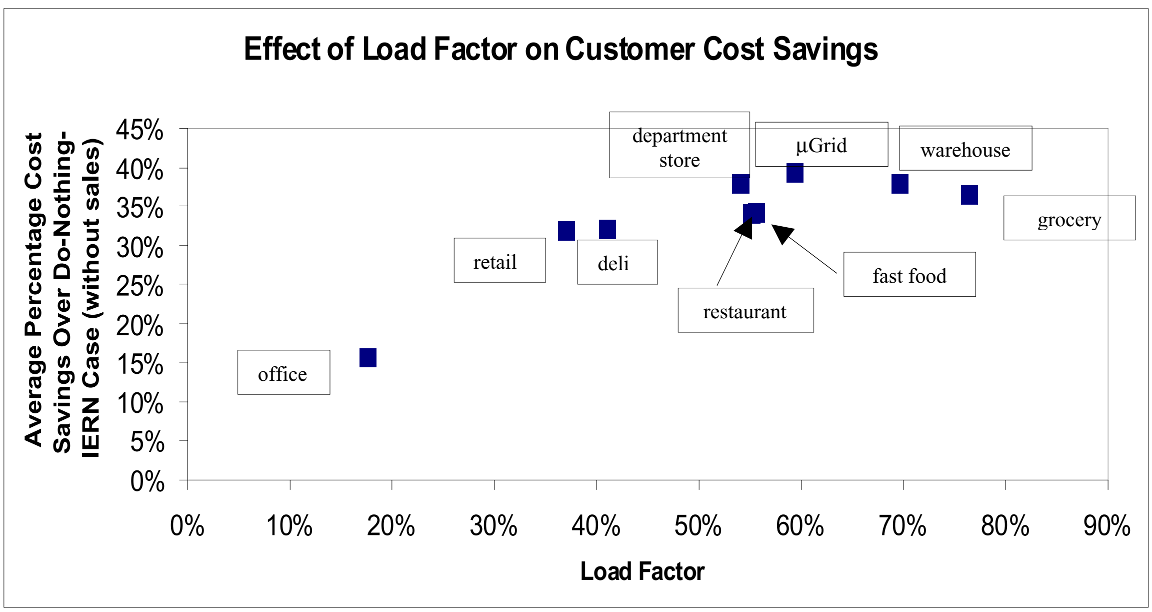

Figure ES- 2. Effect of Load Factor on Customer Cost Savings

Figure ES- 3 and Figure ES- 4 show that customers typically cover most of their peak demand and about half of their energy needs through installed DER capacity. Customers with lower load factors (e.g., the office, retail store, and deli) have relatively high peaks and install comparatively less DER capacity than other customers. Thus, they cover smaller fractions of their peak demand through installed capacity.

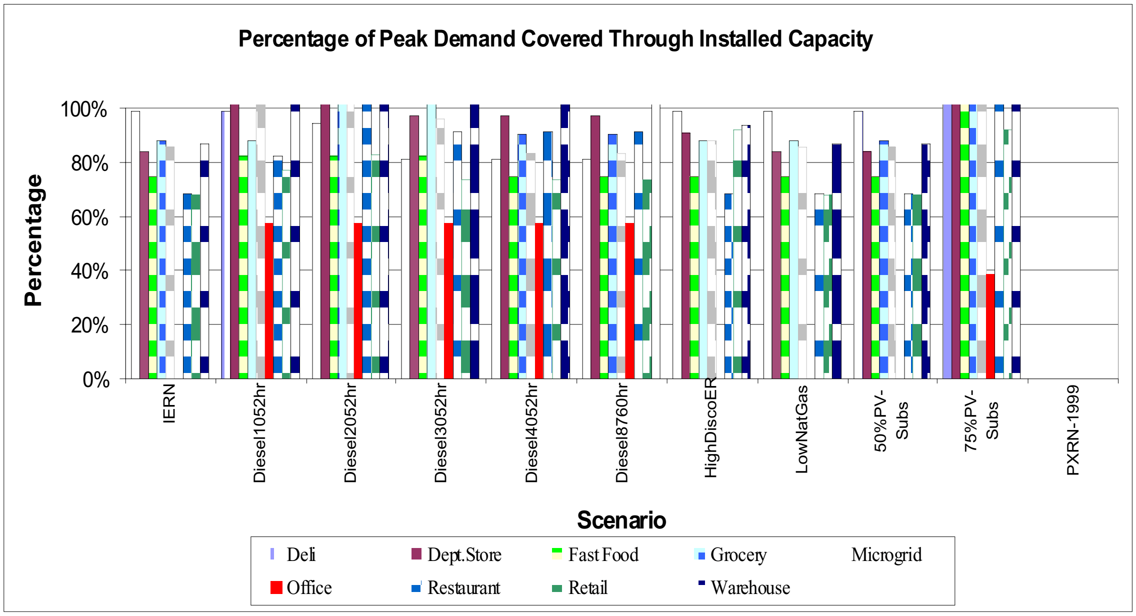

Figure ES- 3. Percent Coverage of Peak Demand through Installed Capacity

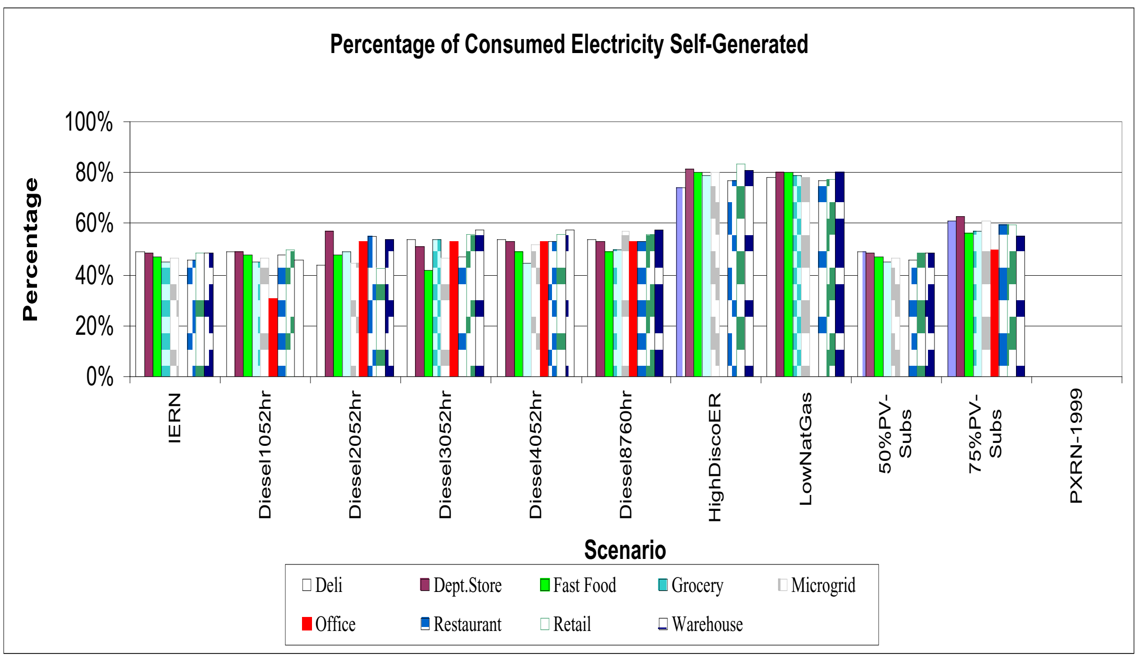

Figure ES- 4. Percent Coverage of Consumed Energy through Installed Capacity

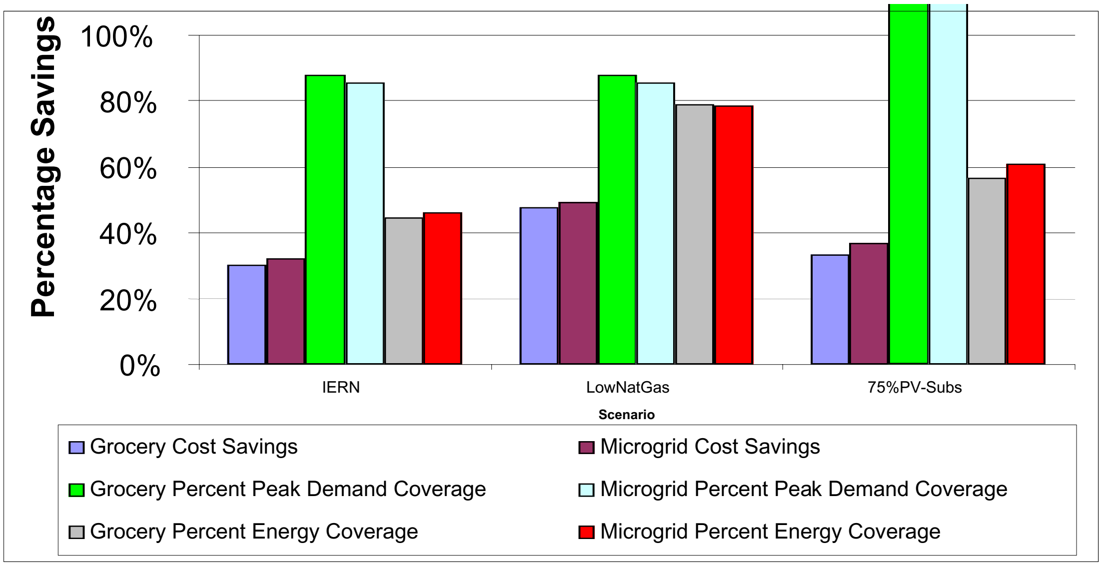

Figure ES- 5. Comparison of Results for Grocery and μGrid

In comparing the relative advantages of DER adoption by the μGrid versus by an individual customer, it is evident from Figure ES- 5 that the μGrid realizes greater cost savings than the grocery does even though the grocery has the highest load factor of the customers. These results are typical of comparisons of μGrid DER versus individual-customer-owned generation. The μGrid 's ability to install specialized equipment and to coordinate the actions of the market participants appears to contribute to its lower costs. Indeed, for all scenarios, the grocery installs more capacity (as a percentage of its peak demand) than does the μGrid. Nevertheless, the μGrid usually covers more of its energy needs with less installed capacity than the grocery. This result is an illustration of the gains in efficiency that can be achieved through the strategic coordination that the μGrid enables.

In general, we find that installation of generation capacity is attractive to customers under a variety of circumstances. Only in the case with low and stable 1999 PX prices is it unattractive for the grocery to install any DER capacity. Although the installed DER capacity is used to generate a significant proportion of each customer s energy (more than 50% in most cases), there are no scenarios, given the IEM prices used, in which the customer opts to disconnect fully from the grid (see Figure ES- 4).

In the base (IERN) scenario, customers buy electricity at the IEM price and cannot sell electricity, while natural gas costs a flat yearlong 8.25 $/GJ and diesel fuel costs 8.46 $/GJ. Use of diesel generators is restricted for air quality reasons to 52 hours per year. Customers significantly lower their average electricity costs over a do-nothing scenario, in the case of the grocery from 13.6 to 9.4 ¢/kWh. Microturbines are the most attractive technology to customers with high load factors, and gas-fired reciprocating engines are chosen by Microgrid Oaks and several individual customers. Microgrid Oaks chooses a large (500-kW) natural gas engine because of the noticeable economy of scale.

When constraints on use of diesel engines are relaxed, diesel generators prove highly attractive to customers, and, again, economies of scale make bigger machines more desirable. It appears that improvement in the environmental performance of these machines (resulting in looser permit conditions) could make them highly attractive for self-generation.

When PV systems are heavily subsidized, they become an attractive option. Interestingly, because PV power is only available during daylight hours, gas engines and microturbines are typically installed as well, yielding the interesting result that most customers individually and Microgrid Oaks as a whole install more generating capacity than their own peak demand. This outcome is rare if PV systems are not included in the mix of DER chosen. When PV systems are chosen, therefore, Microgrid Oaks would be able to sell power even at the time of its own peak demand. Unfortunately, sales to the grid could not be allowed in this study because the IEM price was so high in 2000 relative to the fuel price that generation became enormously profitable and Microgrid Oaks would essentially be turned from a retail mall into a power-generating station, a perverse result. In future work, however, the inclusion of PV resulting in higher capacity installation could prove very interesting because this configuration and amount of DER capacity would permit Microgrid Oaks to readily participate in interruptible load markets.

In most of the reasonable scenarios, customers save 20 to 40 percent on their 2000 electricity bills by self-generating; higher-load-factor and larger customers save more. Joining customers together in the μGrid raises load factor and increases overall size, so customers gain — though not enormously — by forming the μGrid. However, the PXRN assumptions, which replace the 2000 IEM prices with the 1999 PX prices, result in no DER adoption at all, yet customers still save about 50% on their bills relative to the IERN case.

Although installed capacities of DER are quite high in this analysis — almost always between 60 and 100% of peak demand — shares of self-provided energy are much lower, typically 40 to 60% of consumption. Self-provision is uneven during the year; there is less during the low-price first few months than during the high-price periods later in the year.

Limitations and Future Work

Despite the improvements made to the quality of data applied to DER-CAM in this study, the approach still has serious limitations that will be addressed in future work. A critical limitation is that DER-CAM does not address combined heat and power (CHP) systems. This capability is key because the potential of μGrids to capture the economic and environmental benefits of CHP will have a powerful influence on their development. Work in the immediate future will focus first on incorporating CHP technology and the joint optimization of electricity and heat (in the case of California invariably natural gas) consumption. Evaluating the potential benefit of waste-heat use in California s moderate climate will significantly improve the value of DER-CAM s analysis results. To this end, data on CHP technologies are being collected, heat-load shapes for Microgrid Oaks that were not available in the original data set are being developed, and DER-CAM algorithms being installed to accommodate this information.

The second imminent enhancement to DER-CAM will be the incorporation of stochastic effects such as interruptible load market participation into the µGrid s economic opportunities. GAMS has solvers available for problems involving stochastic variables although these are much less well proven and computationally demanding codes than those on which the model currently relies. Inclusion of randomness could significantly enhance the value of DER-CAM s results for both technical purposes (e.g., consequences of equipment failures) and economic (e.g., finding investment strategies robust to price uncertainty) purposes.

Given that CERTS focus is on power system reliability and that popular wisdom insists that early adopters of DER will be motivated by reliability concerns, estimating the improvement in reliability and quality of power supply to end uses within the Grid and its value is also a priority in future work.

Other, lesser limitations of the model include that it does not treat equipment outages, does not permit customers to participate in ancillary services markets or interruptible load programs, does not consider the current crop of DER incentives, and does not address some limitations on DER installation, such as noise restrictions, building codes, and zoning regulations. We hope to address many, if not all, of these limitations in future work.

Better estimation of equipment and operations costs would also improve the model s analysis. However, many cost issues are highly localized in nature and thus are not easily represented in the DER-CAM framework. The feasibility of customers forming and operating Grids will be largely determined by considerations such as zoning, building codes, noise ordinances, air quality permits, etc., that can be effectively represented spatially. Therefore, Berkeley Lab hopes to include these considerations by embedding the DER-CAM analysis within a geographic information system (GIS) framework.

Finally, the analysis is based on simple economics and not a business approach. Enhancement of analysis procedure leading to the equipment adoption decision to better reflect actual business practice would also enhance the value of results.

1. Introduction

1.1 Berkeley Lab Work in Context

This report covers work completed for the California Energy Commission (CEC) at Berkeley Lab during the period July 2000 through June 2001, in the Consortium for Electric Reliability Technology Solutions (CERTS) Integration of Distributed Energy Resources (IDER) project. Berkeley Lab work completed this year focused on the continued development and application of the Distributed Energy Resources Customer Adoption Model (DER-CAM). CERTS research on distributed energy resources (DER) builds on the concept of the microgrid (µGrid). A µGrid is a semiautonomous grouping of generating sources and end-use sinks that share heat and power and are clustered and operated for the benefit of its members. Although capable of operating independently of the macrogrid (the interconnected utility grid), the µGrid is usually interconnected and exchanges energy and ancillary services with the macrogrid. The µGrid maintains energy balance through passive plug and play electronic interfaces that allow operation of the µGrid without active control or fast communication. The design, implementation, operation, and expansion of the µGrid is meant to optimize the overall energy system requirements of participating customers and not the objectives and requirements of the macrogrid. The goal of CERTS research is to solve the technical problems required to make µGrids a viable technology; Berkeley Lab s contribution is to direct the technical research at CERTS partner sites toward the most productive engineering problems.

1.2 Analysis Approach

With CERT s wider goals in mind, Berkeley Lab has build an economic model of customer DER adoption, DER-CAM, that finds the cost-minimizing combination of on-site generation that a customer could have had during a test year (in this report 2000 is the test year). DER-CAM has been implemented in the General Algebraic Modeling System (GAMS) optimization software. The key inputs to DER-CAM are the load shape of a customer s electricity usage, data that describe the operating characteristics of available DER technologies (e.g. energy conversion efficiencies, costs, etc.), and data that describe economic circumstances, such as the tariffs under which the µGrid can buy electricity, the prices of fuels, etc. Groupings of customers can be aggregated into µGrids by pooling of their electrical loads, and the optimal combination of generation for the µGrid can be found. DER-CAM s results are not intended to be thorough financial or engineering evaluations of whether on-site generation makes sense for particular customers and µGrids, nor are the results intended to provide market assessments or forecasts of DER penetration. The objective is simply to look at economic fundamentals and see what DER technologies may be attractive to µGrids, in what combinations they might be installed, and how they might be operated. Always, the intention is to anticipate what are the key technical problems that would need to be solved for a particular µGrid to function. The results obtained from this process are the optimum combination of on-site generation, an elementary operating schedule showing how the equipment should have been used, and summary results for each case, such as total electricity bill, electricity generation and purchases in each hour, etc.

In this study, Microgrid Oaks, a hypothetical strip mall of eight hypothetical commercial buildings in Southern California, is analyzed. Historic end-use metered electrical loads for the eight customers have been massaged into load shapes appropriate for use in DER-CAM. Microgrid Oaks is assumed to be in the San Diego area, so appropriate year-2000 fuel and electricity costs for San Diego during 2000 are applied.

1.3 Justification for the µGrid

The expectation that DER will emerge during the next decade to shape the way in which electricity is supplied stems from the following hypotheses:

1. Electricity demand will continue to grow although more slowly than economic expansion.
2. Small-scale generating technology, both renewable and thermal, will improve significantly.
3. Siting constraints, environmental concerns, fossil fuel scarcity, and other limits will impede continued expansion of the existing electricity supply infrastructure.
4. The potential for application of small-scale combined heat and power (CHP) technologies will tilt power generation economics in favor of generation based closer to heat loads.
5. Customers desire for control over service quality and reliability will intensify.
6. Power electronics will enable operation of semi-autonomous systems.

The last hypothesis above is the driving force behind the CERTS approach, built on the fundamental concept of the µGrid, which could yield a more decentralized power system. A µGrid consists of a localized semi-autonomous grouping of loads and generation operating under a form of coordinated local control, which could be either active or passive, although low-cost, passive, plug and play control is probably the most attractive. The µGrid is connected to the current power system macrogrid in a manner that allows the µGrid to appear to the wider grid as a good citizen; that is, the µGrid performs as a legitimate entity under grid rules (e.g., as what we currently consider a normal electricity customer or generating unit).

The µGrid would most likely exist on a small, dense group of contiguous geographic sites that exchange electrical energy through a low-voltage (e.g., 480-V) network and exchange heat by means of working fluids. In the commercial sector, heat loads may be absorption or desiccant cooling. The generators and loads within the cluster are placed and coordinated to minimize the joint cost of serving electricity and heat demand, given prevailing market conditions, while operating safely and maintaining power balance and quality.

Traditional power system planning and operation hinge on the assumption that the selection, deployment, and financing of generating assets will be tightly coupled to changing requirements and that it will rest in the hands of a centralized authority. The ongoing deregulation of generation represents the first step towards abandoning the centralized paradigm, and the emergence of µGrids represents the second. µGrids will develop their own independent operational standards and expansion plans. This will significantly affect the overall growth of the power system but will tend to occur in accordance with the independent incentives of µGrids. In other words, the power system will be expanding according to dispersed independent goals, not coordinated global ones.

The emergence of µGrids partially stratifies the current strictly hierarchical control of the power system into at least two layers. The upper layer macrogrid is the current power system engineers are familiar with (high-voltage, meshed power grid). A control center dispatches a limited set of large assets in keeping with contracts established between electricity and ancillary services buyers and sellers, while maintaining energy balance and power quality, protecting the system, and ensuring reliability. At the same time, the lower layer of the system, the µGrid, jointly locally controls some generation and load to meet end-use requirements for energy and power quality and reliability (PQR).

Control of the generating and transmission assets of the macrogrid is governed by extremely precise technical standards that are uniform on regional scales, and the key characteristics of the grid, such as frequency and voltage, are maintained strictly within tight tolerances. This control paradigm ensures overall stability and safety and attempts to guarantee that power and ancillary service delivery between sellers and buyers is as efficient and reliable as reasonably possible. However, it should be recognized that uniform standards of PQR are unlikely to match well with the optimal requirements of individual end uses that are highly heterogeneous (i.e., with end uses such as server farms at one end of the reliability requirement spectrum and water pumps at the other). µGrids move the PQR choice closer to the end uses and permits end uses to choose a level of PQR that more closely matches the end use s requirements. µGrids can, therefore, improve the overall efficiency of electricity delivery at the point of end use, and, as µGrids become more prevalent, the PQR standards of the macrogrid can ultimately be matched to the purpose of bulk-power delivery.

1.4 Report Outline

The following two sections describe the development of the input data set to DER-CAM, and section 4 describes the eight customers that form Microgrid Oaks. Section 5 presents some background environmental information to the analysis. Section 6 describes the mathematics of DER-CAM, and section 7 lays out a full set of results for one case, and presents some comparative analysis of cases.

2. DER Technology Cost and Performance Data

2.1 Introduction

Clearly, the quality of the data fed into a model is just as important in producing credible and realistic results as the methods and algorithms of the model itself. Improving on the quality of data used for the DER-CAM analysis is one of the primary objectives of this effort. Using credible data is particularly important for work of this kind because a technology that is represented by incorrectly favorable characteristics will likely do extraordinarily well in competition with other technologies that are more accurately portrayed, so the inaccurate data will figure prominently in the results. Consequently, DER technology data that best reflect actual operations are used wherever possible. The data were collected from various sources including manufacturers technical specifications, phone interviews with company representatives, publicly available literature, and proprietary publications such as Electric Power Research Institute s (EPRI) Technical Assessment Guide (TAG). On the other hand, many of the technologies that will be dominant in µGrids are not yet commercial and certainly not yet mature. Also, the resources available for this study are limited, and few organized data sources currently exist in the public domain. Therefore, realistically, some of the required data are not satisfactorily reliable at this time, and our results should therefore be viewed with appropriate suspicion.

2.2 About the Data

The data were organized around two scenarios: one based on current DER technology operating characteristics and costs, the other anticipating cost and performance information for approximate conditions in the year 2010. These two data sets were used in the two scenarios to determine any differences in customer adoption behavior in 2000 compared with 2010. The 2010 scenario was analyzed to reflect the likelihood that some DER technologies will significantly improve during the next decade. Lowering operating and equipment costs by increasing production volume may make DER a more viable alternative to purchasing electricity from the macrogrid because large-scale generating technologies are mature now, and siting and congestion may raise costs of the macrogrid power in the future.

The DER-CAM model relies upon a variety of input data related to the economics and performance of each technology type. These data include capital costs of equipment, O&M costs, equipment installation costs, conversion efficiencies, and emission rates. These data have been compiled from various sources and are presented in and Table 2.

One important note is that some of the cost data collected were for technologies whose emergence in the market is forthcoming. For example most types of fuel cells (FCs), including the solid-oxide fuel cell (SOFC), are still in the test stages of development; other technologies already available on the market, such as photovoltaics (PVs), are still undergoing significant improvements. Also, forecasted production-volume increases during the next 10 years will bring about further improvements. Therefore, the 2010 data show significant improvements in these emerging technologies but little or no change in mature technologies.

This section presents the characteristics of the collected DER data by technology type. The technologies incorporated in DER-CAM include microturbines, FCs, PV, wind turbines, and diesel and natural gas reciprocating engines currently thought of as back-up generators.

2.3 Present-Day and 2010 Scenario Data

Table 1 below illustrates the data used for the present-day scenario. This data set is slightly abbreviated for space purposes but nonetheless shows most of the parameters that are fed into DER-CAM. Included in this scenario are two microturbines, one FC, two wind turbines, four PV systems, fourteen diesel back-up generators, and five gas-fired reciprocating engine generators.

The parameters considered include the nameplate kW rating, equipment cost, cost for installation, estimated turnkey cost (turnkey costs are defined here as free-on-board equipment cost plus delivery cost plus installation and permitting cost), fixed and variable O&M costs, calculated levelized cost, conversion efficiency or heat rate, and air emissions rates (if available). Entries in the tables with a PR label denote places where the data were available but from a proprietary source that could not be explicitly reported.

For the levelized cost calculation shown, a lifetime of 20 years was assumed for the PV units and a 12.5-year life was assumed for all other DER technologies. The annualized costs reflect amortization spanning the length of equipment lifetime at a real annual interest rate of 9.5%.

Table 1. Present-Day DER-CAM Technology Options

	Name	DER Type	Source	Nameplate kW	lifetime (a)	$/kW cost FOB cost	$/kW cost Turnkey cost	OMFix $/kW/a	OMVar $/kWh	Lev Cost c/kWh	Heat Rate kJ/kWh	NOx g/kWh	PM g/kWh
1	MTL-C-30	MT	SCE	30	12.5	1200	1333	119	in Fix O&M	12.14	12,186		
3	MT-HW-75	MT	SCE	75	12.5	700	753	0.5 c/kWh	in Fix O&M	10.56	11,373	0.238	
4	PAFC-O-200	PAFC	TAG	200	12.5	3500	**PR**	**PR**	**PR**	13.68	**PR**	**PR**	
5	DE-K-15	Diesel Backup	manufacturer	15	12.5	878	2257	26.5	0.000033	N/A	0		
6	DE-K-30	Diesel Backup	manufacturer	30	12.5	473	1290	26.5	0.000033	5.51	11,887	8.17	0.54
7	DE-K-60	Diesel Backup	manufacturer	60	12.5	290	864	26.5	0.000033	6.30	11,201	11.57	0.54
8	DE-K-105	Diesel Backup	manufacturer	105	12.5	212	690	26.5	0.000033	5.48	10,581	12.25	0.54
9	DE-K-200	Diesel Backup	manufacturer	200	12.5	170	514	26.5	0.000033	5.20	11,041	8.85	0.27
10	DE-K-350	Diesel Backup	manufacturer	350	12.5	156	414	26.5	0.000033	4.61	10,032	8.16	0.68
11	DE-K-500	Diesel Backup	manufacturer	500	12.5	166	386	26.5	0.000033	4.65	10,314	8.57	0.16
12	DE-C-7	Diesel Backup	manufacturer	7.5	12.5	213	627	26.5	0.000033	N/A	10,458		
13	DE-C-20	Diesel Backup	manufacturer	20	12.5	440	1188	26.5	0.000033	7.48	12,783		0.54
14	DE-C-40	Diesel Backup	manufacturer	40	12.5	350	993	26.5	0.000033	7.05	11,658		0.54
15	DE-C-100	Diesel Backup	manufacturer	100	12.5	180	599	26.5	0.000033	5.45	10,287		0.54
16	DE-C-200	Diesel Backup	manufacturer	200	12.5	135	416	26.5	0.000033	4.94	9,944		0.27
17	DE-C-300	Diesel Backup	manufacturer	300	12.5	127	357	26.5	0.000033	5.14	10,287		0.41
18	DE-C-500	Diesel Backup	manufacturer	500	12.5	136	318	26.5	0.000033	5.42	9,327		0.16
19	GA-K-25	Gas Backup	manufacturer	25	12.5	522	1730	26.5	0.000033	10.42	15,596		
20	GA-K-55	Gas Backup	manufacturer	55	12.5	290	970	26.5	0.000033	7.55	12,997		
21	GA-K-100	Gas Backup	manufacturer	100	12.5	259	833	26.5	0.000033	9.18	15,200		
22	GA-K-215	Gas Backup	manufacturer	215	12.5	416	1185	26.5	0.000033	7.15	13,157	6.05	
23	GA-K-500	Gas Backup	manufacturer	500	12.5	408	936	26.5	0.000033	7.33	12,003	25.29	
24	WD-1	Wind	Bergey Windpower	1	12.5	3920	8920	3.8	0	39.85			
25	WD-10	Wind	Bergey Windpower	10	12.5	2805	6055	5.7	0	27.05			
26	PV-5	PV	Jeff Oldman, Real Goods	5	20	7150	8650	14.3	0	55.23		0.0	0.0
27	PV-20	PV	Jeff Oldman, Real Goods	20	20	5950	7450	14.3	0	47.56		0.0	0.0
28	PV-50	PV	Jeff Oldman, Real Goods	50	20	5175	6675	5	0	42.62		0.0	0.0
29	PV-100	PV	Jeff Oldman, Real Goods	100	20	5175	6675	2.85	0	42.62		0.0	0.0

Table 2. 2010 DER-CAM Technology Options

	Name	DER Tech Type	Source	Plate kW	lifetime (a)	$/kW cost FOB cost	$/kW cost Turnkey cost	OMFix $/kW/a	OMVar $/kWh	Lev Cost c/kWh	Heat Rate kJ/kWh	NOx g/kWh	PM g/kWh
1	MTL-C-30	MT	SCE	30	12.5	1200	1333	119	in Fix O&M	12.14	12,186		
2	MT-HW-75	MT	SCE	75	12.5	700	753	44	in Fix O&M	10.56	11,373	<0.053	
3	PAFC-O-200	PAFC	TAG	200	12.5	1300	**PR**	**PR**	**PR**	10.15	9,480	**PR**	
4	PAFC-O-1200	PAFC	TAG	1200	12.5	1300	**PR**	**PR**	**PR**	8.14	9,080		
5	SOFC-SW-3100	SOFC-CT	TAG	3100	12.5	600	**PR**	**PR**	**PR**	7.66	6,153		
6	PEM-BA-250	PEM-FC	TAG	250	12.5	710	**PR**	**PR**	**PR**	8.68	9,154		
7	SOFC-C8-500	SOFC	TAG	500	12.5	750	**PR**	**PR**	**PR**	8.97	6,692		
8	PEM-10kW	PEM-FC	Ogden & Kreutz	10	12.5	1546	1600	10	0.0010	13.34	10,800		
9	PEM-25kW	PEM-FC	Ogden & Kreutz	25	12.5	976	1000	4	0.0007	11.75	10,800		
10	PEM-50kW	PEM-FC	Ogden & Kreutz	50	12.5	786	800	2	0.0006	7.70	10,800		
11	FCV-75	FCV-75	Tim Lipman	30	12.5	0	83	20	0.029000	7.75	9,231		
12	DE-K-15	Diesel Backup	manufacturer	15	12.5	878	2257	27	0.000033	N/A	18,288		
13	DE-K-30	Diesel Backup	manufacturer	30	12.5	473	1260	27	0.000033	5.51	11,887	8.17	0.54
14	DE-K-60	Diesel Backup	manufacturer	60	12.5	290	864	27	0.000033	6.30	11,201	11.57	0.54
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28	GA-K-100	Gas Backup	manufacturer	100	12.5	259	830	27	0.000033	9.18	15,200		
29	GA-K-215	Gas Backup	manufacturer	215	12.5	416	1196	27	0.000033	7.15	13,157	6.05	
30	GA-K-500	Gas Backup	manufacturer	500	12.5	408	936	27	0.000033	7.33	12,003	25.29	
31	WD-1	Wind	Bergey Windpower	1	12.5	3920	8920	4	0	39.85			
32	WD-10	Wind	Bergey Windpower	10	12.5	2805	6055	6	0	27.05			
33	PV-5	PV	Jeff Oldman, Real Good	5	20	3580	5080	14	0	32.43		0.0	0.0
34	PV-20	PV	Jeff Oldman, Real Good	20	20	2975	4475	14	0	28.57		0.0	0.0
35	PV-50	PV	Jeff Oldman, Real Good	50	20	2588	4088	5	0	26.10		0.0	0.0
36	PV-100	PV	Jeff Oldman, Real Good	100	20	2588	4088	3	0	26.10		0.0	0.0

2.3.1 Microturbines

Two microturbine options were incorporated in this analysis: a 30-kW Capstone model and a 75-kW unit from Honeywell. The 30 kW Capstone was a low-pressure gas model. Some of the microturbine data, including selected emissions data, were taken from the technical specifications provided by their manufacturers. Hourly fuel-flow rates were used to calculate the heat rate of each microturbine.

The Berkeley Lab received test data from John Auckland of Southern California Edison (SCE) on January 27, 2001 for the two microturbines. These data were collected at SCE s test facility located on the U.C. Irvine campus (Hamilton 1999). The equipment costs, O&M costs, and emissions rates were added to the database to reflect this real-world test case. Both the fixed and variable O&M costs are incorporated in the fixed O&M parameter estimate in Table 1. Estimated installation costs for these three test units were also provided by John Auckland and incorporated into the data set. Wherever possible, the SCE test data replaced pre-existing data provided by the manufacturers to better represent real-world operation.

Although one would expect differences between the manufacturer s claims and real-world test data, for the most part the microturbine data matched up quite well. For example, the free-on-board equipment cost from the manufacturer was different by only +/- 7percent from the real experience data reported by SCE.

No modifications were made for the 2010 scenario, and the same two microturbines were considered in this forecast case.

2.3.2 Fuel Cells

The only FC included in the present-day scenario was a 200-kW phosphoric-acid fuel cell (PAFC) manufactured by ONSI, which is the only FC widely available today. All of the data collected for this model were from the proprietary EPRI Technical Assessment Guide (EPRI 1999 November). The only air emissions data available for this FC were for uncontrolled NOx (nitrogen oxides).

For the 2010 scenario, eight additional FC units were added based on the current likelihood of their emergence in the market within the next 10 years. These options include a second PAFC, four proton-exchange-membrane (PEM) FCs, two sulfur-oxide fuel cells, and one fuel-cell vehicle (FCV) option, ranging in size from 10 kW to 3,100 kW. The heat-rate conversion efficiencies range from 32% to 55%.

The estimated levelized cost for the ONSI 200 kW PAFC option in the present day scenario is 13.68 ¢/kWh. Over the course of the next 10 years, assumed improvements in the production costs of this FC model produce an approximate 26% reduction in costs, down to 10.15 ¢/kWh.

The FCV with a power rating of 30 kW represents a promising DER option. The levelized cost is only 7.75 ¢/kWh in 2010, largely because of the zero equipment cost assumed because the equipment is purchased prior to considering DER options. DER-

CAM assumes that the FCV would be purchased for transportation purposes, and distributed generation would be a by product. Although the 3,100-kW and 500-kW solid-oxide fuel cell (SOFC) units, for which data are available, are predicted to achieve lower costs overall, they are too large for most DER applications in our analysis. Thus, the FCV seems to be an attractive option with its low levelized cost in 2010.

A detailed discussion of the methodology used to derive the 2010 technology cost for FCs is presented in the next section.

2.3.3 Wind

Two wind-technology options are included in the data set for both scenarios. However, wind was not considered a viable option for the urban setting of the current analysis, so this technology was not made available to the customers in the Microgrid Oaks µGrid. The units selected are 1 kW and 10 kW in size, with technology data obtained from a phone interview with Steve Wilke at Bergey Windpower on February 24, 2001. Using the present-day turnkey costs, which just account for the equipment, estimated at 6,055 to 8,920 $/kW, respectively, for these two turbines, the per-kW cost decreases by 32% from the 1 kW to the 10 kW unit. Unfortunately the cost of wind technology for DER applications is one of the highest of the technology options, making it far from viable in the DER-CAM model. The levelized costs for the 1-kW and 10-kW wind options are estimated to be 39.85 ¢/kWh and 27.05 ¢/kWh, respectively, far higher than costs of a diesel or natural gas back-up generator, or even a microturbine or FC.

No wind-technology data adjustments were made for the 10-year outlook scenario. The 2010 costs match those used for the 2000 case because good sources to determine a credible outlook for wind technology costs were lacking. Thus, costs are assumed to remain constant. However, wind was excluded as an option for the test cases reported here because all sites considered were urban and, therefore, unlikely to be appropriate for wind development.

2.3.4 Photovoltaics

The option for customers to choose PV was permitted in the DER-CAM runs reported here. Four different PV systems, ranging in size from 5 to 100 kW, were included. Data were collected from a telephone conversation with Jeff Oldman of Real Goods on April 10, 2001. Cost information, including the installed cost and O&M costs, were provided.

The *Renewable Energy Technology Characterizations 1997* edition book by EPRI, which summarizes and forecasts the operating and economic features of various renewable energy resources, was used to adjust the PV equipment costs for the 2010 case (EPRI 1997). Neither installation costs nor O&M costs were modified from the present-day case because of uncertainty about how these costs would change over time. The projected cost improvement is largely a result of the technological improvement of crystalline-silicon PV modules expected during this period.

2.3.5 Diesel and Gas Back-up Generators

A variety of small-scale diesel- and natural-gas-fueled internal combustion engines currently marketed were included as DER technology options. A total of 14 diesel options ranging in size from 15 to 500 kW and five natural gas generators from 25-500 kW constitute the internal combustion engine DER options. The data were collected primarily from various manufacturers technical specification sheets that provided the kW rating; dimensions and weight; some noise level measurements; fuel-flow rate at various load levels; in some cases HC (hydrocarbon), CO (carbon monoxide), NOx, PM (particulate matter), and SOx (sulfur oxide) emissions rates; exhaust temperature; and fuel-tank capacity. Equipment costs were collected from the manufacturer when possible. The fuel-flow rate was used along with an assumed heat content for diesel and natural gas fuel and the kW rating to estimate the heat-rate conversion efficiency.

The current diesel-fuel cost of $0.29/L ($1.10/U.S. gallon) and energy content for diesel fuel #2 were used to calculate the variable and levelized cost of operating each diesel generator. This calculation assumes a 12.5-year loan term (equivalent to the expected life span of the generator) at an annual rate of 9.5%. The heat content of diesel was assumed to be 38,228 kJ/L (137,157 Btu/U.S. gallon) and was taken as the average of various external sources, and the full-load heat rate was used. The levelized cost calculation assumes a 100% capacity factor and a fuel price of $8.46/GJ for the diesel generators. Microturbines, FCs and natural gas generators assume a natural gas price of $8.25/GJ. The levelized cost estimate for the Cummins/Onan model DNAC was not available because of lack of fuel-flow data from the manufacturer s specifications.

The electrical costs of installing this technology type were roughly estimated using the RSMEANS handbook (Chiang 2000). This source estimates the electricity-related costs, so estimates of the turnkey cost can also be determined (Mossman 2000). Cost information from this book was assumed to account for roughly all the electrical and mechanical costs, at least for a first approximation. Figure 1 shows the function of declining installation costs for generators with increasing kW size. Shown for both the diesel and natural gas generators, this figure clearly shows the economies of scale and how much more economical a larger unit can be on a per kW basis. Using installation cost information for selectively sized units provided from a generator manufacturer, the proportion of installation to kW rating size was used to derive an installation cost for all diesel and gas back-up generators considered in this data set.

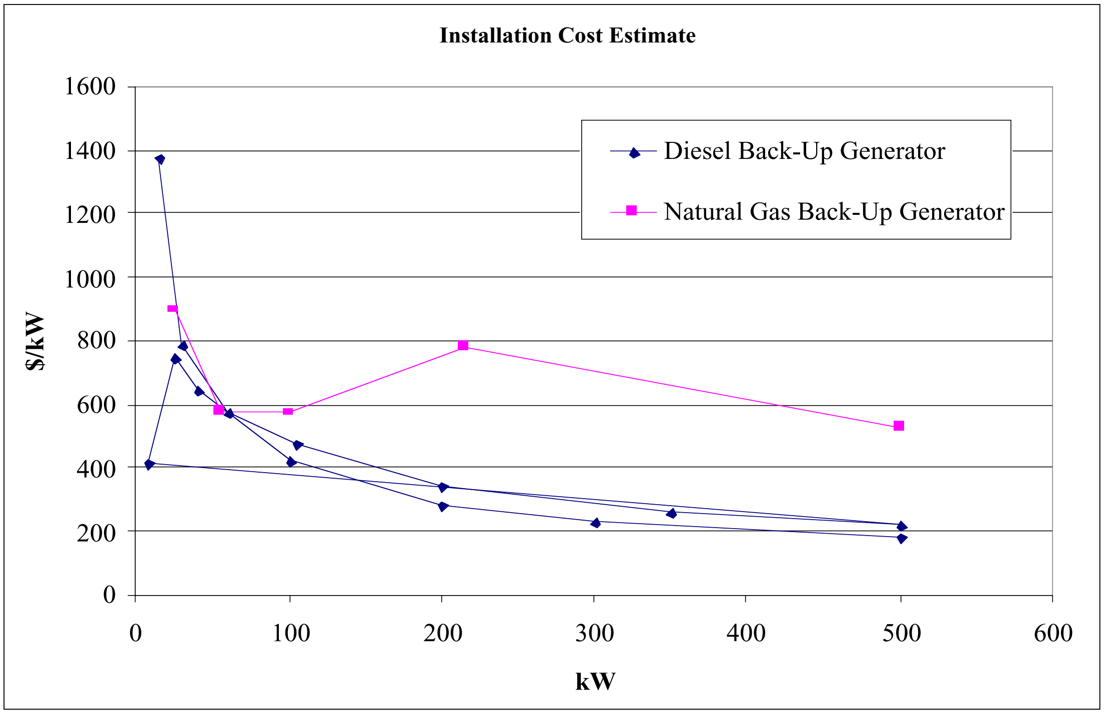

Figure 1. Installation Costs for Diesel and Gas Generators

Although mass production and marketing of reciprocating-engine generators may lower their delivered costs, this technology is the most established of the DER technologies, so no changes in cost or technical specification were deemed necessary for the 10-year outlook.

3. Technology Cost Forecasting

In order to assess potential DG (distributed generation) system adoption in the year 2010 case, it is necessary to forecast the potential costs of DG system types that are not yet mature products. This primarily includes various FC types and PV systems although microturbines and wind turbines are also likely to continue to decline in cost.

Unfortunately, forecasts of technology cost improvement are inherently difficult for many reasons. First, new technologies are constantly in flux with regard to design, materials, and the manufacturing processes implied by the design, so it is very difficult to forecast future generations of technology design with any certainty. Second, it is often difficult to obtain data on the costs associated with adding value to materials at each production step, particularly for projected higher manufacturing volumes with different scales of equipment than are used in prototype or low-volume production. Third, cost data are often particularly sensitive to the individual companies in an industry, and thus, to the extent that critical cost data do exist, they are often proprietary. Further, understanding manufacturing costs may or may not yield good insight into market prices because emerging technology markets may not yet have evolved into competitive ones, and various product-pricing models can be used during the introduction of new technologies. Finally, basic materials costs themselves are subject to fluctuations on commodities markets, and in some cases these fluctuations can be quite volatile. For example: in August of 1999, platinum (a key catalyst material for PEM FC electrodes) traded for approximately 12.35 $/g on the New York metals exchange; currently, in mid-2001 it trades for more than 21.16 $/g (this figure has been converted using 28.35 g/oz). For all of these reasons, technology cost estimation and forecasting carries a considerable degree of inherent uncertainty.

3.1 Issues and Methods

Despite these limitations, however, different types of cost estimation and forecasting are possible and are routinely performed. For business strategy planning, policy analysis, and manufacturing contracts between large original equipment manufacturer (OEM) companies and their suppliers. One method of cost analysis and forecasting involves detailed estimation of materials costs and/or complete manufacturing costs, including labor, overhead, expendable tools, energy costs, and general and administrative expenses. Other methods of analysis are more formulaic in nature. The following sections briefly discuss a few of these methods followed by an assessment of potential cost reductions for the immature DG technologies considered in this analysis.

3.1.1 Detailed Cost Estimation

With sufficient data on costs for product materials, materials processing equipment, labor, energy, expendable tools, facilities, and other general and administrative expenses, potential technology manufacturing costs and retail prices can be estimated. With data on how these costs vary by production volume, costs can be estimated for different production volumes and thus forecasted into the future to some extent. However, in the context of these detailed cost-estimation exercises, it is difficult to account explicitly for the potential future improvements in design and manufacturing process efficiency.

Furthermore, the data needed to conduct this type of detailed cost estimation are extensive and often the detailed data on product and process design and materials, which are needed for a truly detailed analysis, are proprietary and thus difficult to obtain and impossible to publish. Nevertheless, if sufficient data and time are available to conduct this type of analysis, it tends to be the best way to estimate accurately technology manufacturing costs, particularly in the near term.

3.1.2 Cost Forecasting With Experience Curves/Progress Functions

An alternative way to understand technology production costs is a manufacturing experience curve or progress function approach. Although there are only sufficient data to explicitly apply this method to one of the technologies considered in this report, PAFCs, there is an extensive literature on this method, and some discussion of that literature is appropriate. It is also worth noting that the U.S. Department of Energy (DOE) cost forecasts for PV and wind-power systems are based on the National Energy Modeling System (NEMS), which uses manufacturing progress functions to predict cost declines during the initial stages of product commercialization.

Experience curve/progress function analysis traces its roots back to 1936, when T.P. Wright discovered a relationship between the labor hours needed to manufacture metal frames for aircraft and the total number of such airframes built. Wright found that each time the total quantity of airframes produced doubled, the labor hours required to assemble an airframe decreased by a stable percentage (Wright 1936). Since this early work, hundreds of studies have been conducted on the nature and variability of learning curves in industries as diverse as electric power, microchips, beer, and automobiles (Boston Consulting Group 1972; Dino 1985; Ghemawat 1985; Argote and Epple 1990). These studies have allowed the concept of the learning curve, which initially considered only improvements in the labor component of production, to be extended to help explain the dynamics of overall production costs as technologies move from low-volume, prototype production, to learned-out mass production. These overall cost curves have come to be known as manufacturing experience curves or manufacturing progress functions.

Thus, in contrast to Wright's learning curves, experience curves describe the cost path of a manufactured product, beginning with the early history of manufacturing and continuing to the nth unit produced. While learning curves describe only improvements in the efficiency of the labor component of total manufacturing cost, the experience curve applies to the total cost of manufacturing the product. Cost reductions result from four primary factors: 1) scale economies, 2) technological improvements in production processes, 3) improvements in product design (i.e., reduced parts counts and improved design for manufacturability), and 4) improved production worker and organizational efficiency.

Although many different functional forms for the experience curve are possible and have been investigated, the most commonly used expression is the simple log-linear form shown below:

$$C_N = C_1 * V_N^{(\log¶/\log 2)}$$

where:
C_N = Cost of manufacturing nth unit
C_1 = Cost of manufacturing 1st unit
V_N = Cumulative production at nth unit
¶ = Experience curve slope (0-100+%, generally 70-90%)

This relationship predicts that the constant dollar cost of adding value to a product falls by a fixed percentage each time accumulated manufacturing experience doubles. For example, an 80% experience curve predicts that the constant dollar cost of a product will fall by 20% with each doubling of cumulative production volume. Hence, cost reductions are relatively dramatic during the early stages of manufacture as scale economies are captured and the production process is perfected and then drop off as doublings of volume take longer to achieve.

3.1.3 Historical Experience Curves

In addition to being used for forecasting, experience curve analyses can be applied retrospectively. One classic example is in the early history of the automobile industry. Figure 2 depicts the decline in the price of the Model-T Ford from 1909 to 1923. During this period, the price fell from more than $3,000 (in 1958 dollars) to less than $1,000 (Abernathy and Wayne 1974). Note that the same data plotted on a log-log scale in Figure 3 are linear.

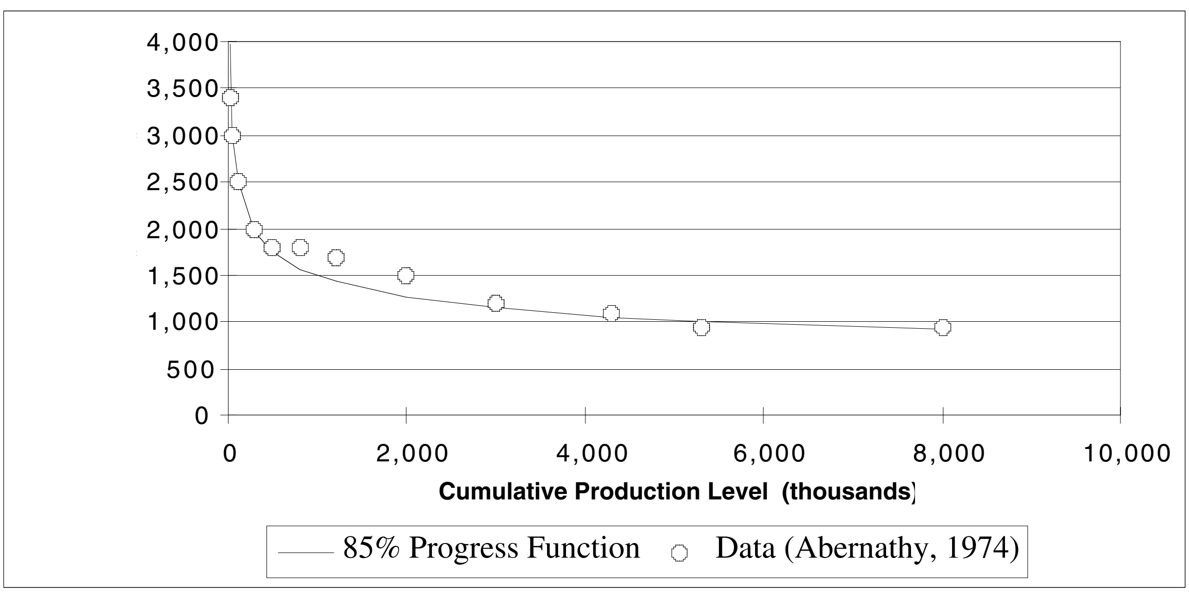

Figure 2. Path of Model-T Ford (1909-1923) with Standard Scale

Source: (Abernathy and Wayne 1974)

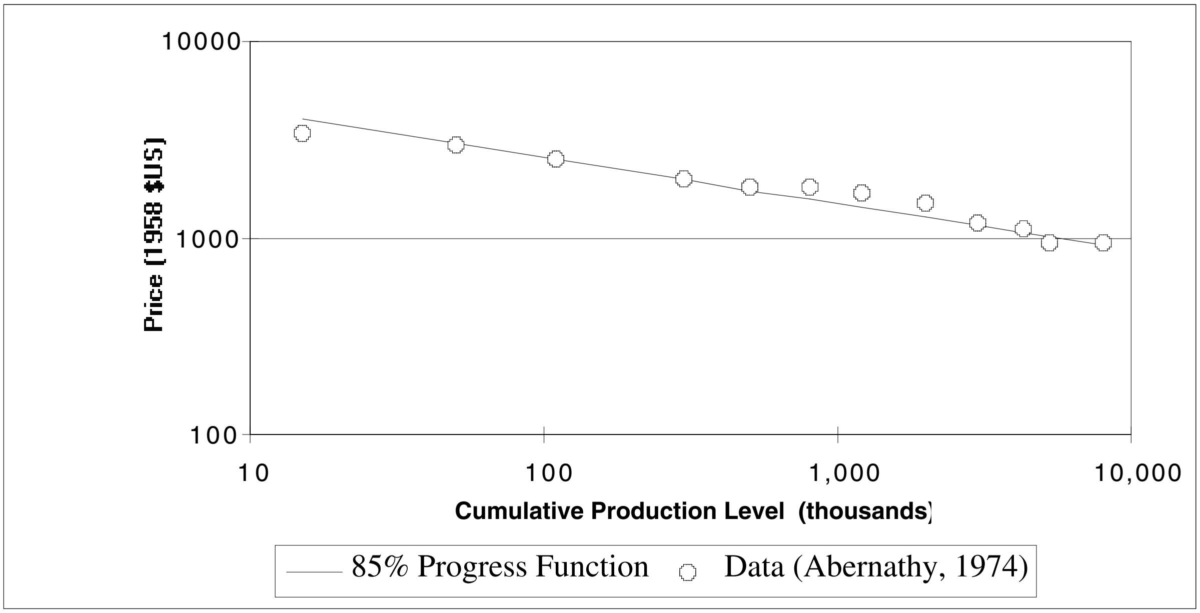

Figure 3. Price Path of Model-T Ford (1909-1923) with Log-Log Scale

Source: (Abernathy and Wayne 1974)

Since a landmark study by the Boston Consulting Group in 1972 that examined the evolution in unit costs of about 2,000 different products (Boston Consulting Group 1972), many additional experience curve studies have been conducted. These studies have shown that the typical rate of unit cost reduction is very often in the range of 10% to 30% each time the cumulative production experience doubles, with rates of around 20% on average (Dutton and Thomas 1984; Ghemawat 1985). This clustering of experience curve slopes has led to the common assumption of an 80% curve for strategic technology forecasting purposes or a 20% decline in costs with each doubling of accumulated production.

The difficulty with conducting *ex ante* experience curve analyses is that it is impossible to know for sure what experience curve slope is appropriate for the product in question, and it is also necessary for the product to have at least some cost or price history (or detailed knowledge of costs). Even if some production cost data are available to estimate the initial part of the curve, experience curve slopes are not always stable for a given product, and simply extrapolating the entire curve from the initial portion may not be accurate. In order to contend with this issue, some form of probabilistic analysis is warranted. This could take the form of simply forecasting two or more different cases, with different corresponding curve slopes, or a more elaborate type of analysis such as Monte Carlo simulation (Lipman and Sperling 1997).

Consider laser diodes produced by Sony starting in 1982; these devices have been produced in great numbers because they are components of the compact disc player, a highly successful consumer product. Figure 4 shows manufacturing cost data for this product from 1982 until 1994 and a set of three manufacturing progress functions with different slopes. There are two interesting features of this figure: first, the overall pattern of cost reduction is reasonably well approximated by an 80% curve slope; second, the data do not perfectly track any given curve slope but rather wander considerably. Thus, depending on the timeline of the forecast, an analysis based on a constant slope may be more accurate at certain points than at others.

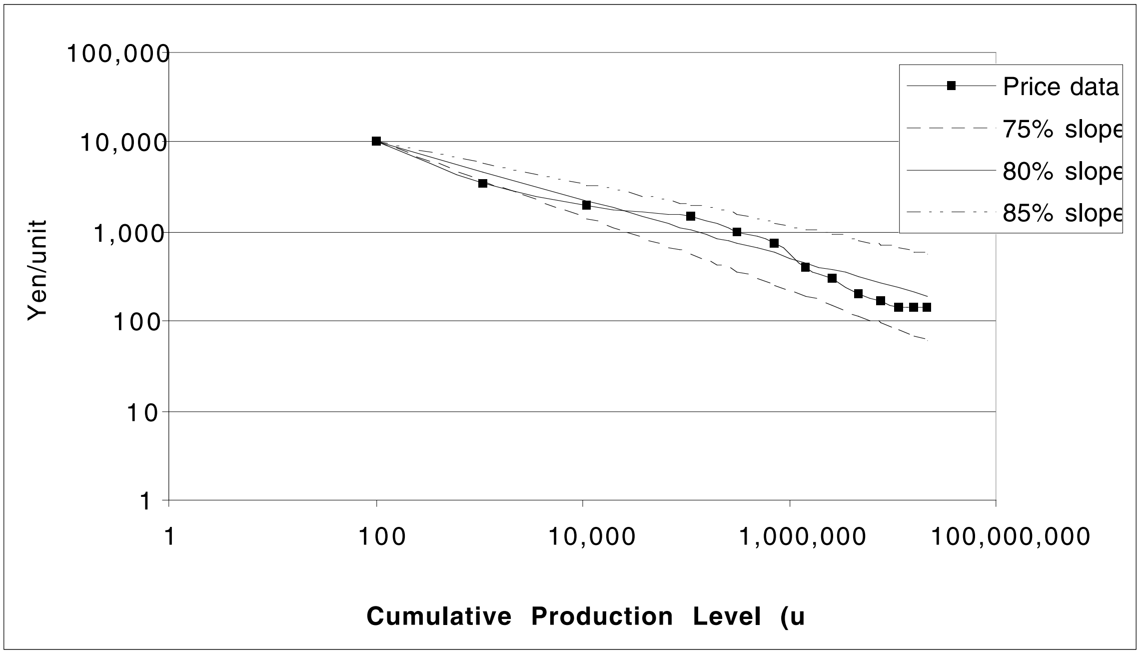

Figure 4. Sony Laser Diode Prices (1982-1994)

Source: (Wood 1998; Wood and Brown 1998)

3.2 Estimates of Fuel-Cell System Costs in 2010

The manufacturing experience curve method of forecasting was applied to the case of the PAFC because it is a commercial product with enough history to permit estimation of the basic parameters needed to calculate a range of manufacturing experience curves. For the PEM and SOFC technologies, for which experience curve projections are more speculative, detailed analyses found in the literature for high-volume production costs of these technologies were used. In other words, rapid deployment of these technologies has been assumed.

The 200-kW PAFC unit that is currently commercially available was developed by United Technologies ONSI division and is now being developed and marketed by United Technologies spin-off partner, International Fuel Cells (IFC). Approximately 200 PAFC units have been placed in service with purchase prices of about $4,000 per kW and installed costs of approximately $4,500 per kW. ONSI has produced three different generations of this technology with improved performance but relatively constant prices. With significant increases in orders, IFC believes it could reduce costs significantly though the 1996 forecast (Figure 5 below) now seems somewhat optimistic.

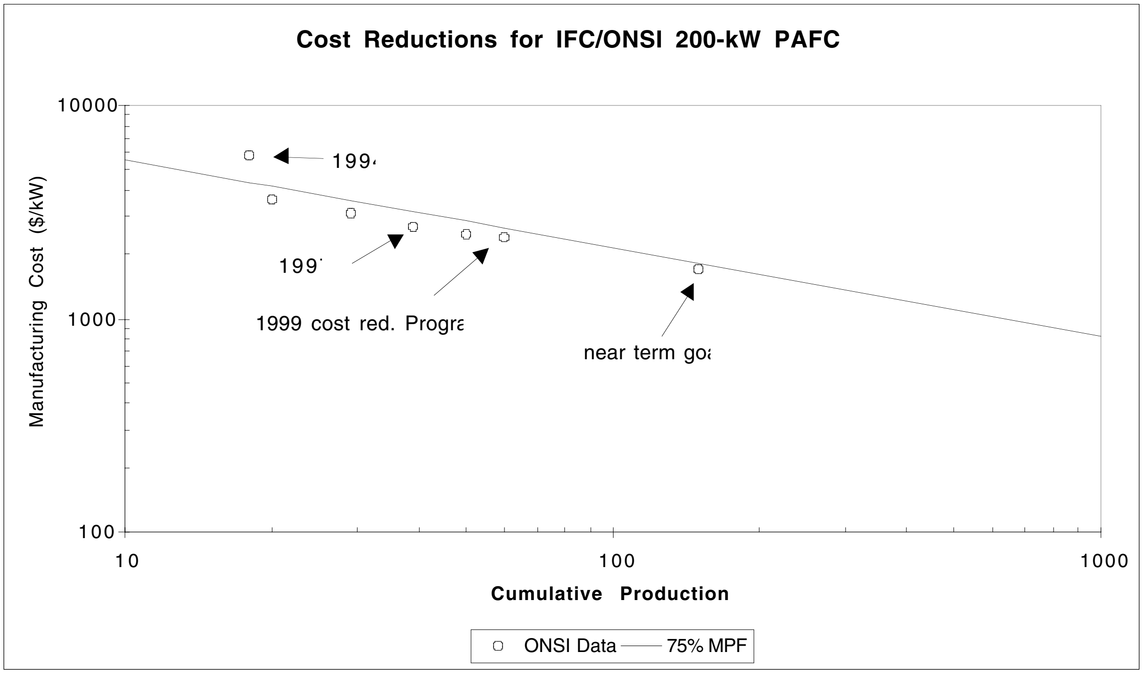

Figure 5. IFC/ONSI 200-kW Phosphoric-Acid Fuel-Cell System Cost Reduction Projections

Source: (Whitaker 1998)

3.2.1 Phosphoric-Acid Fuel-Cell System Cost Forecast

Similar to the example in Figure 5 but with adjusted data, the manufacturing experience curve technique was used to extrapolate costs from current costs of $3,000 to $4,000 per kW (it is unclear what, if any, profit margin ONSI is realizing with current sales prices) at ~50 MW of cumulative production (200 200-kW systems have been sold by IFC, plus some early prototype production). Three cases are examined with 75%, 80%, and 85% curves in order to capture a range of variation that is possible for the slope of the experience curve (see the learning/experience curve literature cited above for discussions of the statistical distributions of historical experience curve slopes). Figure 6 shows these three PAFC system cost forecasts.

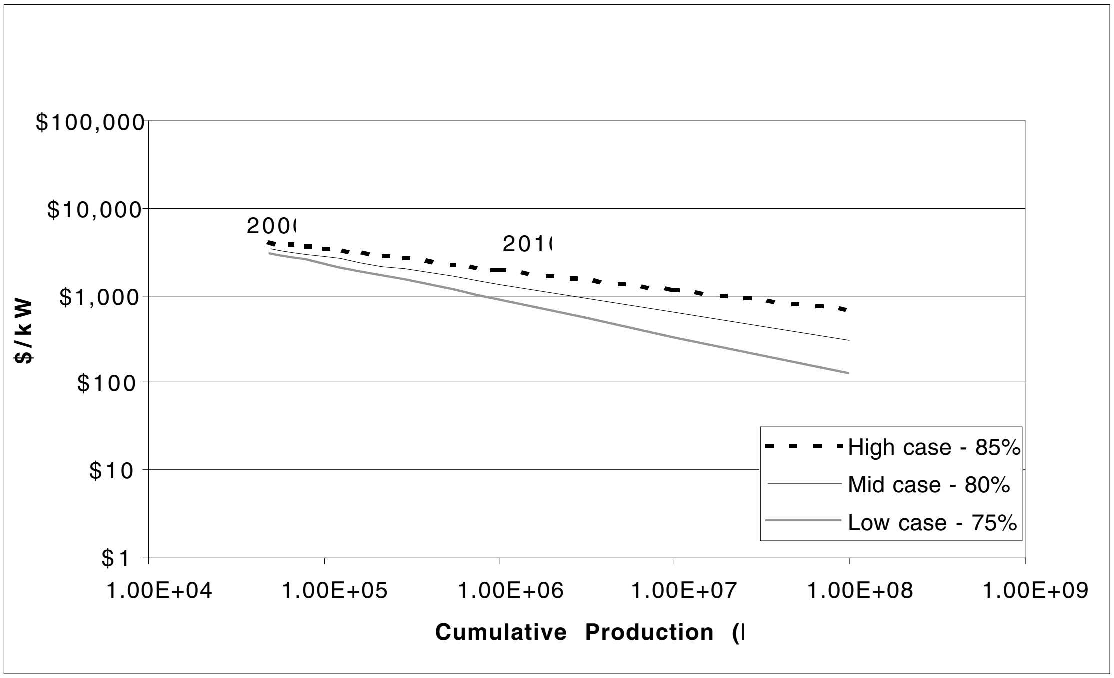

Figure 6. PAFC System Cost Forecast

The central case estimate for PAFC (80% curve) yields 2010 costs of $1,300 per kW (year-2000 dollars). This assumes that an additional 1 GW of FC production is PAFC by 2010. This estimate is based on a forecast that a cumulative15 GW of FC will have been installed by 2010 (Ozbek 2001). This is considered an optimistic case for the PAFC technology, which is expected to face strong competition from PEM, SOFC, and molten-carbonate fuel cell technologies when they are commercialized during the next few years. The low-cost-case estimate (75% curve) would predict a cost of about $850/kW in 2010, also with 1 GW of additional cumulative production. To these capital costs, one should add approximately $75,000 to $100,000 for installation, depending on the site requirements for grading, security fences, building integration, and fuel and electrical connections.

3.2.2 Solid-Oxide Fuel-Cell System Cost Estimates

Relatively few detailed estimates of SOFC system costs are available in the public domain, and because SOFC systems are not yet commercial, forecasting costs with manufacturing progress functions is not yet possible. The U.S. Department of Energy has set goals of $800 per kW by 2003 and $400 per kW by 2010 for SOFC stacks, with additional costs for auxiliary systems, power electronics and controls, and installation (Singhal 2001).

SOFC system cost estimates are based on a study performed by Chen et al. (1996) in a collaborative effort between Bechtel Corporation, TDA Research, and the Gas Research Institute. This study examined potential SOFC system costs based on a wide range of potential operating temperatures and pressures. In this study, the lowest electricity costs are seen for systems operating at ~800 ¡C. The corresponding capital costs for the ~800 ¡-C systems were estimated to be approximately $700-800 per kW. Based on these estimates and in light of the U.S. DOE goal to drive down SOFC costs, an estimate of $750 per kW has been used for SOFC systems in the year 2010 (in year-2000 dollars), including manufacturer profit but not including installation and building integration costs.

3.2.3 Proton-Exchange-Membrane Fuel-Cell System Cost Estimates

Several PEM system cost forecasts have been performed, based either on detailed or experience curve methods. These estimates, most of which have focused on light-duty automotive applications of PEM technology, tend to forecast dramatic declines in the current prices of PEM systems. However, the ultimate cost for PEM FCs in high-volume production is the product of many complex assumptions and depends significantly on the stack design, the quantity and cost of platinum catalyst material, and the assumed level of efficiency of operation of the FC stack (because this affects stack size and material requirements).

The small PEM systems currently available have been sold or leased for several thousand dollars per kW and have been applied to only a few specialized and demonstration applications. However, there is intense industry activity around the development of PEM FCs, and large production volumes are forecast by 2010.

The PEM system cost estimates used in this study are based on a recent analysis by Kreutz and Ogden (2000), which draw on the detailed analysis performed on automotive FCs and adjusts the results of that analysis for a range of stationary PEM system sizes. Kreutz and Ogden estimated potential purchase prices for sizes of from 1 kW to 50 kW, and in lower- (10,000 units/year) and higher-volume production (100,0000+ units/year) scenarios. In lower-volume production, they estimate that a 10-kW system would have a price of $1,600/kW or $16,000 per unit, a 25-kW system would be priced at $1,000/kW or $25,000, and a 50-kW system would be $800/kW or $40,000. In higher-volume production, the 10-kW system would be $500/kW or $5,000, the 25-kW system would be $300/kW or $7,500, and the 50-kW system would be $240/kW or $12,000 (Kreutz and Ogden 2000).

Because it is not clear whether PEM systems will be in very high-volume production by 2010 (at or greater than 100,000 units per year), Kreutz and Ogden s lower production volume estimates were used for this study. It seems as though PEM system development will take some time to achieve these cost levels with consistent system durability of 40,000 to 50,000 hours between major system overhauls and that the PEM market may take more than 10 years to grow to the level at which production is at the multiple-GW-per year scale. Kreutz and Ogden s estimates have been adjusted upward slightly because they include installation costs and the present value of maintenance costs in these estimates but do not appear to include any contingency costs or manufacturer profit. We added operation and maintenance costs and used the resulting estimates as installed system costs. Because system costs do not seem to decline very much as system sizes approach 50 kW, an installed PEM FC system cost estimate of $750 per kW was used for systems in the 200 to 250 kW size range.

3.2.4 Fuel-Cell Vehicles as Stationary Generators

In addition to being used as clean transportation technologies, FCVs could, in principle, act as generators when parked at homes, offices, and shopping centers. Kempton et al. (2001) and Lipman (2001) have recently investigated the potential of different types of electric-drive vehicles to produce electricity for the peak-power, emergency back-up power, and utility grid ancillary services markets. FCVs were found to be potentially attractive as generators for peak power, backup power, or as spinning reserves. The cost of electricity from fuel FCVs is sensitive to the assumed fueling arrangement and the price of fuel as well as to the degree and cost of FC system degradation from the additional usage. Optimistic costs of perhaps 0.80 $/kWh to 0.10 $/kWh are possible based on the assumption that early generation FCVs will be equipped with fuel reformers that are capable of reforming natural gas as well as methanol or gasoline (such multi-fuel reformers are currently being developed). If a dedicated off-board reformer is needed to support one or more vehicles, then the cost will be higher (Kempton, Tomic et al. 2001; Lipman 2001).

FCVs are included among the other DG-technology options for 2010, and it is assumed that the vehicles are fueled with natural gas hookups that feed multi-fuel reformers that are integrated into the vehicles. Further, it is assumed that the natural-gas price is the same as in the base case, and that the cost of FC degradation is a stack replacement and system refurbishment cost of $75/kW, with an effective stack life of 10,000 h in stationary generating mode (we assume that relatively low-power stationary operation has double the approximately 5,000 h of life of dynamic operation for transportation). These assumptions, along with an estimate of $2,500 per vehicle for natural-gas and electricity connections for each vehicle in a group of vehicles that is connected to an office building load for eight to 10 hours per day, result in a cost of electricity of approximately $0.075/kWh for this potential generation source.

3.3 Additional Costs and Performance Measures

For FC and other technology operating and maintenance costs, published data and analyses of the fixed and variable costs expected for minor and major (e.g., stack refurbishment) system maintenance, expressed as $/kW/a plus $/kWh, are very helpful. Installation costs for FC systems are based on data obtained from IFC for typical PAFC system installation costs, and on published estimates for PEM and SOFC installation costs. PV solar and wind-system installation costs are based on data obtained from manufacturers and retailers of these systems (see Table 3).

Adjustments were made to estimate the costs for PV systems in 2010 similar to the adjustments made for FCs. Taking what was used in 2000 as a base, the equipment costs were adjusted as a percent reduction predicted in EPRI s TAG (EPRI 1999 November). The percent change between the 2000 and 2010 TAG equipment cost estimates was used to adjust the 2000 costs for the 10-year outlook to reflect the significant change in costs during the 10 years. In general, the equipment cost was reduced by approximately 50%. The installation and various operations and maintenance costs were kept consistent with the 2000 estimates because of a lack of data to forecast such costs.

In general, the heat rates for FC systems in 2010 are expected to be lower than those of competing systems, with a range of about 6,700 kJ/kWh for SOFC systems to 10,800 kJ/kWh for small PEM systems. These compare with heat rates of 12,000 to 18,000 kJ/kWh for gas and diesel generator systems, and 11,300 to 12,200 kJ/kWh for microturbines (see Table 2). These FC system heat rates are somewhat uncertain given potential advances in technology and the fact that heat rates for FCs and generators vary with load and thus are to some extent dependent on how the systems are operated. The overall efficiency of FCs could also be increased substantially with the use of waste heat, particularly with high-temperature FC systems although lower-temperature FCs and microturbines also have significant cogeneration potential.

4. Preparation and Selection of Building Electrical Load Shapes

4.1 Introduction

This section describes the preparation of the load shapes employed in the modeling effort. A central objective of this work was to obtain and apply real-world load shapes in the distributed energy resources customer adoption model, and considerable effort was undertaken to achieve this objective. The reasons for using actual metered data are twofold: first, the analysis reported here is more valuable to real-world applications; and second, developing a collection of customer load shapes with submetered end-use data is an integral precursor to planned future analysis that includes CHP technologies and direct load control.

4.2 Background

This analysis uses metered end-use load shape data in an effort to assess the DER adoption behavior of a commercial building owner. Without a realistic set of customer load profiles, DER-CAM results would likely not properly represent the most cost-minimizing deployment of DER technology. Although simulated and hybrid load shape data are the function of a μGrid under specific realistic economic conditions available [e.g., from the market analysis and information systems (MAISY) data set and from DOE-2 simulations] and have been used in prior work, actual metered data are statistically preferable. However, metered loads for commercial buildings are not easy to find. Berkeley Lab had an available archived set of commercial hourly load data that had been collected by SCE in 1988-1989 (SCE 1989; Akbari 1993). Even though the data may be regarded as old, this is not a problem for this work since our analyses are meant as examples of how a μGrid might work in a particular situation. Berkeley Lab recovered these data and recreated load shapes to use in current modeling efforts.

4.3 Data Description and Preparation

The initial version of the SCE load data set consisted of a statistical analysis software (SAS) data set containing hourly load data for 53 commercial premises located in the SCE service territory. For each business site, the data spanned approximately one year, from June 1988 to June 1989. For confidentiality reasons, detailed information on the businesses were suppressed, but for most premises, business type, total floor area, conditioned floor area, and a corresponding set of hourly weather data were available. Table 3 summarizes the data available by business type.

Table 3. Number of Premises for which Load Data were Available, by Business Type

Building Type	Number of premises
Grocery	14
Office	12
Restaurant — Fast Food	4
Restaurant — Sit-Down	10
Retail	10
Warehouse	3

Based on the hourly data, Berkeley Lab calculated a variety of load shapes, each corresponding to a predefined set of days, for each business site. These load shapes served as input data for our modeling efforts (see Section 5). Following the conventions used in an earlier report (Rubio et al. 2001), load shapes were calculated for the following periods:

- average weekday by calendar month (1 day type x 12 months)
- average weekend by calendar month (1 day type x 12 months)
- average of the three peak days per month where peak is defined as the highest daily load, which we calculated as the sum of the 24 hourly loads (1 day type x 12 months)

For each hour of an average load shape for a particular business site, the hourly values were the average of all loads for that hour and day type. The result was a library that contained 36 load shapes for each business site.

The load-shape data used for this analysis were taken from a report by Akbari et al. 1993, which uses this same SCE data set. Figure 7 illustrates a sample building type (here, an office) and its corresponding hourly load profile by end use. Office site #5 was a 10,925 m^2 (117,600 ft^2) building that typically accommodated 435 people daily at the time the data were measured in 1989. The building typical business hours were from 7 am to 6 p.m. This graph shows the average hourly loads that were obtained by monitoring the building s energy use. The end-use categories in this example are heating, ventilation, and air conditioning (HVAC), lighting, and other , which included the building plug loads and for all of the energy that was unaccounted for between the total observed load and the monitored end-use loads (Akbari 1993).

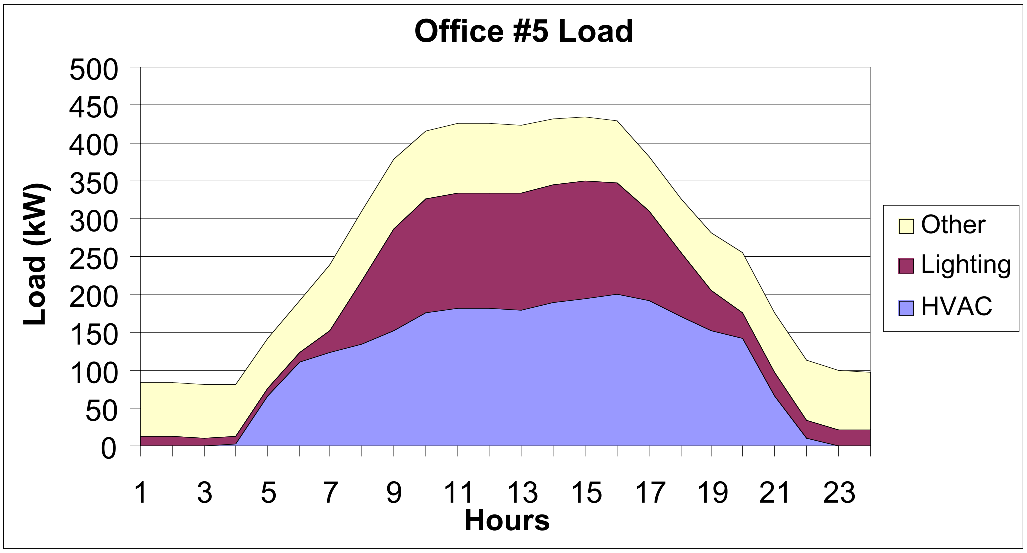

Figure 7. End-Use Load for Office #5

4.4 Selection of Microgrid Oaks Businesses

The sites used to make up Microgrid Oaks were selected with many considerations in mind though not using a scientific process. The aim was simply to select a diverse group of businesses that one might reasonably expect to see in a typical southern California[1] strip mall. Because businesses with high electricity requirements are more likely to find DER attractive, these types of businesses were favored. Also, the focus was on customers for whom the available data were most complete. It is worth restating here that our choice of businesses for Microgrid Oaks does not imply that these are the business types which DER would be particularly attractive. In fact, the commercial sector as a whole may well not be the most fertile ground for DER. This work focuses on the likely patterns of DER technology adoption with an eye to limiting the technical problems to be solved to make DER viable; we did not attempt either a full market assessment or a detailed planning study for a particular site.

Some sites have peaky electricity load patterns; others have higher load factors (ratio of average load to peak load). For example, the office building has much higher peak demands during the week and the business hours of 6 a.m. to 6 p.m. Another feature of the office load shape is much higher loads in the summer, largely because of air conditioning use. Figure 8 shows the monthly peak-day loads of the office for each hour.

[1] San Diego was chosen as the µGrid location because it is one of the few cities in the United States where the county government has collected a large amount of GIS land use data and made most of it available free to the public. It is assumed that the electrical load data would be similar for the different utility service regions, at least within the natural variability resulting from local climate conditions within a service region (such as proximity to the coast). Furthermore San Diego has stringent air quality regulations that influence DER technology adoption such as limiting the number of hours diesel generators may operate.

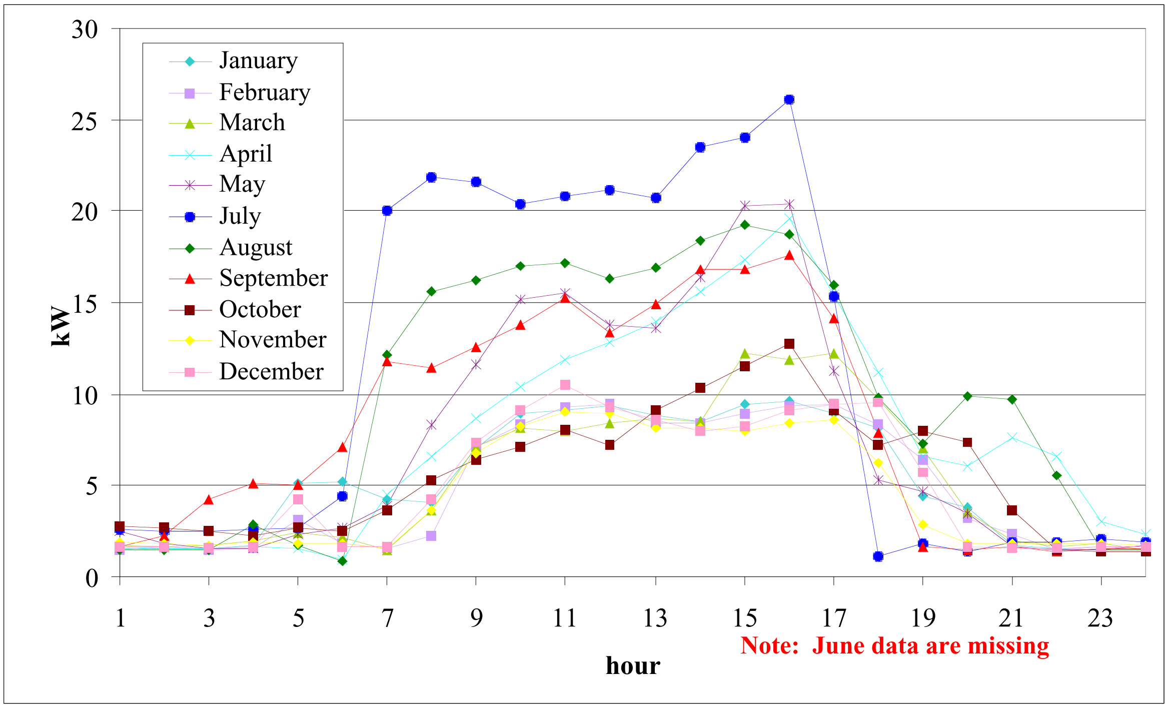

Figure 8. Great Vistas Real Estate Office Monthly Peak Load

Other sites, for example one grocery, have flatter loads, as can be seen in Figure 9. In a site with loads of this type, steady energy consumption is most likely by end uses that are usually on at all hours of the day, such as the grocery lighting, refrigeration, freezing, and air conditioning. Because of the similar energy load during most hours of the day, this site s loads show small deviations between the peak and average loads.

The office was the only building selected for Microgrid Oaks that contained missing data. Although complete data sets were desirable, in this instance the site was chosen for its unusual load profile and small size. A simple average of the adjacent months was performed to estimate the missing data for the month of June.

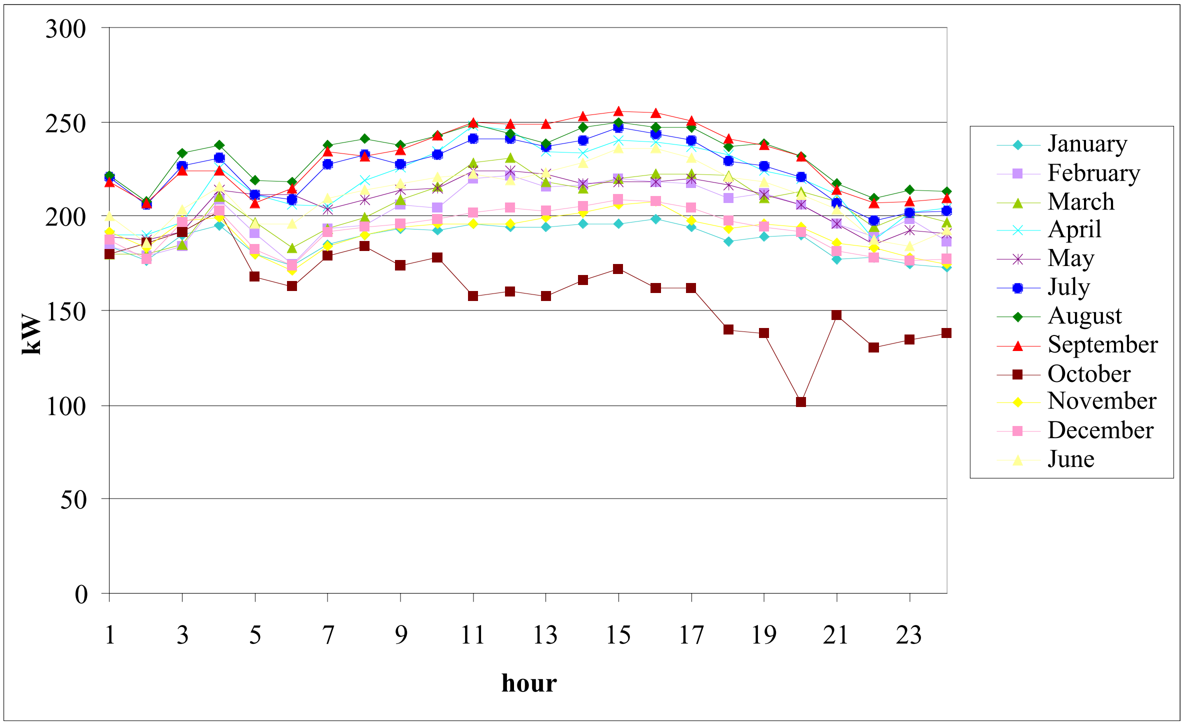

Figure 9. Grocery Peak Loads

Eight sites were selected to constitute Microgrid Oaks. Table 4 illustrates the composition of Microgrid Oaks for this analysis.

Table 4. Summary of Microgrid Oaks Mall

Type of Business	Name of Site	Floor Area (m^2)	Tot. Ann. Energy (kWh)	Energy Density (kWh/m^2•a)	Peak Load (kW)	Peak Hour	Load Factor	Data Comments
1. Supermarket	Dangerway	1,536	1,708,581	1,112	255	Sept 15:00	76%	complete
2. Office	Great Vistas Real Estate	223	40,269	181	26	July 16:00	18%	june missing
3. Sitdown Restaurant	Nan Hideaway	1,003	529,231	528	110	Sept 17:00	55%	complete
4. Fast Food Restaurant	Burger Queen	339	487,973	1,439	100	July 12:00	55%	complete
5. Deli Restaurant	Sub Safe Harbor	674	199,553	296	56	July 13:00	41%	complete
6. Department Store	Spacy's	6,466	1,459,949	226	309	Sept 12:00 & 15:00	54%	complete
7. Retail Store	Drum Buster Stereo	1,347	263,367	196	81	July 13:00-16:00	37%	complete
8. Warehouse Store	Ram's Club	N/A	1,821,001	N/A	299	July 15:00	69%	complete
9. Total Microgrid	Microgrid Oaks Mall	11,588*	6,370,206	405*	1253	July 14:00	58%	june missing

* not including warehouse since floor area data is not available

Besides the grocery and the office, three restaurants, two retail stores and one warehouse were included in the mall. All businesses were given fictional names that parady mainstream stores of the same type. It is important to differentiate these businesses using more detailed classifications than, for example, *restaurant* or *retail* because the load shapes of different types of restaurants or retail shops vary.

Table 4 lists the fictitious names, the floor area in m^2, annual energy usage (kWh), combined energy density per floor space (kWh/m^2•a), peak load (kW) and hour it occurs, and load factor (%) for each of the eight building sites. The Ram s Club warehouse consumes the largest share of energy in Microgrid Oaks. Burger Queen fast food restaurant has the highest energy use per square meter of floor space at 1,439 kWh/m^2•a (floor space data were not available for the warehouse site). The Great Vistas real estate office, uses the smallest amount of energy, only 181 kWh/m^2•a, with a peak load of 26 kW. The largest peak load belongs to Spacy s department store at 309 kW; the Ram s Club warehouse peak load is 299 kW, and the Dangerway supermarket is not far behind with a peak load of 255 kW. Not surprisingly, the real estate office also exhibits the smallest load factor at only 18%. The warehouse has a 69% load factor, but the supermarket shows an even higher factor of 76% for the given year. All these sites peak either in July or September although the time of day varies.

5. Environmental and Regulatory Issues

The DER-CAM results indicate the need to address environmental concerns associated with DER deployment. The results do not always describe outcomes that are environmentally favorable to the siting location. Therefore, it is important not only to assess the environmental impacts from each scenario, but also to address any pertinent legislation affecting DER use. In California, the energy crisis has drawn attention to use of diesel back-up generators, and legislation is in the making to control the permitting and emissions of DER-sized technologies. This section describes this situation as well as control technologies that can help reduce emissions from some DER options.

5.1 Recent Executive Orders by Governor Gray Davis (California)

California is currently experiencing a generating capacity shortfall. Although measures to expedite the permitting of new generators have been implemented to address this energy crisis, the relatively slow process of siting and constructing new power plant facilities means that new power plants are unlikely to solve the problem quickly. This energy crisis has resulted in implementation of some measures to encourage the use of DER technologies, especially during high peak demand periods. In addition to speeding up power plant permitting procedures, the state is also promoting conservation measures and ways of allowing existing on-site back-up generators to generate under looser air quality restrictions.

Most on-site generators currently in place are back-up generators fueled by diesel. More than 10,000 of these emergency or standby generators are operating in California with more than two thousand of them in the San Francisco Bay Area (California Air Resources Board 2000). Significant electricity demand relief could be achieved if these generators were able to run during peak power periods without constraints on total operating hours. However, there are serious environmental concerns associated with these generators, which should be addressed as the Governor has used his executive powers to temporarily override some pre-existing legislation limiting the number of hours during which these generators can operate.

Beginning in early February 2001, Governor Gray Davis began issuing a series of executive orders to address the state s energy crisis and help prepare for the coming high summer electricity demand. These orders addressed expediting the application process for power plants, increasing public awareness of energy conservation through media campaigns, offering customer rebates and other rewards for reduced energy use, and lifting operating caps on the number of hours during which small generators can run. Executive Order D-24-01, issued on February 8, 2001, gave local air pollution and air quality management districts the power to set their own limits on the number of hours that small generators could operate.

As a result, the South Coast Air Quality Management District (SCAQMD) established its own series of executive orders. Executive order 01-01 was issued on January 26, 2001 and allows internal combustion engine generators to operate up to 500 hours in any one year (up from 200 h/a) if using diesel fuel below 15 ppm (parts per million) sulfur.

Small-scale back-up generators are limited to operating only during an imminent or actual blackout if over the 200 h/a operation time.

Executive order 01-03 pertained to the REgional CLean Air Incentives Market (RECLAIM) program and was terminated and superceded as amendments to the RECLAIM program were issued May 11, 2001. The amendments basically called for a removal of power generators from the RECLAIM program. Prohibited from buying excess emissions credits from the RECLAIM market, SCAQMD set up a mitigation fee program designed to offer emissions credits based on a set fee to generators who emit beyond their allowance.

Adopted in 1993, the RECLAIM program was designed to limit the amount of NOx and SOx each stationary power plant could emit, with caps decreasing each year through 2003. The amendments passed on May 11, 2001 allow power plants to generate more electricity while minimizing their impact on the environment. Power plants are separated from the RECLAIM program and required to install of pollution control equipment during the next 2 to 3 years; they must pay a mitigation fee of $16.50/kg ($7.50 per pound) to emit NOx over the RECLAIM allocation. The funds collected will be used to clean up some of the dirty equipment that has so far eluded air pollution regulations to ensure permanent reductions of both smog-forming emissions and cancer-causing diesel soot.

The San Diego area is the focus region for this analysis. Within this area, the recent executive orders in California have affected DER. The San Diego Air Pollution Control District established a strict limit on the number of hours that diesel emergency and non emergency generators can operate. Because of the severe air quality problems within this air district, the regulations are more restricted than in other parts of California. Under the rules and regulations, emergency generators are permitted 100 h of maintenance each year and an additional 52 h for generating during near-stage-3 electricity emergency episodes. If the DER generator is located at a nuclear plant, it is allowed 100 h of generator use in addition to the 100 h of maintenance. For this analysis, some DER-CAM model scenario runs were performed incorporating varying annual operating constraints for the diesel back-up generators. Sensitivity case analysis based on these annual restrictions of 52 h/a and even some extreme cases of more than 1000 h/a to was performed to determine the importance of varying the operating use.

5.2 Senate Bill 1298

On September 25, 2000, Governor Gray Davis signed SB 1298 into law, which resulted in the establishment of a working group in January of 2001 to help the California Air Resources Board (CARB) develop the regulations and guidance this law requires. The law requires the California Air Resources Board (CARB) to adopt a certification program and uniform emissions standards for distributed generation currently exempt from permitting requirements (typically smaller-scale generators). Starting on January 1, 2003, all electrical generation technologies are required to be certified by the state board or permitted by the air district prior to use or operation. Authority is given to the local air districts to establish DG technology emissions standards that are more stringent than those established by the CARB.

The CARB is also required, as part of SB1298, to offer guidance to local air districts on the permitting or certification of electricity generation technologies under the air districts regulatory jurisdiction.   This gives the local air districts support in developing the steps necessary to comply by the start date and becoming district more prepared for the transition.

This bill will undoubtedly have a significant impact on the siting of new DER. As part of the legislation, a working group was established to determine the logistics of the legislation, the entities to which it will apply, and what limits will be placed on those entities. As of June 2001, the working group has decided to ignore the existing population of small diesel generators, focusing only on new installed systems. Although this simplifies the permitting and emissions tracking process, it does not address the need to improve the existing inventory of operating generators, especially dirty ones.

5.3 Environmental Control Technologies

Some DER technologies are friendlier to the environment than others, making it important to consider control technologies that could further minimize emissions impacts on local air quality.

This section covers techniques for reducing air emissions of DER technologies. Air emissions may be reduced through energy efficiency, technology choice, limitations on hours of operation, combustion modification, or post-combustion treatment. The type of generating technology influences the options for combustion modifications and post-combustion treatment. All of these techniques have their benefits and drawbacks. Common drawbacks include cost, reduction in efficiency, and a potential increase in emissions of other pollutants.

Combustion modifications for reciprocating spark-ignition engines include lean-burn combustion control land-rich burn with a catalytic after-treatment (OIT 1999). Lean-burn engines decrease temperatures in the combustion chamber by consuming 50 to 100% excess air as a way of reducing the creation of NOx, CO and non-methane hydrocarbons (OIT 1999).

Using rich-burning engines with a catalytic after-treatment is another technique for emissions reduction. Catalytic converters can perform reducing and oxidizing functions. A reducing catalyst converts NOx to N_2 and oxidizes some of the CO to CO_2 (OIT 1999). Electronic ignition also helps to reduce the amount of emissions from the combustion process.

Diesel engines may employ post-combustion technologies such as selective catalytic reduction where ammonia is injected into the exhaust gas. This technique is expensive and maintenance intensive, however. Particulate emissions are a major problem of diesel engines. Particulate traps designed for diesel engines are about 90% effective (OIT 1999). The filters also require maintenance and regeneration of the catalyst.

In addition to emissions controls, another potentially serious concern when siting DER is noise control. Noise and vibration problems may be addressed by installing generation equipment on a shock-isolated pad. Silencing equipment for the exhaust is available for turbines and engines. In general, noise-abatement techniques have worked, so noise has not caused siting problems in residential and commercial areas, but wider deployment of DER sources could result in strong neighbor opposition (EPRI 1999 November).

Although a number of emissions control technologies exist to reduce air-quality impacts, the regulatory permitting is far from ideal in terms of ensuring a smooth process. From surveys of DER installation sites it was found that the most challenging aspects of the siting and permitting process were the paperwork, regulatory interpretation, and annual testing procedures involved in obtaining an air pollution permit. Sites in California s South Coast Air Basin have to comply with a limit for all pollution sources aggregated at the location. The most costly aspects of environmental controls are the site testing (if required) along with legal and engineering fees (EPRI 1999 November).

5.4 Environmental Impacts from DER Deployment

Although DER shows promise for alleviating constraints on the central station power grid and improving electricity reliability, it also presents some environmental concerns. Many DER technologies are environmentally friendly, e.g. PV and wind, but some DER technologies, e.g. diesel-fueled generators, can be more polluting than central station power plants.

The mature internal combustion engine and its widespread use of diesel fuel for emergency and back-up utility generators (BUGs) create a potentially serious environmental problem. Diesel BUGs are the most common DER technology in use today. According to the SCAQMD, each diesel BUG emits approximately 300 times more smog-forming pollution than a new power plant (SCAQMD 2001). By itself, a single diesel BUG doesn t contribute significant airborne pollution, but in large numbers these generators can adversely affect the air quality conditions in an air district.

Given the differences in environmental impacts of different DER technologies, it is important to determine the level of environmental stress created by customer adoption scenarios. A comparison of the environmental impact of the various scenarios is shown in Table 6. Table 5 presents the range of present-day scenario emissions factors that are assumed for the selected unit sizes of the various DER technology options in DER-CAM. Underneath each line in parentheses is an example range from other sources. These sources include a report prepared for the California Air Resources Board (CARB) by Joseph Iannucci et al., where emissions from DER are estimated based on DER economic potential (Iannucci 2000). DER emissions factors from the Environmental Protection Agency s (EPA) AP-42 source were also used, and other sources, including data presented by Ron Ishii (Alternative Energy Systems Consulting) at the annual meeting of the West Coast section of Air & Waste Management Association (EPA 1997; Ishii 2001).

(The abbreviation N/A indicates cases that the data were not available or emissions do not apply for that DER technology.) Estimates from these various sources are used to illustrate the variability in obtaining realistic emissions factors from DER. The lack of real-world test data contributes to this large range of emissions rates and illustrates the difficulty in deriving credible estimates of DER environmental impacts.

Table 5 shows that the emissions rates assumed in this analysis tend to fall on the lower end of the given ranges. This is especially true for microturbines because the emissions rates are taken from the manufacturers technical specifications, which are likely to be optimistic. Emissions rates from diesel and natural-gas back-up generators fall in the mid range relative to the ranges presented from external sources. With limited data available for comparison, it is easy to see how the emissions factors could fall on either end of our spectrum, given the wide range of the external literature. Clearly, the NOx emissions rates of the natural gas back-up generators are the worst of the DER technologies presented (PV and wind were not included because no air emissions result from operation of these technologies). The diesel BUGs are also dirty, especially the NOx emissions from smaller units.

Table 5. Present-Day DER Technology Emissions Rates in g/kWh

	NOx	CO	PM
Fuel Cell			
250 kW	**N/A**	**N/A**	**N/A**
	(0.01-0.02)	**(0.01-0.05)**	
Microturbine			
75 kW	**0.24**	**0.24**	**N/A**
	(0.24-0.64)	**(0.24-1.29)**	**(0.01-0.04)**
Diesel Back-up			
7.5 kW	**8.17**	**3.26**	**0.54**
500 kW	**8.57**	**0.54**	**0.16**
	(7.71-18.61)	**(0.54-13.6)**	**(0.16-1.36)**
Gas Back-up			
55 kW	**6.05**	**N/A**	**N/A**
500 kW	**25.29**	**5.66**	**N/A**
	(0.1-25.29)	**(0.7-5.66)**	**(0.27-2.15)**
Encina	**0.351**	**0.219**	**0.002**

sources: (EPA 1997; Iannucci 2000; Ishii 2001)

Using the above emissions factors and the results from the DER-CAM scenarios, we derived rough estimates of annual NOx and CO emissions for selected cases for the grocery and for the entire µGrid as shown in Table 6. In addition to providing the kg/a, the table also illustrates how these DER emissions compare to the emissions from a running central station, like the Encina natural gas power plant in San Diego County.

This plant was selected to represent a typical central station power plant in the San Diego area. Emissions factors for NOx and CO were derived from the Environmental Protection Agency s National Emissions Trends Data inventory (EPA 2001). Also included are the comparable automobile emissions showing the number of equivalent miles driven on the road, considering the average car, which includes both cars that meet California State smog regulations and those that do not. This parameter is denoted in vehicle miles traveled by the average car on the road.

Selected results are presented in Table 6 for the grocery and µGrid cases for the present-day scenario. Within these cases, three different scenario results are shown — the 75% PV subsidy, the IERN (imbalance energy revenue neutrality), and the low natural gas price. A brief comparison to the 2010 results for these same cases is also provided.

Table 6. Present-Day Emissions Results from Selected DER-CAM Scenarios

	NOx				CO				PM			
	DERCAM kg/a	possible range (kg/a)	equivalent central station kg/a	car mile equivalent (VMT)	DER-CAM kg/a	possible range (kg/a)	equivalent central station kg/a	car mile equivalent (VMT)	DER-CAM kg/a	possible range (kg/a)	equivalent central station kg/a	car mile equiva-lent (VMT)
GROCERY												
IERN	203	N/A	299	112,654	203	39+	186	11,928	N/A	N/A	2	N/A
Low Natural Gas	358	N/A	527	198,627	358	N/A	328	21,031	N/A	N/A	3	N/A
75% PV Sub	1,482	186 - 4,473+	378	823,198	N/A	N/A	236	3,606	N/A	N/A	2	N/A
µGRID												
IERN	83,462	518-83,462+	1,282	46,367,941	91	N/A	799	5,336	N/A	N/A	8	N/A
Low Natural Gas	140,039	518-83,462+	2,163	77,799,564	156	N/A	1,348	9,203	N/A	N/A	14	N/A
75% PV Sub	29,970	660-31,594+	1,718	16,649,996	211	N/A	1,070	12,427	N/A	N/A	11	N/A

The results in Table 6 indicate that for the grocery year-2000 case, emissions are not always cleaner than the Encina central station power plant. Under the 75% PV Subsidy case, DER-CAM chooses two 100-kW PV systems, one 75-kW microturbine, and two 55-kW gas generators for a total installed DER capacity of 385 kW. This makes the NOx emissions from the grocery site nearly four times dirtier than Encina, amounting to more than 820,000 car equivalent vehicle miles traveled (VMT). This value is based on an average car in the state of California, including both registered and non registered vehicles on the road for a realistic estimate of a typical mile traveled on the road. The IERN and low natural gas cases both install three 75-kW microturbines, which total 225 kW of self-generating capacity. NOx missions from these cases are estimated to be approximately 32% cleaner than the emissions from Encina. This case is almost 9% worse for CO emissions relative to central station generation in the IERN case and equivalent to nearly 12,000 VMT.

For the Microgrid Oaks year 2000 case, the 75% PV subsidy case installs three 75-kW microturbines, eight 100-kW PV units, and one 500-kW gas generator, which results in significant NOx emissions. Because of the installation of the large gas generator, the total NOx emissions are more than 17 times that from the Encina plant, equivalent to nearly 17 million VMT. The IERN and low natural gas cases produced more than 80,000 kg and more than 140, 000 kg of NOx/a, respectively. This is more than 65 times the amount of NOx estimated from Encina under both cases for the same amount of generation and this is equivalent to 46 to 78 million VMT for an average car in California for the IERN and low natural gas cases, respectively.

For the 2010 scenario, only the IERN case is modeled of the three scenarios assessed; it indicates how the forecasted cost curves presented in Section 3 can influence a forecast scenario. Modeling both the grocery and Microgrid Oaks scenarios under the IERN case resulted in the sole installation of the 250-kW PEM FC by Ballard. In the grocery case, the customer installs one 250-kW PEM FC, saving the equivalent of 365 kg of NOx at the Encina station, assuming zero NOx emissions. In the Microgrid Oaks case, the customers install four 250 kW PEM FCs, reducing NOx emissions by 1,425 kg, the amount equivalent to the Encina station. Thus, the 2010 scenario significantly improves the deployment of cleaner DER technologies, like FCs, allowing the cost to compete better with the other established and dirtier technologies.

6. Mathematical Model

6.1 Introduction

This section presents the latest version of DER-CAM. This version of the model has been programmed in GAMS.[2] This section contains a brief description of the GAMS software and the reasons behind its selection for the task, concluding with a description of the present version of the model as well as its mathematical formulation. The results presented are not intended to represent a definitive analysis of the benefits of DER adoption but rather as a demonstration of the current DER-CAM. For example, the only equipment first-cost data available were from the manufacturer; delivery and installation costs are estimated. Indeed, developing better estimates of realistic customer costs is a key area in which improvement is not just possible but essential. While the model might underestimate equipment cost, it also excludes benefits accruing from reliability and CHP applications. Hence, although the model's results may not be completely accurate, they are not clearly biased in any particular direction. DER-CAM executes a straightforward optimization of one year s operation. Given the electricity purchasing options available, the cost of fuels, and the costs and operating characteristics of DER technologies available, DER-CAM picks the optimal combination of DER for any customer during that year and shows an optimal output schedule for that DER combination.

6.2 Model Description

In a previous report, the first spreadsheet version of the Customer Adoption Model was described and implemented (Marnay 2000); a subsequent report describes the model s programming in GAMS (Rubio 2001). The model s objective function, which has not changed, is to minimize the cost of supplying electricity to a specific customer by optimizing the installation of distributed generation and the self-generation of part or all of its electricity. [3] In other words: the focus of this work continues to be strictly economic. To address this focus, we consider the following issues:

- Which is the lowest-cost[4] combination of distributed generation technologies that a specific customer can install?
- What is the appropriate level of installed capacity of these technologies that minimizes cost?
- Will disconnecting from the grid be economically attractive to any kind of customer?
- How should the installed capacity be operated so as to minimize the total customer bill for its electricity load?

For this study, it is assumed that the customer wishes to install distributed generation to minimize the cost of electricity consumed on site. Consequently, it should be possible to

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[2] GAMS is a proprietary software product used for high-level modeling of mathematical programming problems. It is owned by the GAMS Development Corporation (http://www.gams.com) and is licensed to Berkeley Lab.

[3] Marnay, et al., 2000.

[4] Here, costs include turnkey (purchase, delivery, and installation) costs as well as fixed and variable operational costs.

determine the technologies and capacity the customer is likely to install, to predict when the customer will be self-generating and/or transacting with the grid, and to determine whether it is worthwhile for the customer to disconnect entirely from the grid.

Key inputs into the model are:

- The customer s load profile.
- The customer s electricity purchasing option, which could be open market prices, or the default San Diego Gas and Electric (SDG&E) tariff.
- The capital, O&M, and fuel costs of the various available DER technologies, together with the interest rate on customer investment.
- The basic physical characteristics of alternative generating technologies.

Outputs to be determined by the model are:

- Optimal cost-minimizing technology or combination of technologies.
- Optimal capacity of each technology to be installed.
- When and how much of the capacity installed will be running.
- Total cost of supplying electricity.

Some of the assumptions that were established from the previous study (Rubio 2001) have been maintained and others have changed (see Section 6.3). The key assumptions that were maintained are as follows:

- Customer decisions are to be based only on direct economic criteria. In other words, the only DER benefit that the customer can achieve is a reduction in electricity bill.
- All the electricity generated in excess of that consumed is sold to the grid. No technical constraints to selling back to the grid at any particular moment are considered. If more electricity is consumed than generated, the customer will buy from the grid under pre-determined contractual agreements or at the default tariff rate. No other market opportunities, such as sale of ancillary services or bilateral contracts, are considered.
- No deterioration in output or efficiency during the lifetime of the equipment is considered. Furthermore, start-up and other ramping constraints are not included.
- CHP benefits, reliability and power-quality benefits, and economies of scale in O&M costs for multiple units of the same technology are not taken into account.
- Possible reliability or power quality improvements accruing to customers are not considered.
- DER equipment is perfectly reliable. That is, there are no forced outages.

6.3 Additions to the Model

The main advantage of DER-CAM is its flexibility. The use of GAMS enables the model to be complex without hindering the ability of researchers to make adjustments in the details. Consequently, run time is minimal, and ultimately this code could be embedded in a broader customer adoption decision tool.

The new features added to the customer adoption model are good examples of the flexibility that has been previously mentioned. In the previous study (Rubio 2001), the following features were added:

- Evaluation of more DER options. Currently, almost 30 different types of distributed energy generation options are considered simultaneously.
- Endogenous determination of more detailed hourly operation of adopted equipment.
- Improvement to make the optimal investment combination and associated hourly operation almost always feasible and quickly identified.
- Ease access to some important information, such as the effective marginal price of electricity to the customer, which could be either the net effect of the customer s monthly bill of an incremental kW in a certain hour or the marginal operating cost of an adopted technology.
- Ease of implementation of new tariffs.
- Increased solution speed - typically in seconds.
- Addition of options: three different ways to handle sales, three different ways to purchase electricity, and application of a stand-by charge at will. These options will be explained later.
- In the current work, the following additions have been made:
- A greater variety of DER options, including PV systems is now available. To this end, solar insulation data have been collected to determine the power that PV can provide during any hour of the year.
- More reliable DER technology data, as described Section 2, are available.
- Electricity market prices have been updated to include the (remarkable) 2000 data.
- More accurate customer load data have been gathered to use in constructing a viable µGrid, as described in Section 4.
- Constraints on hours of diesel generation that approximate California air-pollution permitting are implemented. The shadow prices on these constraints yield the marginal value of hours allotted for diesel generation.

6.4 Justification for Using GAMS

Electricity utility expansion planning and operations simulation has a long history, and many methods have been developed for solving the utility-scale problem that is very similar to the one addressed in this work. Some of the established approaches are based on rule-of-thumb chronological simulation of system operation, some are based on mathematical approximations of actual system operation, and yet others apply optimization techniques (Marnay 1989). The reason the economics of customer adoption can be readily modeled by a mathematical optimization problem rests on the assumption that the customer always tries to minimize internal cost. Moreover, the use of optimization techniques has the added advantage of offering robust and powerful tools that can almost guarantee finding an optimal solution quickly.

Obviously, the use of classic optimization techniques has some significant limitations; notably, some customer decisions (adoptions) are likely to be more qualitative than quantitative. For example: some benefits, such as greater perceived control over electricity supply, cannot be easily translated to economic values. However, in the context of the present work these limitations are not expected to be important although efforts will certainly be made in subsequent years to address them. There are additional purely mathematical limitations that will eventually arise. For example, neither the turnkey nor the operating costs of small-scale generators are fixed, as is required in DER-CAM s current formulation, but will tend to decrease as a customer's experience with a certain technology accumulates. In other words, while the first unit of a certain generating technology may not be the most attractive to a customer, subsequent units may become attractive as the customer gains experience with the technology.

In other work at Berkeley Lab, some less mature simulation tools, such as autonomous agents models, were also reviewed. These are being applied to DER operational problems in some cases (Gibson 1999).

Ultimately, the GAMS software was selected because it:

- Provides a high-level language for the compact representation of large and complex models.
- Allows changes to be made in model specifications simply and safely.
- Allows unambiguous statements of algebraic relationships.
- Permits model descriptions that are independent of solution algorithms.

While there are some other optimization software packages that have these same qualities, GAMS is widely used and well known to the research team.

6.5 Mathematical Formulation

This section describes in detail the core mathematical problem solved by DER-CAM. The solution process has three main parts. First, the names of all input parameters are listed. Second, the decision variables are defined. And third, the mathematical formulation is presented for two possible tariff options.

Variables and Parameters Definition

6.5.1.1 Parameters (input information)

Customer Data

Name	**Description**
$Cload_{m,t,h}$	Customer Load in kW during hour *h*, day type[5] *t*, and month *m*.

Market Data

Name	**Description**
$RTPower_{s,p}$	Regulated demand charge under the default tariff for season[6] *s* and period[7] *p* ($/kW)
$RTEnergy_{m,t,h}$	Regulated tariff for energy purchases during hour *h*, type of day *t*, and month *m* ($/kWh)
RTCCharge	Regulated tariff customer charge ($)
RTFCharge	Regulated tariff facilities charge ($/kW)
$IEM_{m,t,h}$	CAISO (California Independent System Operator) IEM (imbalance energy market) price during hour *h*, type of day *t*, and month *m* ($/kWh)

Distributed Energy Resource Technologies Information

Name	**Description**
$DERmaxp_i$	Nameplate power rating of technology *i* (kW)
$DERlifetime_i$	Expected lifetime of technology *i* (years)
$DERcapcost_i$	Overnight capital cost of technology *i* ($/kW)
$DEROMfix_i$	Fixed annual operation and maintenance costs of technology *i* ($/kW)
$DEROMvar_i$	Variable operation and maintenance costs of technology *i* ($/kWh)
$DERCostkWh_i$	Production cost of technology *i* ($/kWh)
$DERhours_i$	Maximum number of hours per annum that technology *i* is allowed to generate (hours)

[5] There are three day types: peak (the average of the three days with the biggest load), week (the remaining working days), and weekends.

[6] There are two seasons: summer and winter.

[7] There are three different time-of-use periods (for tariff purposes only): on-peak, mid-peak, and off-peak. Every tariff, TOU-8 for example, has a different definition of these periods.

Other parameters

Name	***Description***
IntRate	Interest rate on DER investments (%)
DiscoER	UDC (utility distribution company) non-commodity revenue neutrality adder[8] ($/kWh)
FixRate	Fixed energy rate (¢/kWh) applied in some cases[9]
StandbyC	Standby charge in $/kW/month that SCE currently applies to its customers with autonomous generation
$Solar_{m,h}$	Average solar insulation as a percentage of the maximum possible during hour *h* and month *m* (%)

6.5.1.2 Variables

Name	***Description***
$InvGen_i$	Number of units of the *i* technology installed by the customer
$GenL_{i,m,t,h}$	Generated power by technology *i* during hour *h*, type of day *t*, and month *m* to supply the customer s load (kW)
$GenX_{i,m,t,h}$	Generated power by technology *i* during hour *h*, type of day *t*, and month *m* to sell in the wholesale market (kW)
$DRLoad_{m,t,h}$	Residual customer load (purchased power from the distribution company by the customer) during hour *h*, type of day *t*, and month *m* (kW)

Only the three first variables are decision variables. The fourth one (power purchased from the distribution company) could be expressed as a relationship between the second and third variables. However, for the sake of the model's clarity, it has been maintained.

6.5.2 Problem Formulation

There are two slightly different problems to be solved depending on how the customer acquires the residual electricity needed in addition to the power that is self-generated:\

- buying that power from the distribution company at the regulated tariff
- purchasing power at the IEM price plus an adder that would cover the non-commodity cost of electricity

In this work, a surcharge was introduced in the form of a revenue reconciliation term that was added to the IEM price or the fixed price. This term was calculated such that, if the customer s usage pattern was identical under the IEM pricing option and the tariff option, the Utility Distribution Company (UDC) would collect identical revenue from the customer.

[8] This value is added to the IEM price when the customer buys its power directly to the wholesale market.
[9] If the model user selects this option the customer always buy its energy at the same price.

6.5.2.1 Option 1: Buying at the Default Regulated Tariff

The mathematical formulation of the problem follows:

$$\min_{InvGen, GenL, GenX} \sum_{m} RTFCharge \cdot max(DRLoad_{m,t,h}) + \sum_{m} RTCCharge$$
$$+ \sum_{s} \sum_{m \in s} \sum_{p} RTPower_{s,p} \cdot max\left(DRLoad_{m,(t,h) \in p}\right)$$
$$+ \sum_{i} \sum_{m} \sum_{t} \sum_{h} \left(GenL_{i,m,t,h} + GenX_{i,m,t,h}\right) \cdot DERCostkWh_{i}$$
$$+ \sum_{i} \sum_{m} \sum_{t} \sum_{h} \left(GenL_{i,m,t,h} + GenX_{i,m,t,h}\right) \cdot DEROMvar_{i}$$
$$+ \sum_{i} InvGen_{i} \cdot \left(DERcapcost_{i} + DEROMfix_{i}\right) \cdot AnnuityF$$
$$+ \sum_{m} \sum_{i} InvGen_{i} \cdot DERmaxp_{i} \cdot StandbyC$$
$$- \sum_{i} \sum_{m} \sum_{t} \sum_{h} \left(GenX_{i,m,t,h} \cdot IEM_{m,t,h}\right) \tag{1}$$

Subject to:

$$Cload_{m,t,h} = \sum_{i} GenL_{i,m,t,h} + DRLoad_{m,t,h} \quad \forall_{m,t,h} \tag{2}$$
$$GenL_{i,m,t,h} + GenX_{i,m,t,h} \leq InvGen_{i} \cdot DER\max p_{i} \quad \forall_{i,m,t,h} \tag{3}$$
$$GenX_{i,m,t,h} = 0 \ \ if \sum_{i} GenL_{i,m,t,h} < Cload_{m,t,h} \quad \forall_{i,m,t,h} \tag{4}$$
$$AnnuityF = \frac{IntRate}{\left(1 - \frac{1}{(1 + IntRate)^{DERlifetime_{i}}}\right)} \tag{5}$$
$$GenL_{j,m,t,h} + GenX_{j,m,t,h} \leq InvGen_{j} \cdot DER\max p_{j} \cdot Solar_{m,h} \quad \forall_{m,t,h} \ \ if \ \ j \in \{PV\} \tag{6}$$
$$\sum_{m} \sum_{t} \sum_{h} \left(GenL_{i,m,t,h} + GenX_{i,m,t,h}\right) \leq InvGen_{i} \cdot DER\max p_{i} \cdot DERhours_{i} \ \forall_{i} \tag{7}$$

- Equation (1) is the objective function, which says that the customer will try to minimize total cost, consisting of: total facilities and customer charges, total monthly demand charges, total on-site generation fuel and O&M costs, total DER investment cost, total standby charges, and *minus* the revenues generated by any energy sales to the grid.
- Equation (2) enforces energy balance.
- Equation (3) enforces the on-site generating capacity constraint.

- Equation (4) prohibits the customer from buying and selling energy at the same time. When this constraint is removed, the model assumes that the customer has a double meter, i.e., the customer can buy from the UDC and sell to the IEM at the same time but cannot buy from the UDC and resell the same energy to the IEM. Indeed, this would create an unbounded arbitrage possibility in some circumstances.
- Equation (5) simply annualizes the capital cost of owning on-site generating equipment.
- In Equation (6), the actual energy output of any customer operating PV cells is the customer s rated capacity scaled down by the amount of solar insulation.
- Finally, in Equation (7), the maximum total amount of energy that any given generator *i* can produce throughout the year is effectively restricted by the parameter $DERhours_i$. This constraint is intended mainly to prevent the diesel generators from operating more than the maximum legal allowable number of hours.

6.5.2.2 Option 2: Buying from Alternative Energy Providers

The problem mathematical formulation follows:

$$\begin{aligned}
\min_{InveGen, GenL, GenX} \quad & \sum_m \sum_t \sum_h DRLoad_{m,t,h} \cdot \left(IEM_{m,t,h} + DiscoER \right) \\
& + \sum_i \sum_m \sum_t \sum_h \left(GenL_{i,m,t,h} + GenX_{i,m,t,h} \right) \cdot DERCostkWh_i \\
& + \sum_i \sum_m \sum_t \sum_h \left(GenL_{i,m,t,h} + GenX_{i,m,t,h} \right) \cdot DEROMvar_i \\
& + \sum_i InvGen_i \cdot \left(DERcapcost_i + DEROMfix_i \right) \cdot AnnuityF \\
& + \sum_m \sum_i InvGen_i \cdot DERmaxp_i \cdot StandbyC \\
& - \sum_i \sum_m \sum_t \sum_h \left(GenX_{i,m,t,h} \cdot IEM_{m,t,h} \right)
\end{aligned} \tag{1a}$$

Subject to:

Equations (2) through (7)

This formulation differs only in the objective function, equation (1a), which now charges the IEM energy price for each hourly time step plus the non-commodity revenue neutrality adder. Note that the same mathematical formulation can be used if the model user wants to simulate a fixed price for all customer energy purchases. In that case, all IEM hourly prices are simply set to the desired fixed value.

7. Results

This section discusses the various operating scenarios for distributed generation technologies, results from the analysis based on DER-CAM described in the previous section, and the sensitivity of certain variables to changes in parameters. First, the run cases will be described and then the results and sensitivity analysis will be presented.

7.1 Scenarios

The base case in this study is imbalance energy revenue neutrality. The customer is free to install generation equipment and can purchase electricity at the CAISO IEM price plus an adder that guarantees revenue neutrality for the UDC under equivalent usage patterns. Variations on the base case examine how the results change in response to different economic and regulatory environments. Table 7 lists the scenarios and their descriptions.

Table 7. Scenarios for Purchasing Electricity

Scenarios	**Description**
IERN (IEM + revenue neutrality)	In this scenario the customer can buy all of its electricity at the IEM price, but it also has to pay an extra fee (named *DiscoER* in the mathematical formulation) in order to achieve revenue neutrality for the distribution company (compared with the tariff scenario, later described). With the extra fee, the customer s purchase costs are the same as in the tariff scenario (see below). Diesel generators are limited to 52 h/a of operation. The customer buys diesel at 8.46 $/GJ and natural gas at 8.25 $/GJ constant prices. This scenario is selected as the base case because it is the most representative.
Diesel1052hr.	Operation constraint is relaxed to 1,052 hours per annum for each diesel generator.[10]
Diesel2052hr.	Operation constraint is relaxed to 2,052 hours per annum for each diesel generator.
Diesel3052hr.	Operation constraint is relaxed to 3,052 hours per annum for each diesel generator.
Diesel4052hr.	Operation constraint is relaxed to 4,052 hours per annum for each diesel generator.
Diesel8760hr.	Diesel generation constraint is removed.
IERN-Sales	This is the similar to the first scenario, but now the customer can sell its electricity at the IEM price without fully meeting its own load.[11]
50%-PV-Subs	Turnkey cost of all PV equipment is given a 50% subsidy.
75%-PV-Subs	Turnkey cost of all PV equipment is given a 75% subsidy.
HighDiscoER	*DiscoER* term is doubled.
IERN-2010	Same as the first scenario, but now year 2010 technology data are used.
LowNatGas	The current spot price of natural gas is halved.
PXRN-1999	Same as the first scenario, but 1999 PX prices replace 2000 CAISO IEM prices.

[10] In all of the diesel generation constraint relaxation scenarios, the number of hours of diesel generation permitted is increased by the same number of hours for all generators regardless of their capacities.
[11] In all cases except "IERN-Sales," the customer cannot sell power into the IEM market. This case relaxes that constraint and allows the customer to sell power.

7.2 Outline of Results

For each scenario, the following annual results are obtained:

- Total customer electricity supply cost ($)
- Energy payments to the distribution company during peak hours ($)
- Energy payments to the distribution company during mid-peak hours ($)
- Energy payments to the distribution company during off-peak hours ($)
- IEM Purchases ($)
- Power payments to the distribution company ($)
- Self-generation investment costs ($)
- Self-generation variable costs ($)
- Energy sales to the IEM ($)
- Consumed energy (kWh)
- Average paid price ($/kWh)
- Installed capacity (kW) and number of units of each DER technology type installed
- Hourly marginal cost of electricity supply ($/kWh)
- Hourly electricity production of every DER technology

7.3 Grocery Results

In this subsection, we present the full set of example results for the grocery store, Dangerway. We present this customer s results in detail as an example of complete results from the analysis. Also, Dangerway is an interesting case because its flat load is similar to the load of Microgrid Oaks as a whole, and its high and flat refrigeration end-use load may present an interesting CHP opportunity for future work. The next section provides a summary of results that gives an overview of all customers decisions.

7.3.1 Grocery Do-Nothing Scenario

It is important to review the characteristics of the grocery prior to reviewing this customer s autonomous generation adoption under the various scenarios and sensitivities; in other words, this section defines the do-nothing scenario.

In Table 8, the total cost of purchasing from the IEM is presented along with the breakdown of energy and power payments.

Table 8. Breakdown of Electricity Purchase Costs for Grocery (Do-Nothing-IERN Scenario)

Total Supply Cost ($)	232,146
IEM Energy Purchases ($)	232,146
Consumed Energy (kWh)	1,708,581
Average Price (¢/kWh)	13.59

The grocery s load shapes for the three different types of days and for representative months are presented below in the following three figures:

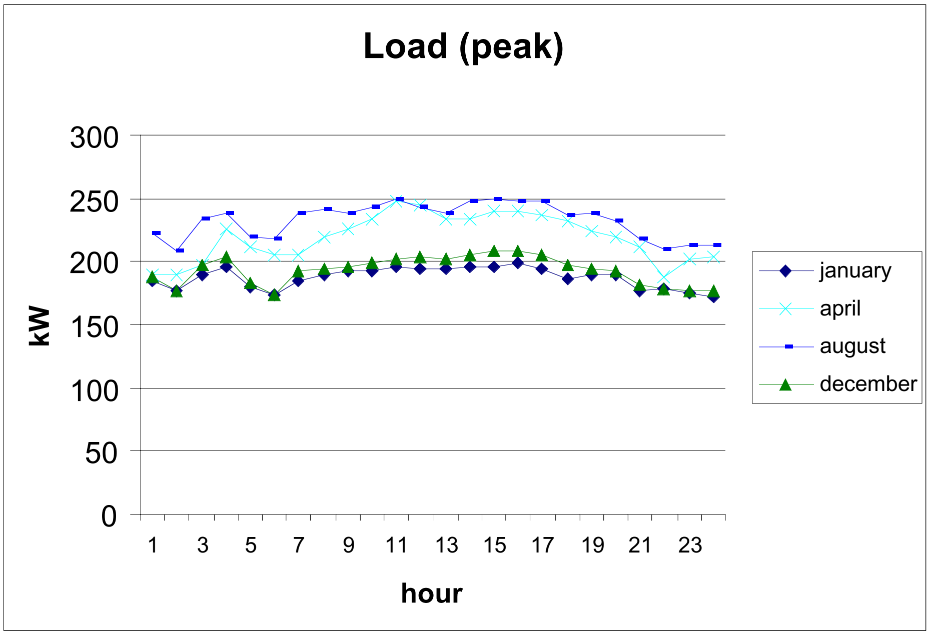

Figure 10. Grocery Peak Load Shape

Dangerway has the flattest load among the members of Microgrid Oaks. As can easily be seen in Figures 15 and 16the maximum demand is not much larger than the average, which results in a high load factor of 0.76 [12]. Annual average demand is 195 kW, the maximum demand is 255 kW, and the base load of 100 kW is driven by one anomalous month, October, which may suggest a data inaccuracy, or an exceptional event.

[12] This is the ratio of the average load to the peak load.

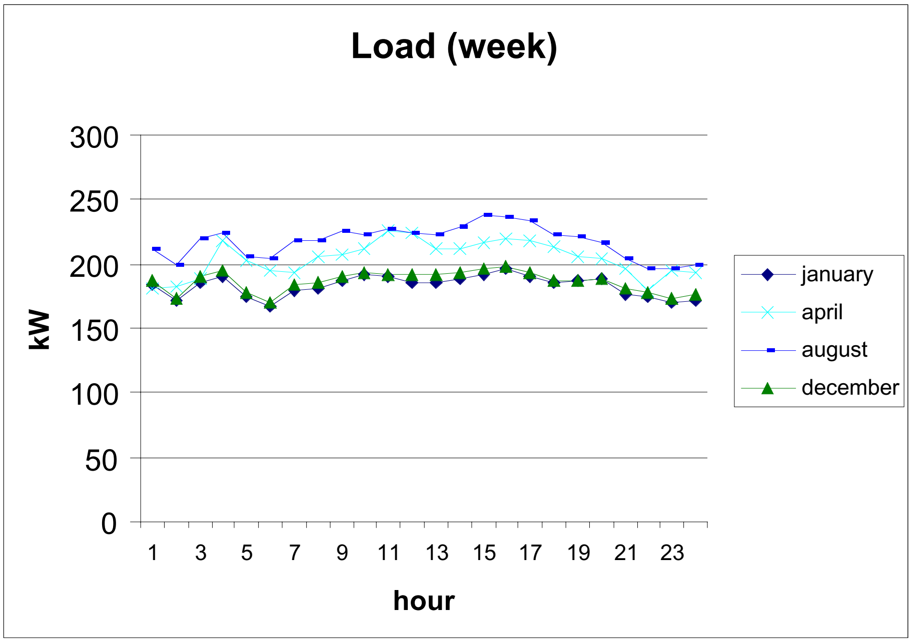

Figure 11. Grocery Week Load Shape

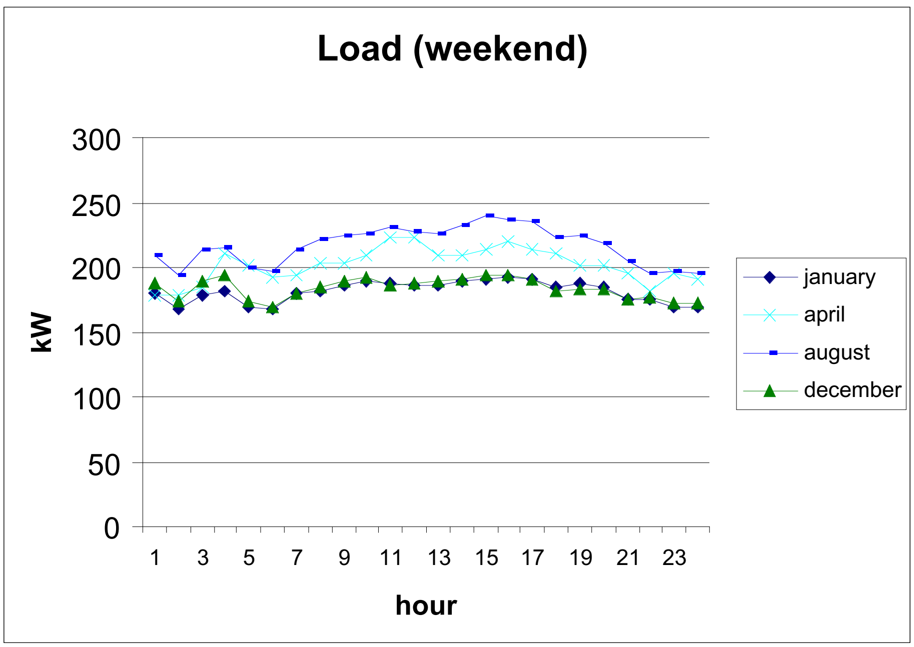

Figure 12. Grocery Weekend Load Shape

Other illuminating data include the hourly marginal price of electricity consumed by Dangerway. The hourly marginal price of electricity in the do-nothing-IERN scenario can be compared to the hourly marginal price using on-site generation. The marginal price patterns for the three types of days are presented in Figure 13 through Figure 15.

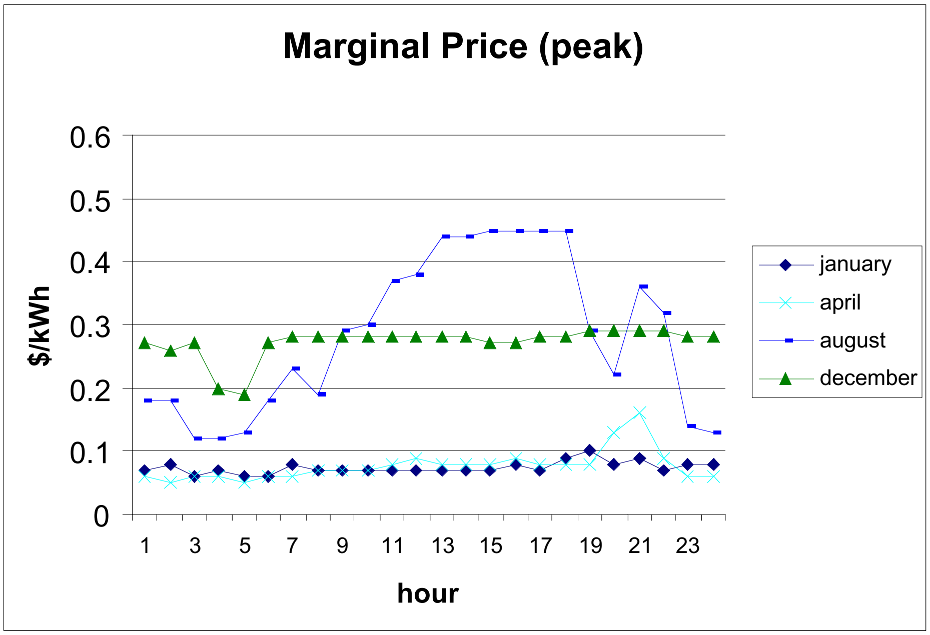

Figure 13. Marginal Price (peak hours)

Figure 14. Marginal Price (week)

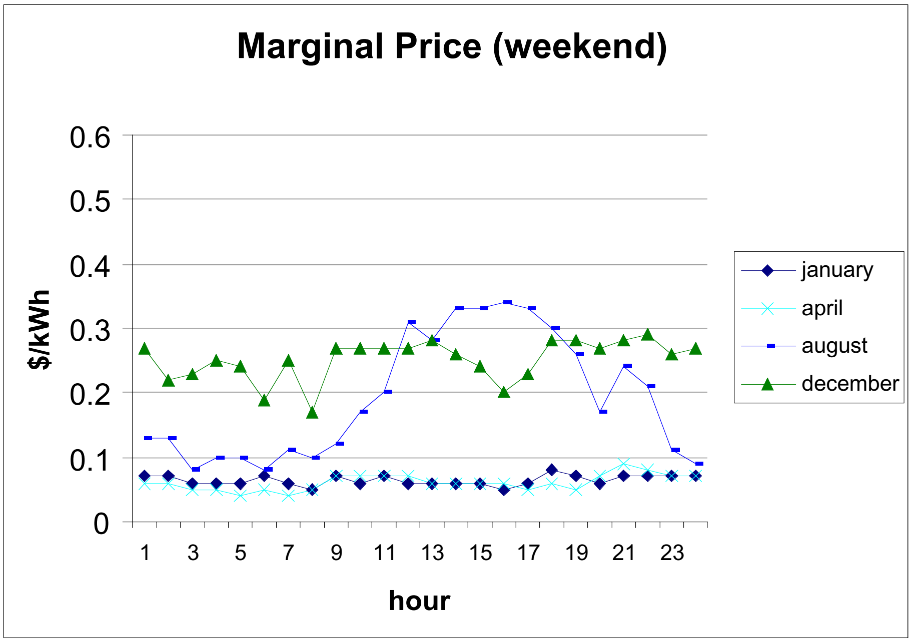

Figure 15. Marginal Price (weekend)

Because the grocery is purchasing all of its electricity through the IEM, the different shapes of the marginal prices simply reflect the pattern of the IEM price during the year 2000. As the figures suggest, the IEM price was low and stable during the first half of 2000, even during peak days and the high-demand afternoon hours. After June 2000, however, as binding transmission constraints, high fuel costs, and exercise of market power by independent generators began to influence the situation, the IEM price cleared in excess of $100/MWh, even during weekends. This sharp contrast in the level of IEM prices impacts the adoption and operation of on-site generation technologies by customers.

Prices in the CAISO-IEM hit the varying level of the cap many times in the later part of 2000. The highest prices, not shown in Figure 15, were in June when the prevailing cap of 75 ¢/kWh was reached. The December weekday marginal price curve shows that prices settled at the then-cap-level of 25 ¢/kWh for most of the time; that is, the effective price to Dangerway was 25¢ plus an adder, or 28.5¢. While these prices are, hopefully, exceptional, they offer an excellent opportunity to exercise DER-CAM.

7.3.2 Base Scenario: IERN

As indicated in Section 7.1, the base case is IERN. That is, the customer can buy its electricity from the IEM but is subject to an adder to the IEM price to compensate the UDC for the non-energy costs of power delivery, transmission distribution, taxes, etc. This additional term means that customers pay exactly the same amount for energy as they would pay under the SDG&E tariff under their base patterns and levels of consumption.

Table 9. Breakdown of Electricity Purchase Costs for the Grocery Base Case (IERN)

Total Supply Cost (k$)	161.246
IEM Energy Purchases (k$)	58.708
Self-Generation Investment Costs (k$)	22.596
Self-Generation Variable Costs (k$)	79.941
Percentage of Consumed Energy Self-Generated	50%
Installed DER Capacity as a Percentage of Peak Load	88%
Average Price (¢/kWh)	9.44
Installed Capacity (kW)	225
Technologies	3 - MT-HW-75

As shown in, the installation of DER technologies reduces the average price of electricity from 13.59 ¢/kWh to 9.44˚¢/kWh. It is interesting here to observe the residual demand (the demand that the distribution company serves, i.e., calculated by subtracting the self-generation from the original customer load) because it indicates the extent of the customer's exposure to market prices. A rational response by the customer would be to reduce market exposure by using on-site generation extensively during periods of high IEM prices. In this case, Dangerway installs three microturbines of the MT-HW-75 type, for a total capacity of 225 kW, 30 kW shy of its peak load of 255 kW. This choice of only one technology is unusual among the cases we ran, but is not surprising given Dangerway s flat load shape.

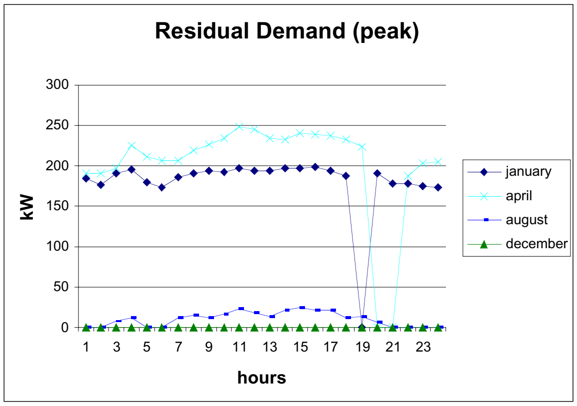

Figure 16. Grocery IERN Residual Demand (peak)

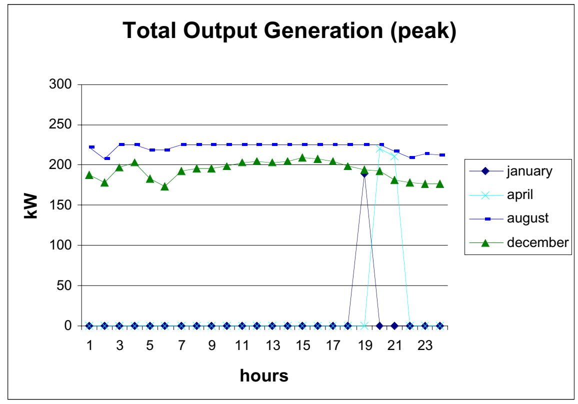

Figure 17. Grocery IERN Total Output Generation (peak)

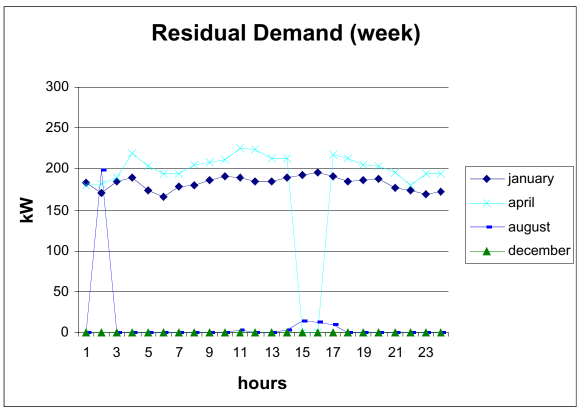

Figure 18. Grocery IERN Residual Demand (week)

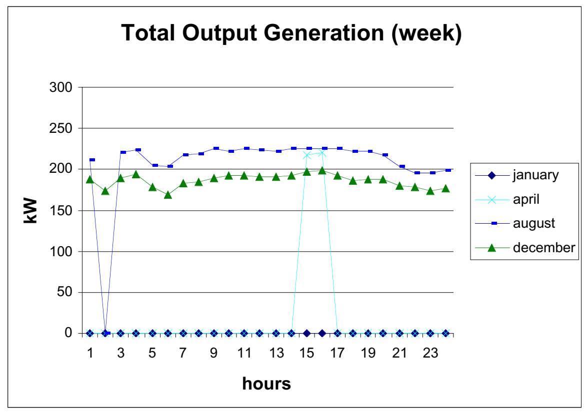

Figure 19. Grocery IERN Total Output Generation (week)

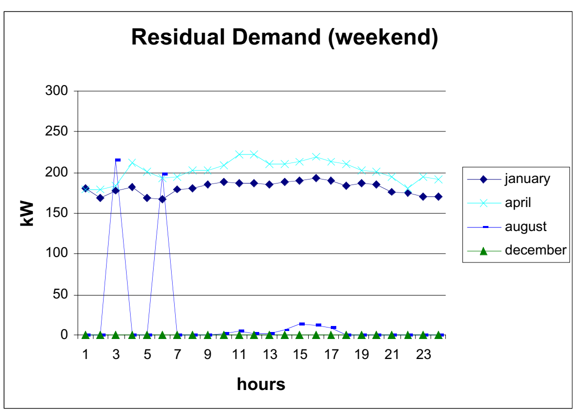

Figure 20. Grocery IERN Residual Demand (weekend)

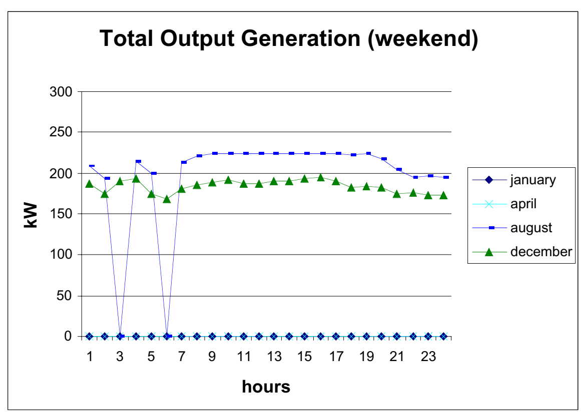

Figure 21. Grocery IERN Total Output Generation (weekend)

Figure 16 through Figure 21 indicate that the grocery s generators produce enough electricity to cover the demand *most* of the time during the second half of the year. Because it is not economic to cover the peak demand through self-generation, the IEM usually supplies the remaining energy during these hours and during most of the hours in the first four months of the year when IEM prices are low. The high IEM price during the second half of the year encourages the grocery to increase its self-generation.

Because the combination of DER installed is so simple in this case, it is only necessary to note that the microturbines follow the load shape. Furthermore, without any operating constraints on microturbines, the grocery is free to turn them on at will during periods of high IEM prices such as during hours 20 and 21 of the April peak day. Clearly, this is an unrealistic situation because, although microturbines can ramp to full power in a matter of minutes, duty cycles as seen in Figure 17, Figure 19, and Figure 21 are highly unlikely because of the high implied O&M and labor costs. Incorporating these considerations is an area of possible future work.

The last piece of relevant information about the IERN results is the marginal price, which indicates how much the customer is paying for electricity at any given hour. The graphs of these marginal prices shown in Figure 22 through Figure 24 indicate that the installation of DER reduces and equilibrates their values relative to the do-nothing-IERN scenario. Now these curves show the IEM adder price when Dangerway is buying electricity and the fuel plus O&M cost when it is fully self-providing. The level December curves show the MT-HW-75 marginal cost is 9 ¢/kWh.

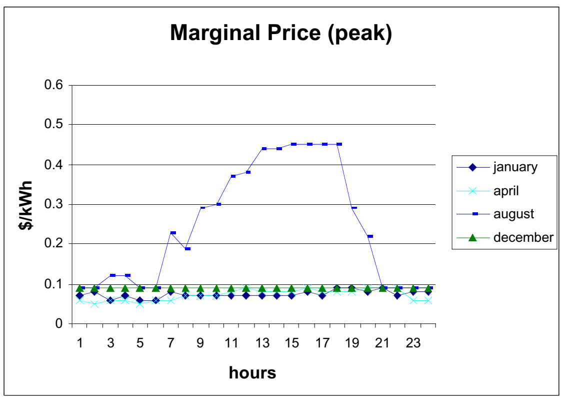

Figure 22. Grocery IERN Marginal Price (peak)

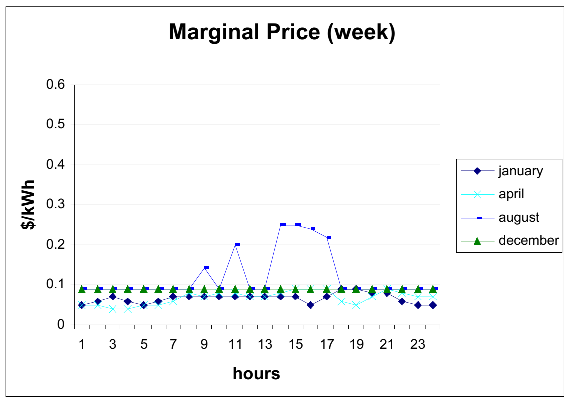

Figure 23. Grocery IERN Marginal Price (week)

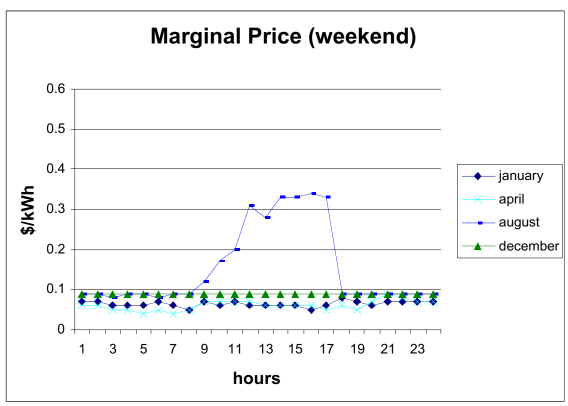

Figure 24. Grocery IERN Marginal Price

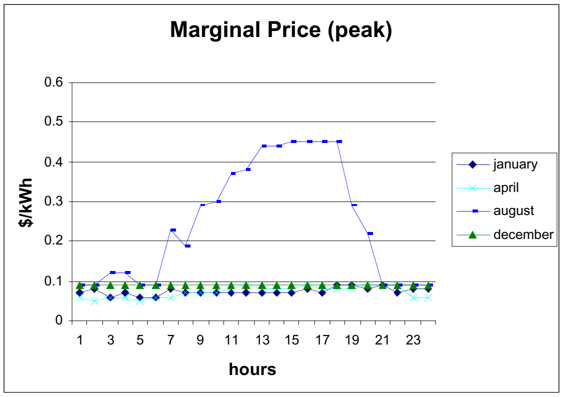

Figure 25. Grocery IERN Marginal Price (peak)

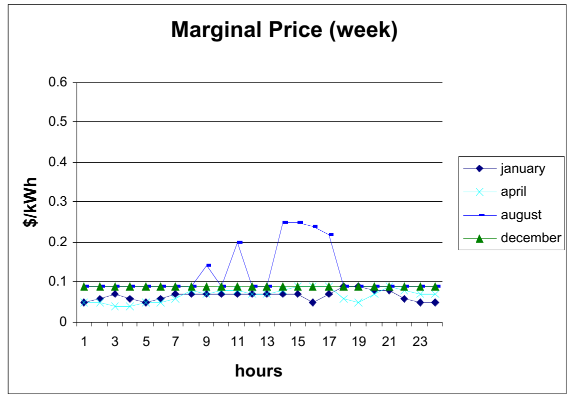

Figure 26. Grocery IERN Marginal Price (week)

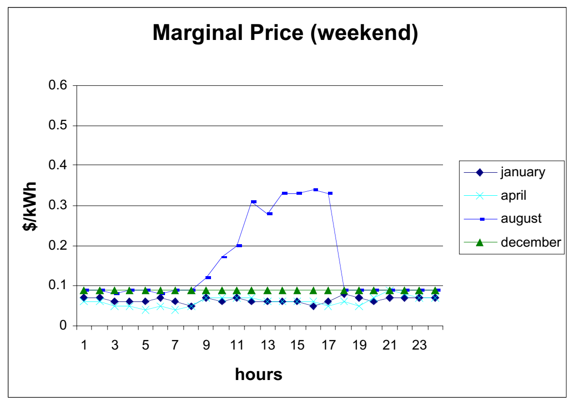

Figure 27. Grocery IERN Marginal Price (weekend)

In other words, the new marginal price curves have the characteristic that they are almost always constant, except during the peak hours, when autonomous generation is not able to cover the whole demand. The different marginal prices during the peak are due to the volatile IEM prices in these hours.

7.3.3 Relaxed Diesel Constraints

7.3.3.1 1,052 Hours Per Annum

In this scenario, the customer still purchases electricity from the IEM, but also has its diesel generation constraint relaxed by an additional 1,000 hours per annum beyond the IERN limit of 52 h.

Table 10. Breakdown of Electricity Purchase Costs for the Grocery 1,052 Hours Diesel Scenario

Total Supply Cost (k$)	158.927
IEM Energy Purchases (k$)	68.583
Self-Generation Investment Costs (k$)	26.608
Self-Generation Variable Costs (k$)	63.737
Fraction of Consumed Energy Self-Generated	44%
Installed DER Capacity as a Percentage of Peak Load	218%
Average Price (¢/kWh)	9.30
Installed Capacity (kW)	555
Technologies	1-DE-C-500 1-GA-K-55

Once the diesel generation constraints are relaxed, the total supply cost is reduced by a tiny 1.43% from the level in the IERN case (see

Table 10), but the technologies chosen are totally different: one 500-kW diesel generator and one 55-kW natural-gas-fired generator. Note that this level of installed capacity is far more than required. There are several levels to understanding this strange result. First, the low cost of diesel compared to the other DER options encourages as much diesel generation as possible, hence the large diesel capacity. Second, in order to meet its electricity needs, the grocery operates the diesel generator frequently, which in turn makes the 500-kW diesel generator more cost effective than, for example, a 300-kW one because of its lower fuel consumption. And third, even when all the allowed diesel generation has been exhausted, there are still enough high IEM price hours to justify the second 55-kW natural gas unit. The fact that the shadow price on the diesel constraint is positive ($0.04/hour) implies that the grocery would find it profitable (by four cents) to have the diesel generator operate for an additional hour. The effects of the IEM prices that appeared in the IERN case are also apparent here as the grocery exposes itself less to market forces by self-generating more during months of high IEM prices. Hence, although the investment decisions of the grocery are different in this scenario, the operation of the equipment follows a pattern similar to that in the IERN case. The residual demand and total generation output are presented below (see Figure 28 through Figure 33).

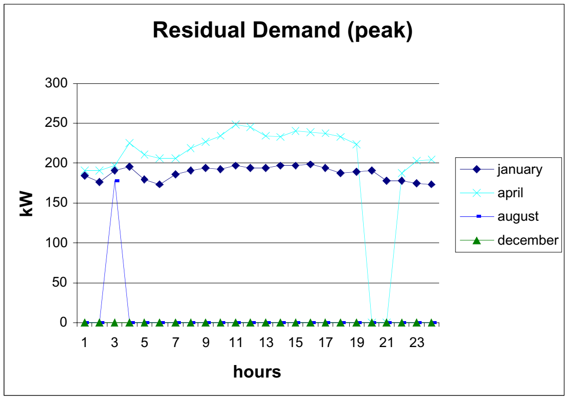

Figure 28. Grocery 1,052 Hours Diesel Residual Demand (peak)

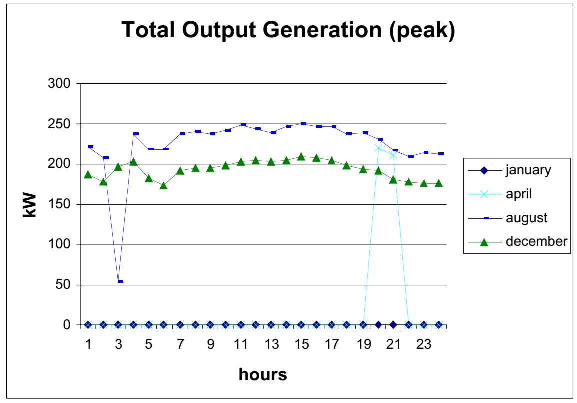

Figure 29. Grocery 1,052 Hours Diesel Total Output Generation (peak)

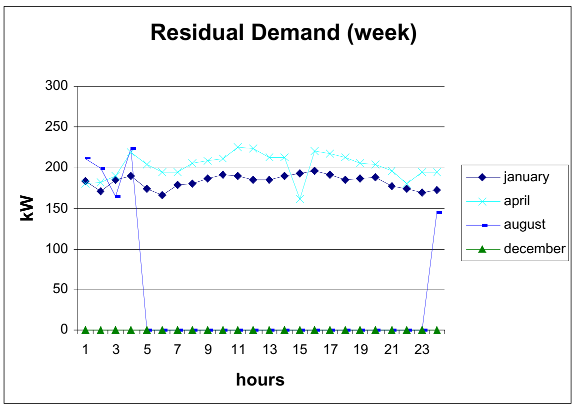

Figure 30. Grocery 1,052 Hours Diesel Residual Demand (week)

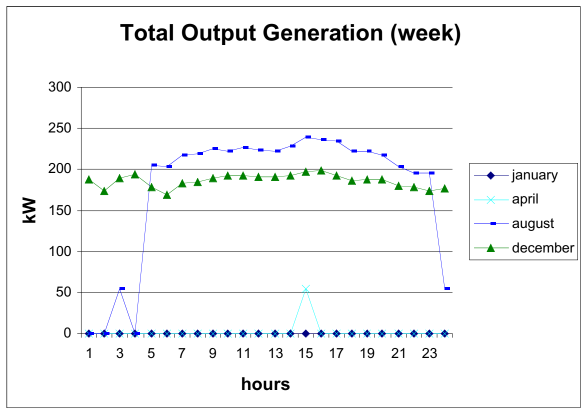

Figure 31. Grocery 1,052 Hours Diesel Total Output Generation (week)

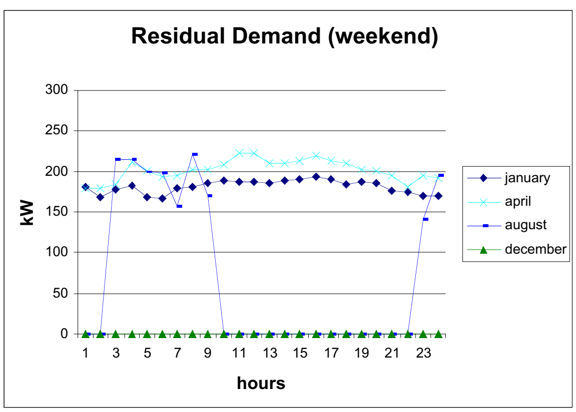

Figure 32. Grocery 1,052 Hours Diesel Residual Demand (weekend)

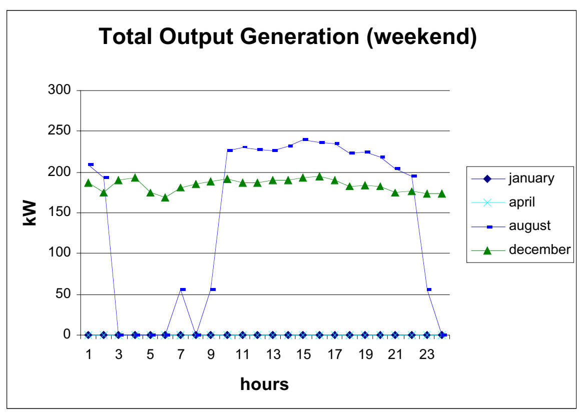

Figure 33. Grocery 1,052 Hours Diesel Total Output Generation (weekend)

In Figure 34 through Figure 36, the marginal cost is plotted. Compared to the IERN case, there is a reduction in the peak period marginal cost as the diesel capacity has a relatively inexpensive fuel cost and it serves to meets all load during hours of IEM price spikes. Consequently, the marginal price is almost always in the \$0.06-\$0.12/kWh range.

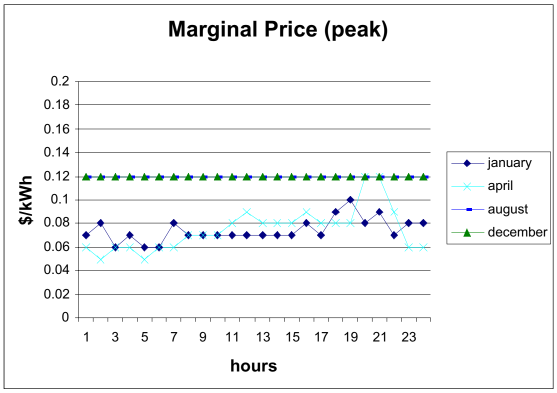

Figure 34. Grocery 1,052 Hours Diesel Marginal Price (peak)

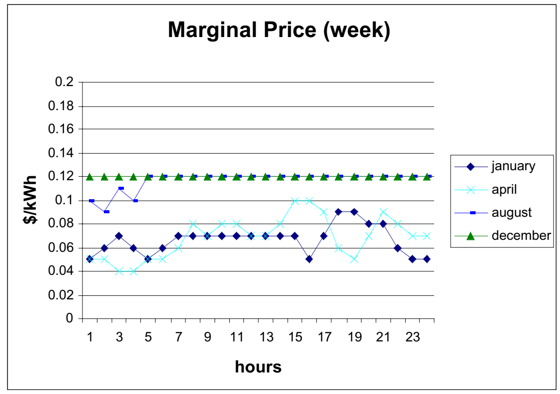

Figure 35. Grocery 1,052 Hours Diesel Marginal Price (week)

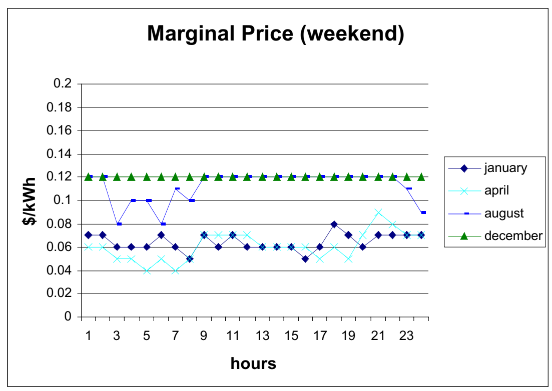

Figure 36. Grocery 1,052 Hours Diesel Marginal Price (weekend)

7.3.3.2 2,052 Hours Per Annum

Here, the diesel generation constraint is relaxed by an additional 1,000 hours per annum, resulting in a 10% cost reduction from the IERN case. This makes it possible for the grocery to minimize its electricity costs using only the 500-kW diesel generator (see **Table 11**). This excess capacity also results in a zero shadow price on the diesel generation constraint. The pattern of generation is similar to that observed in the previous cases with investment: the grocery self-generates more during periods of high IEM prices (see Figure 37 through Figure 42) yielding a constant level of marginal price for the year (see Figure 43 through Figure 45).

Table 11. Breakdown of Electricity Purchase Costs for the Grocery 2,052 Hours Diesel Scenario

Total Supply Cost (k$)	145.278
IEM Energy Purchases (k$)	42.969
Self-Generation Investment Costs (k$)	21.710
Self-Generation Variable Costs (k$)	80.599
Fraction of Consumed Energy Self-Generated	60%
Installed DER Capacity as a Percentage of Peak Load	196%
Average Price (¢/kWh)	8.50
Installed Capacity (kW)	500
Technologies	1-DE-C-500

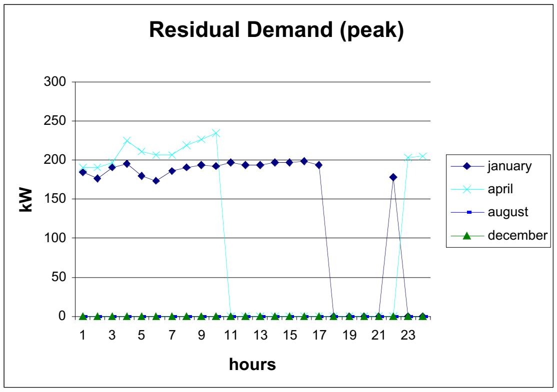

Figure 37. Grocery 2,052 Hours Diesel Residual Demand (peak)

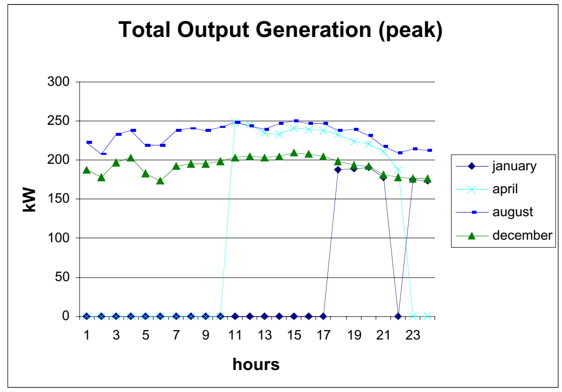

Figure 38. Grocery 2,052 Hours Diesel Total Output Generation (peak)

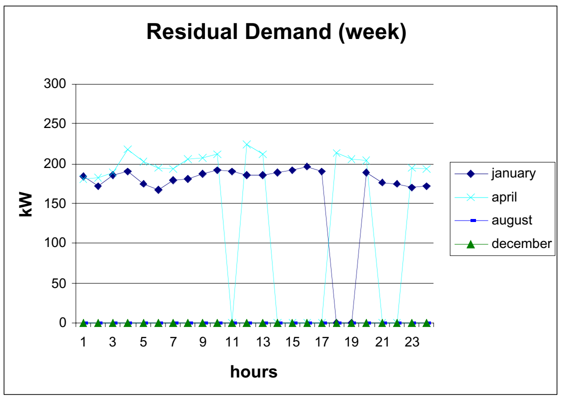

Figure 39. Grocery 2,052 Hours Diesel Residual Demand (week)

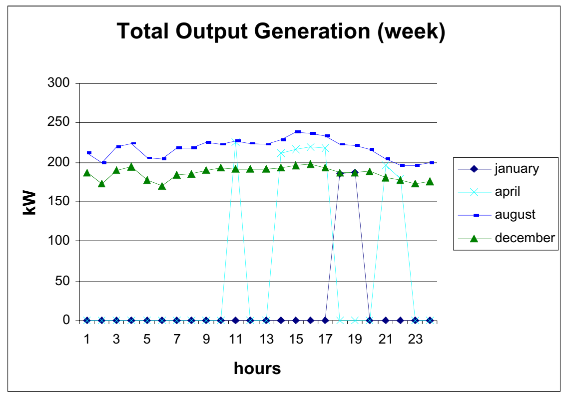

Figure 40. Grocery 2,052 Hours Diesel Total Output Generation (week)

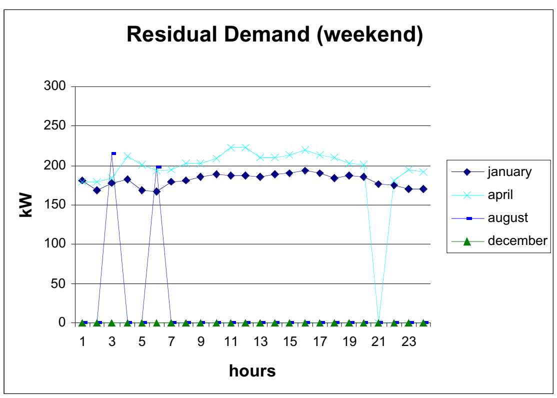

Figure 41. Grocery 2,052 Hours Diesel Residual Demand (weekend)

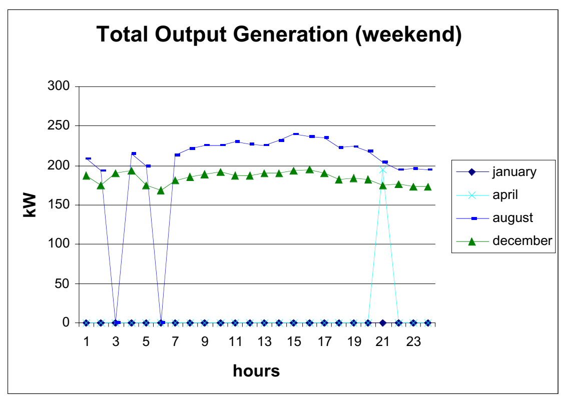

Figure 42. Grocery 2,052 Hours Diesel Total Output Generation (weekend)

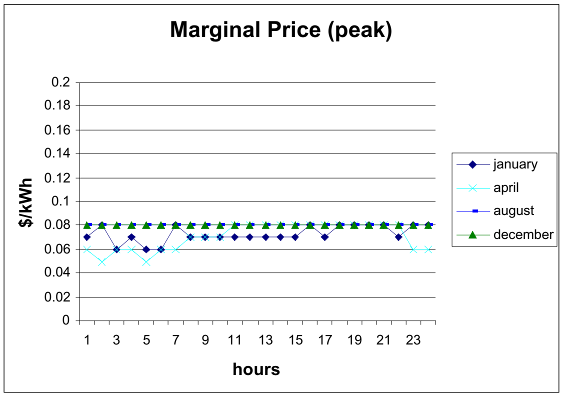

Figure 43. Grocery 2,052 Hours Diesel Marginal Price (peak)

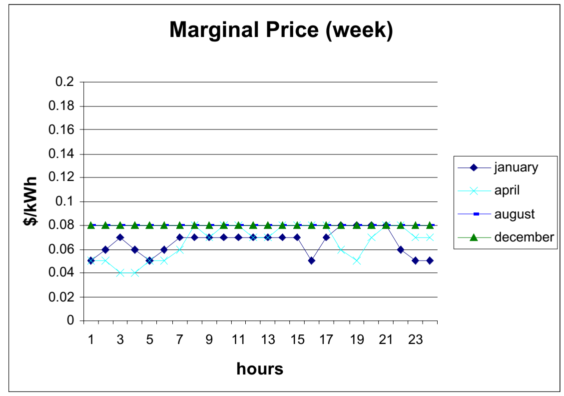

Figure 44. Grocery 2,052 Hours Diesel Marginal Price (week)

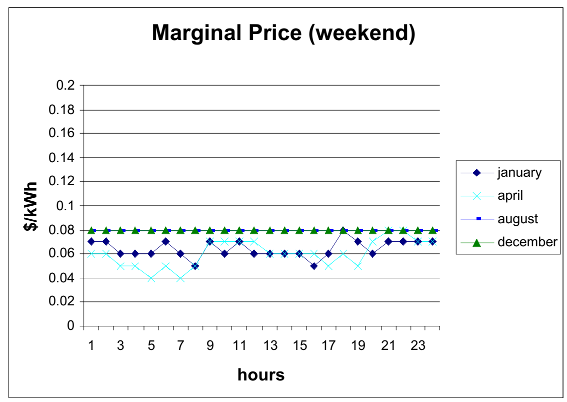

Figure 45. Grocery 2,052 Hours Diesel Marginal Price (weekend)

7.3.3.3 3,052 Hours Per Annum

When the diesel generation constraint is relaxed by another 1,000 hours per annum, the solution is not affected.

7.3.3.4 4,052 Hours Per Annum

If the diesel generation constraint is relaxed by a further 1,000 hours per annum, surprisingly, the optimal solution for the grocery changes. Although there is little reduction in the supply cost from the other diesel generation scenarios, the grocery now installs four 7.5-kW and one 200-kW diesel generators. With additional hours of diesel generation now permitted, the grocery does not optimize by investing in a single large generator in order to produce ample electricity during a relatively small number of hours. Instead, because it can produce during more hours than before, less capacity generates the same amount of energy per annum. Also, the greater operational flexibility of more numerous smaller units outweighs the greater economy of larger ones, tipping the scales against investment in the large 500-kW diesel generator. Interestingly, the shadow prices on the diesel generation constraints are zero, implying that even if the constraints were relaxed by an additional hour, the grocery would not find it profitable to operate the generators further.

Table 12. Breakdown of Electricity Purchase Costs for the Grocery 4,052 Hours Diesel Scenario

Total Supply Cost (k$)	143.610
IEM Energy Purchases (k$)	53.907
Self-Generation Investment Costs (k$)	13.625
Self-Generation Variable Costs (k$)	76.078
Fraction of Consumed Energy Self-Generated	53%
Installed DER Capacity as a Percentage of Peak Load	90%
Average Price (¢/kWh)	8.41
Installed Capacity (kW)	230
Technologies	4-DE-C-7 1-DE-C-200

The pattern of self-generation is again similar to that in previously discussed scenarios. The only change is that now the 200-kW diesel generator covers base load, and the 7.5-kW diesel generators meet peak load (see Figure 46 through Figure 51). This is precisely the result one would expect because operating costs are lower on larger generators. Furthermore, because the grocery does not have excess capacity in this case, it is often forced to purchase electricity from the IEM during peak demand periods, which correspond with peak IEM prices. This can be seen in Figure 52 through Figure 54.

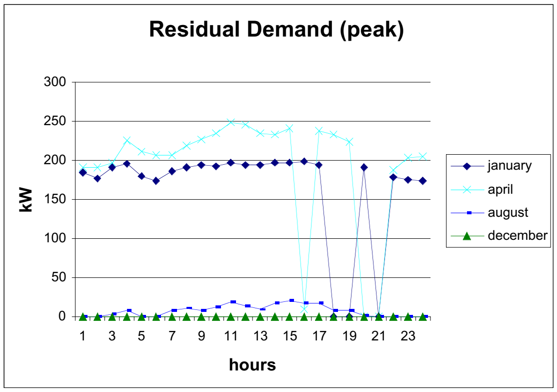

Figure 46. Grocery 4,052 Hours Diesel Residual Demand (peak)

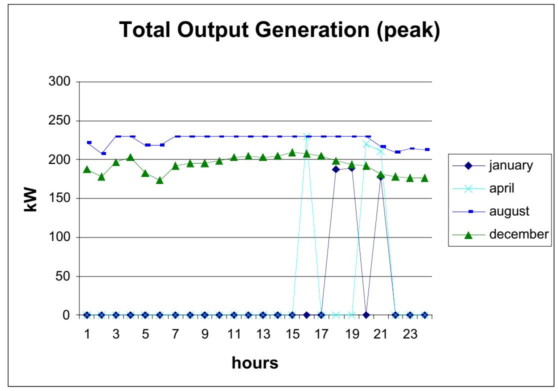

Figure 47. Grocery 4,052 Hours Diesel Total Output Generation (peak)

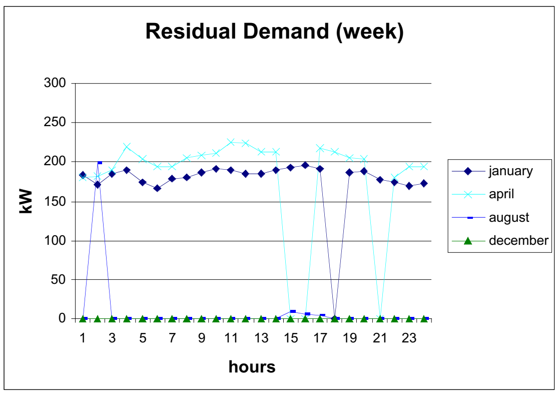

Figure 48. Grocery 4,052 Hours Diesel Residual Demand (week)

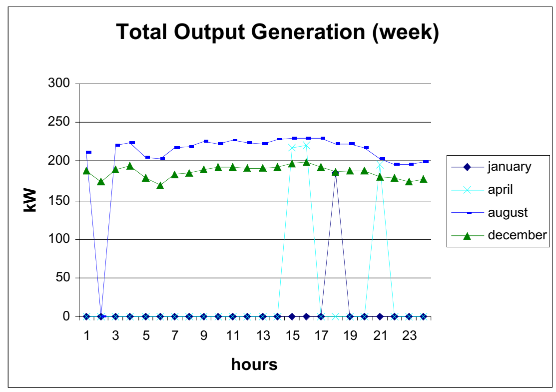

Figure 49. Grocery 4,052 Hours Diesel Total Output Generation (week)

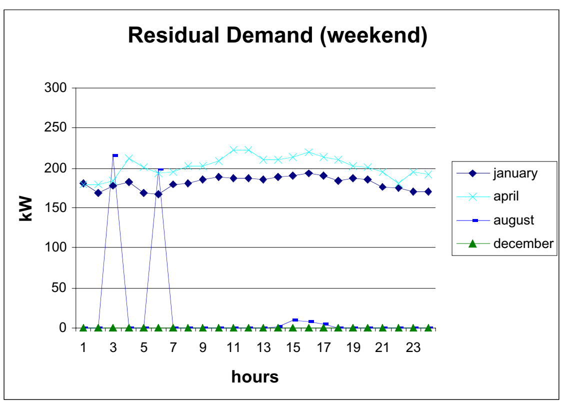

Figure 50. Grocery 4,052 Hours Diesel Residual Demand (weekend)

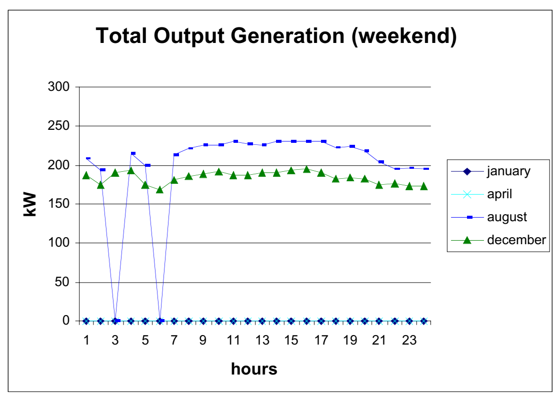

Figure 51. Grocery 4,052 Hours Diesel Total Output Generation (weekend)

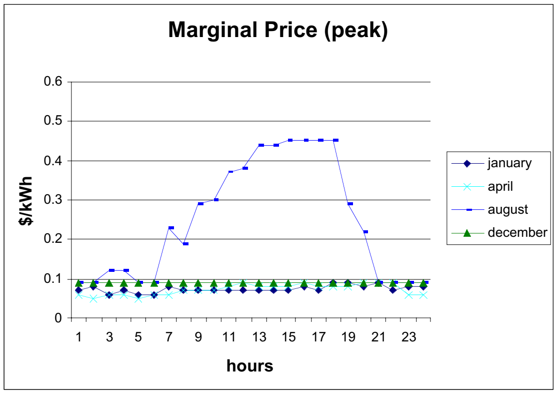

Figure 52. Grocery 4,052 Hours Diesel Marginal Price (peak)

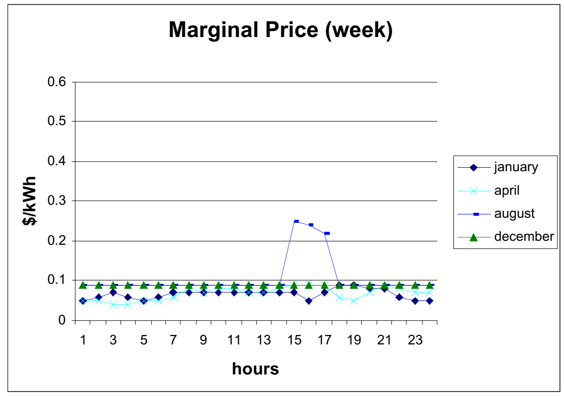

Figure 53. Grocery 4,052 Hours Diesel Marginal Price (week)

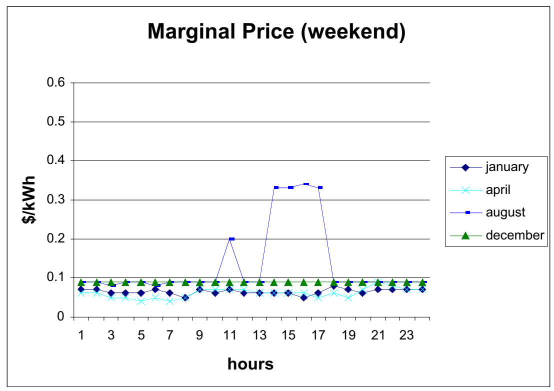

Figure 54. Grocery 4,052 Hours Diesel Marginal Price (weekend)

7.3.3.5 8,760 Hours Per Annum (Unrestricted)

If the diesel generation constraint is completely eliminated, then the resulting optimal solution for the grocery is identical to the one for the 4,052 hours per annum constraint.

Table 13. Breakdown of Electricity Purchase Costs for the Grocery 8,760 Hours Diesel Scenario

Total Supply Cost (k$)	143.610
IEM Energy Purchases (k$)	53.907
Self-Generation Investment Costs (k$)	13.625
Self-Generation Variable Costs (k$)	76.078
Fraction of Consumed Energy Self-Generated	53%
Installed DER Capacity as a Percentage of Peak Load	90%
Average Price (¢/kWh)	8.41
Installed Capacity (kW)	230
Technologies	4-DE-C-7 1-DE-C-200

7.3.4 IERN With Sales

In this scenario, the customer is allowed to sell electricity into the IEM without first meeting its own demand. Because of the high levels of IEM prices in 2000, this turns out to be a perverse scenario in which the grocery realizes profits of almost $22 million per annum. Essentially, the grocery installs all the generators allowed on its premises and effectively becomes a generation plant rather than a grocery store. DER-CAM arbitrarily caps the number of units of each type of generator at 100 although further refinements to the model could permit the number of units to correspond to a feature of the customer s site, e.g., amount of floor space. This case serves primarily as a reminder that the prevailing conditions in 2000 were exceptional and that all the results presented here must be viewed in that light. One of the reasons that on-site generation became so attractive is that DER-CAM could not accommodate varying fuel prices, which under the conditions in 2000, made generation unrealistically attractive in the model. This limitation of DER-CAM has since been rectified.

7.3.5 50% PV Subsidy

In this scenario, the grocery is given a 50% subsidy of the turnkey costs of all PV equipment. However, this subsidy did not affect the grocery's DER investments. The optimal solution in the IERN case is also optimal here, with identical patterns of generation and marginal prices. In other words, this level of subsidy, given all other assumptions, is not sufficient to make PV attractive.

7.3.6 75% PV Subsidy

Once the grocery is given a 75% subsidy of the turnkey costs of PV equipment, installation of two units of the 100-kW PVs becomes cost effective. From **Table 14**, it can be seen that the grocery achieves 11.5% savings on its total supply cost in comparison to the IERN case. Besides the PVs, a 75-kW microturbine and two 55-kW gas back-up generators are also installed. Because PVs are often not running at their power rating, installing other generators to back up PVs becomes cost effective, and the total amount of capacity installed (385 kW) is greater than the grocery's peak load (255 kW). The pattern of generation output (see Figure 55 through Figure 60) indicates that the PVs are used during daylight hours to meet the grocery's base load while the microturbine and gas backup generators are used at night and to meet the peak load. The consequent marginal prices (see Figure 61 through Figure 63) also indicate this usage pattern: interestingly the marginal price is zero or very low, because the operating cost of PV is zero during daylight hours but peaks at night when the grocery is forced to buy electricity from the IEM or self-generate using more expensive natural gas. These results also raise some interesting questions that cannot be answered within the limitations of the current framework. One is: does any additional benefit to the customer, or the grid, result from the (economic) overcapacity? Another is: how would storage compete with the surplus generators?

Table 14. Breakdown of Electricity Purchase Costs for the 75% PV Subsidy Scenario

Total Supply Cost (k$)	142.689
IEM Energy Purchases (k$)	44.411
Self-Generation Investment Costs (k$)	50.281
Self-Generation Variable Costs (k$)	47.997
Sales at the IEM Price ($)	0
Fraction of Consumed Energy Self-Generated	63%
Installed DER Capacity as a Percentage of Peak Load	151%
Average Price (¢/kWh)	8.35
Installed Capacity (kW)	385
Technologies	1-MT-AS-75 2-GA-K-55 2-PV-100

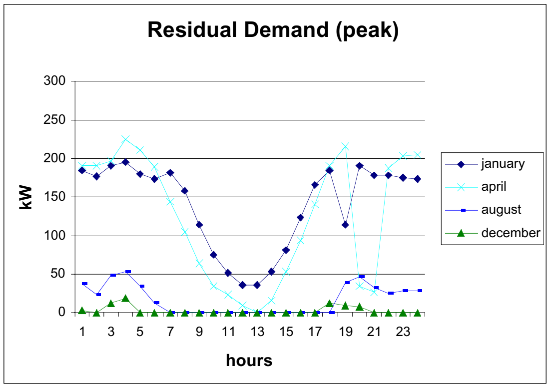

Figure 55. Grocery 75% PV Subsidy Residual Demand (peak)

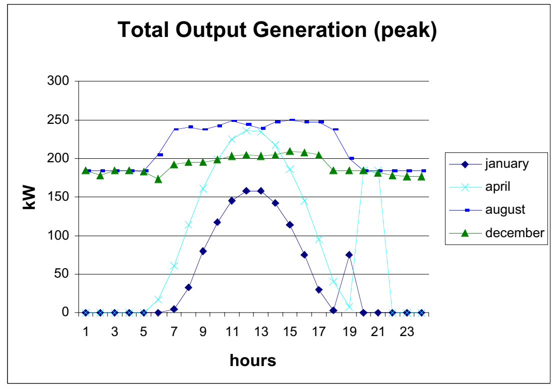

Figure 56. Grocery 75% PV Subsidy Total Output Generation (peak)

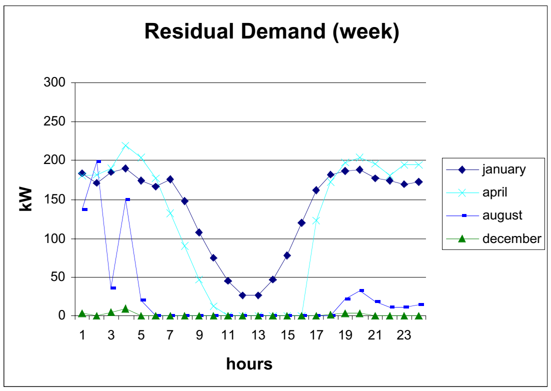

Figure 57. Grocery 75% PV Subsidy Residual Demand (week)

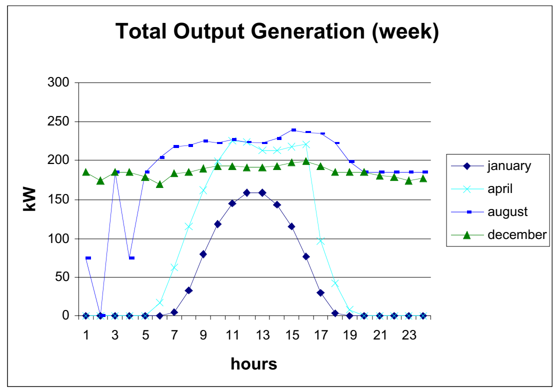

Figure 58. Grocery 75% PV Subsidy Total Output Generation (week)

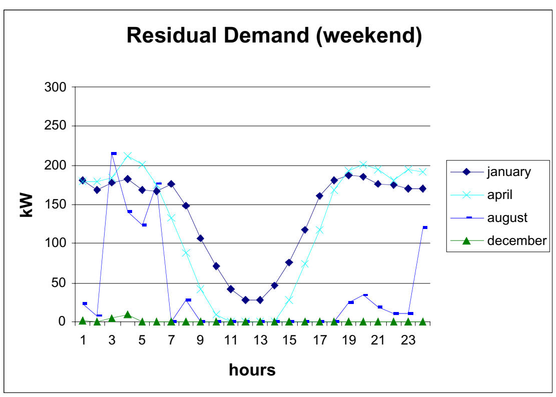

Figure 59. Grocery 75% PV Subsidy Residual Demand (weekend)

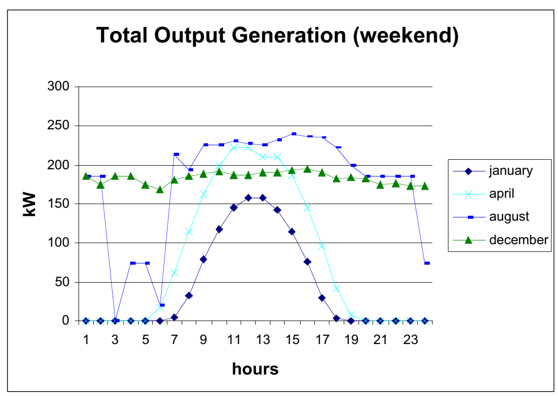

Figure 60. Grocery 75% PV Subsidy Total Output Generation (weekend)

The characteristic midday hump or valley in Figure 55 - Figure 60 shows the PV output, which follows the rate of solar insolation. The marginal cost results in Figure 61 - Figure 63 are revealing. There are basically three levels of marginal cost. First, in sunny months, near midday, marginal cost falls to zero, showing that PV is providing all of Dangerway s electricity. Second, for many hours marginal cost is flat between around

0.07 to 0.1 $/kWh when the gas-fired generators are marginal. And third, when Dangerway is purchasing electricity, marginal cost is the IEM+adder price, which, in December, is often near the cap of 28.57 ¢/kWh.

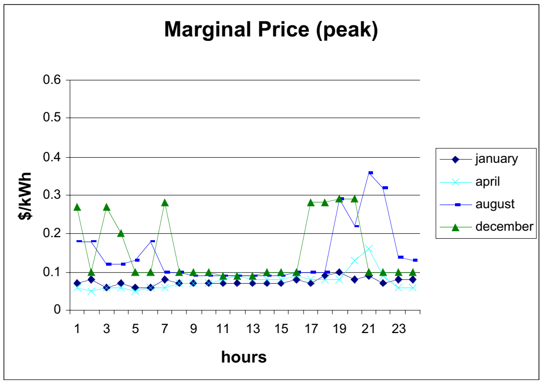

Figure 61. Grocery 75% PV Subsidy Marginal Price (peak)

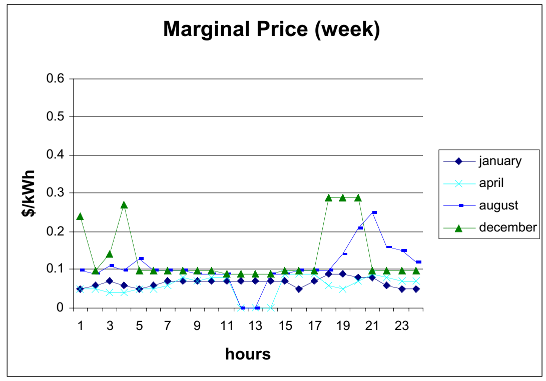

Figure 62. Grocery 75% PV Subsidy Marginal Price (week)

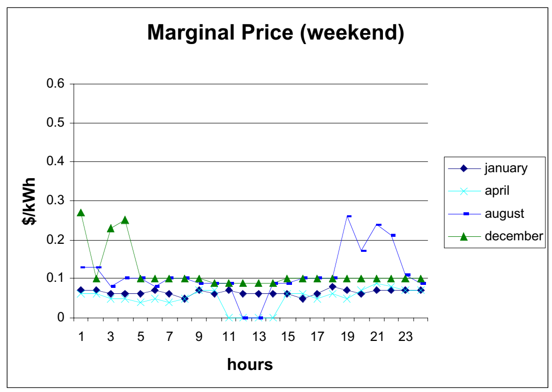

Figure 63. Grocery 75% PV Subsidy Marginal Price (weekend)

7.3.7 High DiscoER

In this scenario, the DiscoER term is doubled (from 3.57 cents/kWh to 7.14 cents/kWh), implying that the grocery is required to pay a higher adder to the IEM price. While the total supply cost increases by more than 13% relative to the IERN case, the optimal DER investment remains the same (see Table 15). The higher adder, however, spurs the grocery to avoid IEM purchases. Hence, it self-generates more in comparison to the IERN case (see Figure 64 through Figure 69), with more stable marginal prices (see Figure 70 through Figure 72) reflecting the variable costs of microturbine generation.

Table 15. Breakdown of Electricity Purchase Costs for the High DiscoER Scenario

Total Supply Cost (k$)	182.429
IEM Energy Purchases (k$)	19.253
Self-Generation Investment Costs (k$)	22.596
Self-Generation Variable Costs (k$)	140.580
Sales at the IEM Price ($)	0
Fraction of Consumed Energy Self-Generated	88%
Installed DER Capacity as a Percentage of Peak Load	88%
Average Price (¢/kWh)	10.68
Installed Capacity (kW)	225
Technologies	3-MT-AS-75

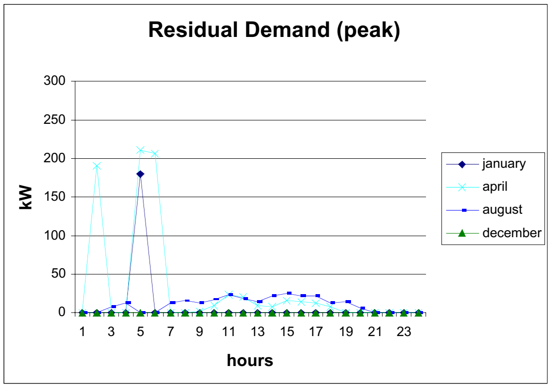

Figure 64. Grocery High DiscoER Residual Demand (peak)

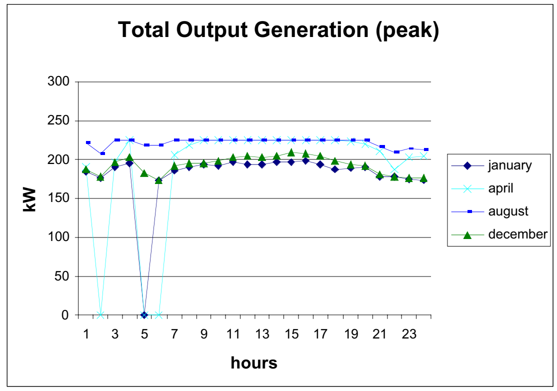

Figure 65. Grocery High DiscoER Total Output Generation (peak)

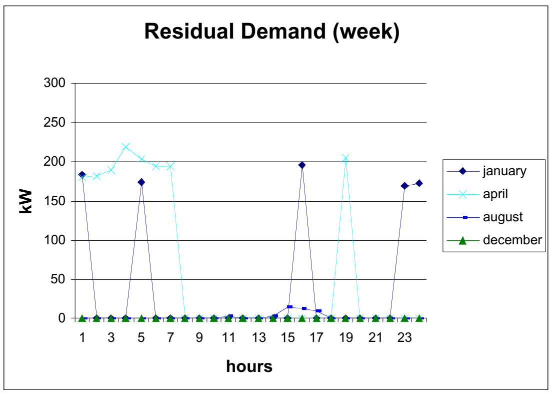

Figure 66. Grocery High DiscoER Residual Demand (week)

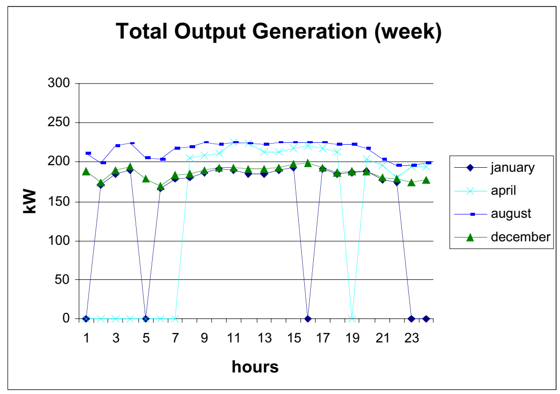

Figure 67. Grocery High DiscoER Total Output Generation (week)

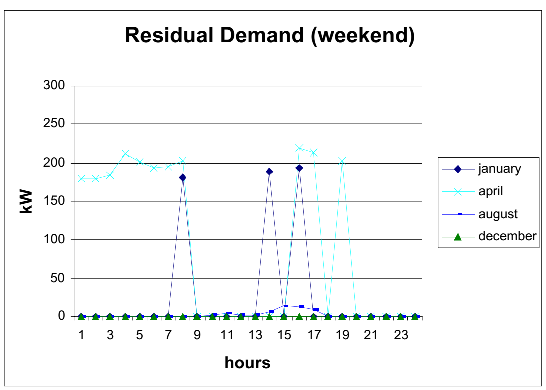

Figure 68. Grocery High DiscoER Residual Demand (weekend)

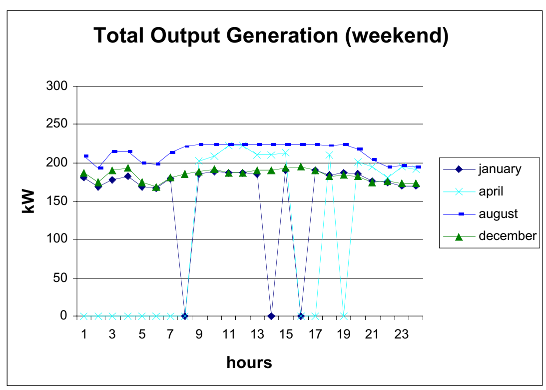

Figure 69. Grocery High DiscoER Total Output Generation (weekend)

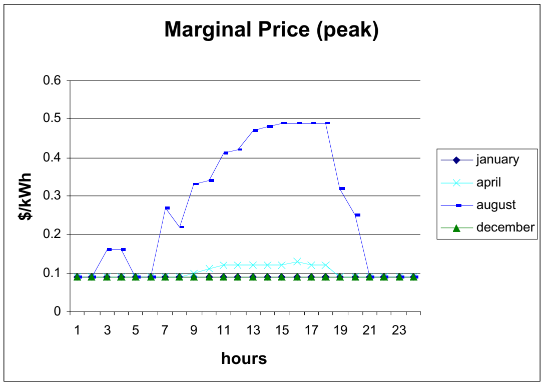

Figure 70. Grocery High DiscoER Marginal Price (peak)

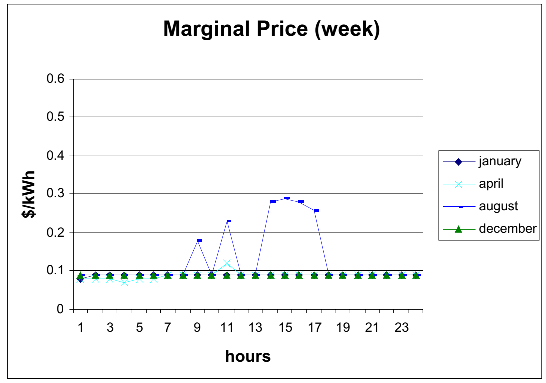

Figure 71. Grocery High DiscoER Marginal Price (week)

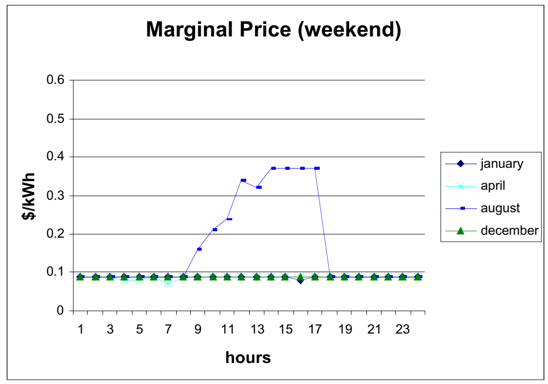

Figure 72. Grocery High DiscoER Marginal Price (weekend)

7.3.8 IERN with Year 2010 Technologies

In this scenario, technology data based on year 2010 forecasts (as described in Section 2) are used in the model. Total supply costs decrease by 8.5% as a single 250-kW PEM FC is installed. The patterns of generation (see Figure 73 through Figure 78) indicate that the FC is used primarily to meet base-load demand. The marginal prices (see Figure 79 through Figure 81) confirm this pattern as the prices stay stable with only a few spikes when the grocery is forced to purchase from the IEM.

Table 16. Breakdown of Electricity Purchase Costs for the IERN with 2010 Technologies Scenario

Total Supply Cost (k$)	147.665
IEM Energy Purchases (k$)	41.435
Self-Generation Investment Costs (k$)	25.548
Self-Generation Variable Costs (k$)	80.682
Sales at the IEM Price ($)	0
Fraction of Consumed Energy Self-Generated	61%
Installed DER Capacity as a Percentage of Peak Load	98%
Average Price (¢/kWh)	8.64
Installed Capacity (kW)	250
Technologies	1-PEM-BA-250

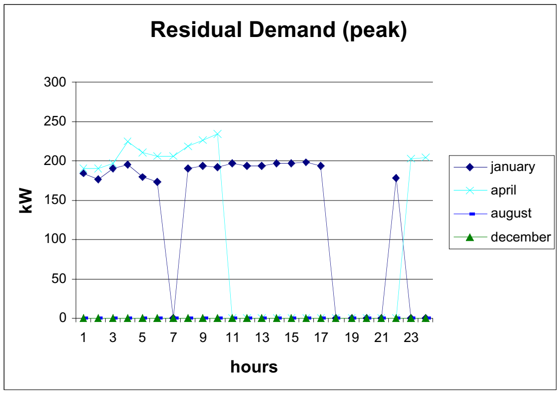

Figure 73. Grocery IERN 2010 Technologies Residual Demand (peak)

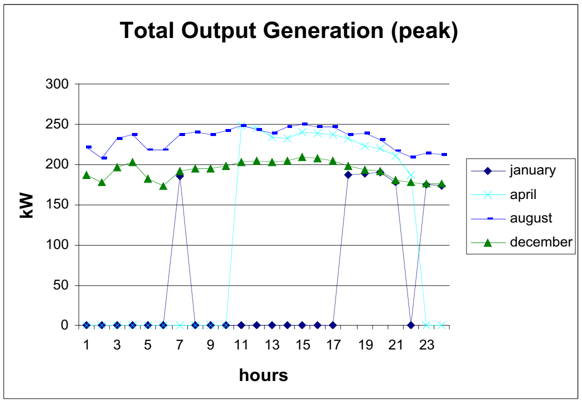

Figure 74. Grocery IERN 2010 Technologies Total Output Generation (peak)

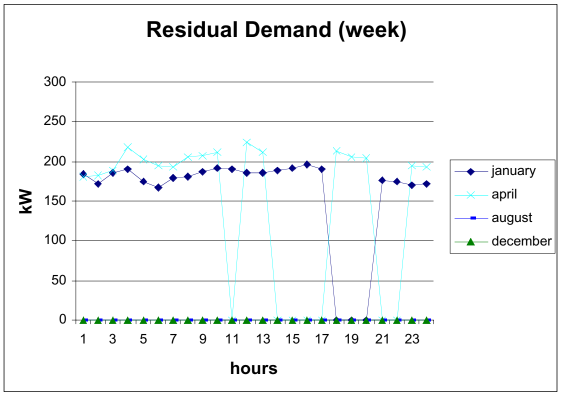

Figure 75. Grocery IERN 2010 Technologies Residual Demand (week)

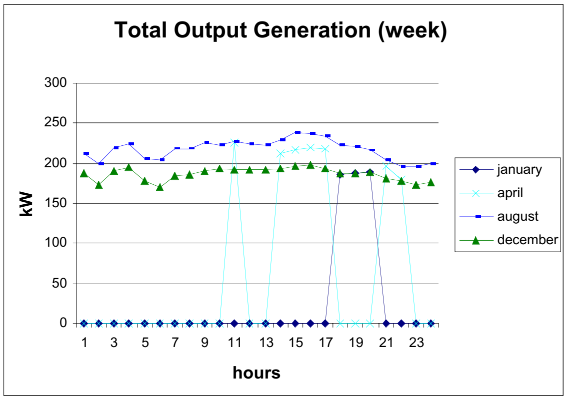

Figure 76. Grocery IERN 2010 Technologies Total Output Generation (week)

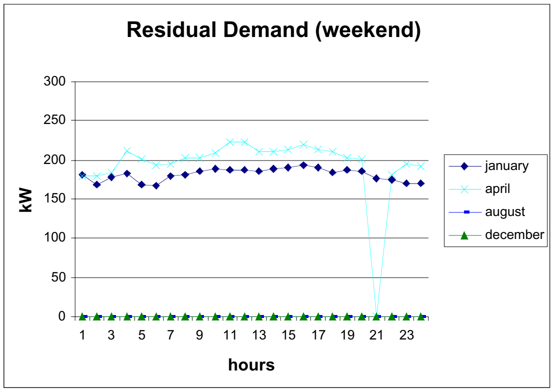

Figure 77. Grocery IERN 2010 Technologies Residual Demand (weekend)

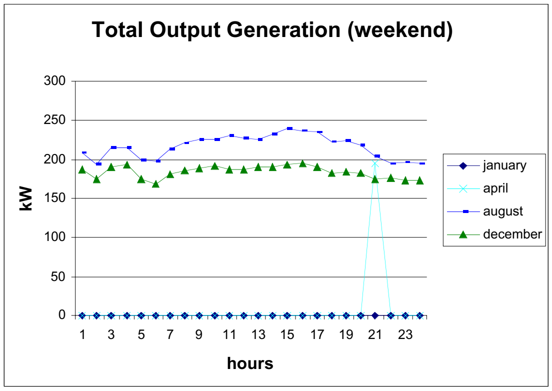

Figure 78. Grocery IERN 2010 Technologies Total Output Generation (weekend)

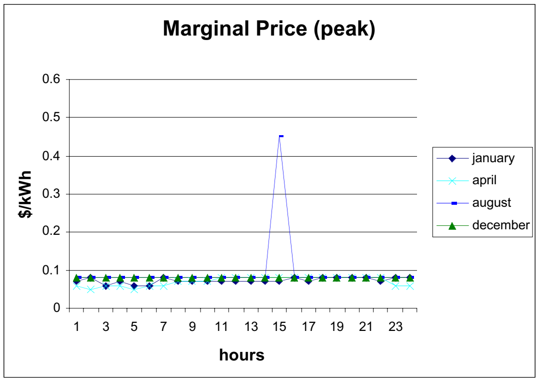

Figure 79. Grocery IERN 2010 Technologies Marginal Price (peak)

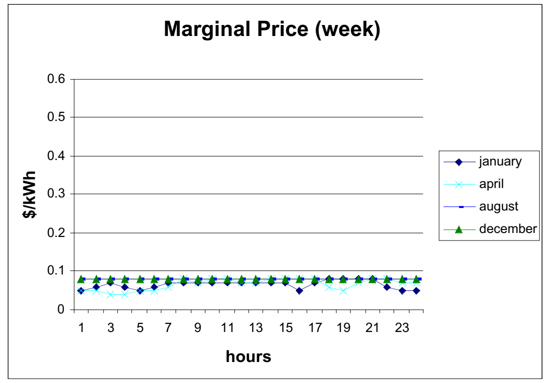

Figure 80. Grocery IERN 2010 Technologies Marginal Price (week)

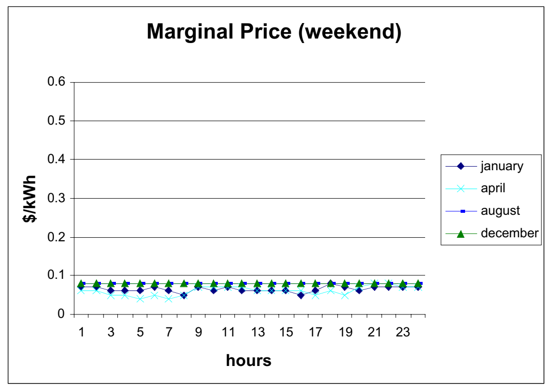

Figure 81. Grocery IERN 2010 Technologies Marginal Price (weekend)

7.3.9 Low Natural Gas Price

In this scenario, the natural gas price is decreased from \$8.25/GJ to \$5.06/GJ, reflecting a 50% decrease in the spot price component.[13] This is quite an unrealistic scenario given that the IERN natural gas prices are already too favorable. But this scenario serves as a revealing sensitivity because, as in the High DiscoER scenario, Dangerway retains its investment in the three microturbines. However, the lower fuel cost naturally encourages the grocery to use the microturbines more frequently because they are more cost effective relative to IEM purchases. The low fuel price reduces Dangerway s total supply cost by 25% in comparison to the IERN case (see Table 18). The patterns of generation (see Figure 82 through Figure 87) indicate that the grocery reduces most of its exposure to the high IEM prices. Meanwhile, the marginal prices are stable, as in the High DiscoER scenario (see Figure 88 through Figure 90).

[13] The natural gas transmission cost is left unchanged.

Table 17. Breakdown of Electricity Purchase Costs for the Low Natural Gas Price Scenario

Total Supply Cost (k$)	120.563
IEM Energy Purchases (k$)	11.518
Self-Generation Investment Costs (k$)	22.596
Self-Generation Variable Costs (k$)	86.449
Sales at the IEM Price (k$)	0
Fraction of Consumed Energy Self-Generated	88%
Installed DER Capacity as a Percentage of Peak Load	88%
Average Price (¢/kWh)	7.06
Installed Capacity (kW)	225
Technologies	3-MT-AS-75

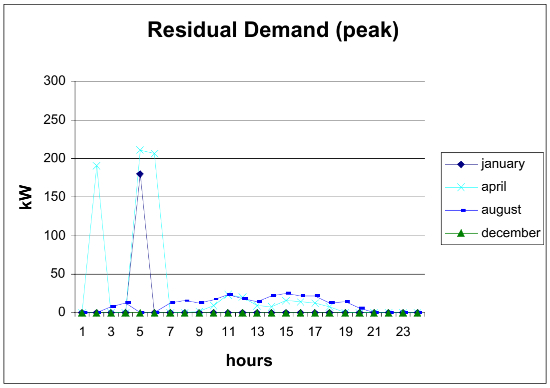

Figure 82. Grocery Low Natural Gas Prices Residual Demand (peak)

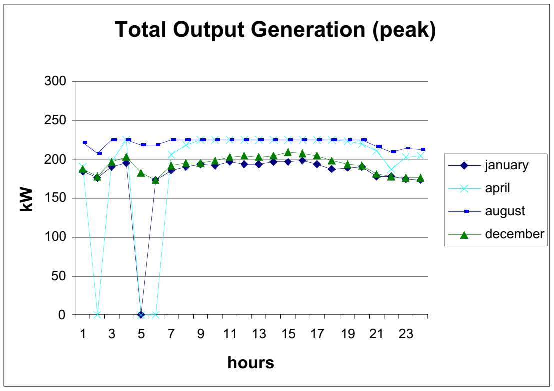

Figure 83. Grocery Low Natural Gas Prices Total Output Generation (peak)

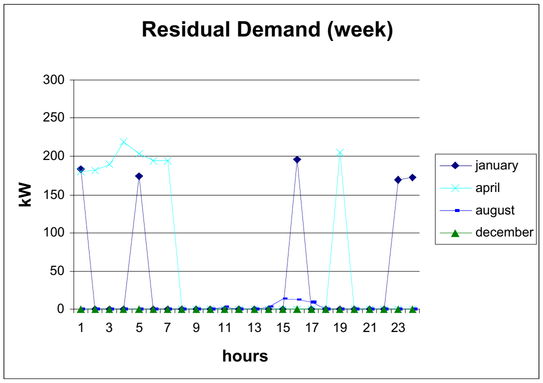

Figure 84. Grocery Low Natural Gas Prices Residual Demand (week)

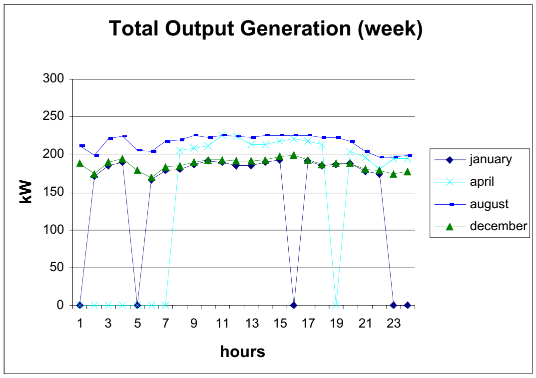

Figure 85. Grocery Low Natural Gas Prices Total Output Generation (week)

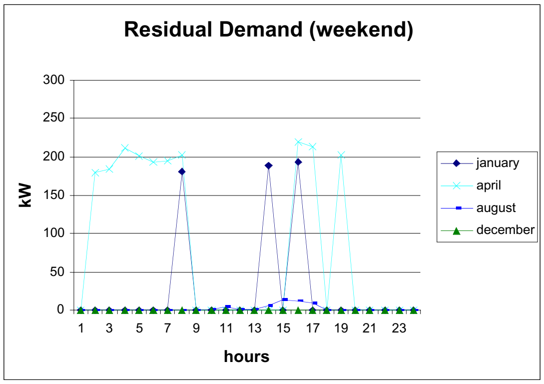

Figure 86. Grocery Low Natural Gas Prices Residual Demand (weekend)

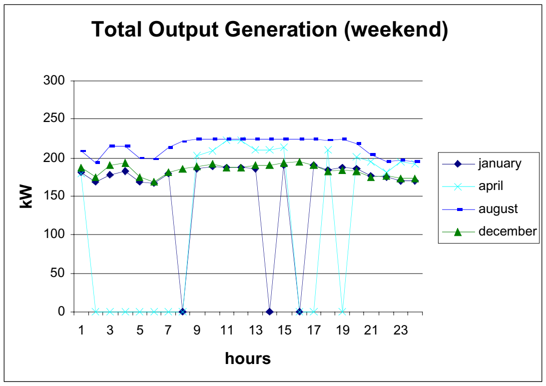

Figure 87. Grocery Low Natural Gas Prices Total Output Generation (weekend)

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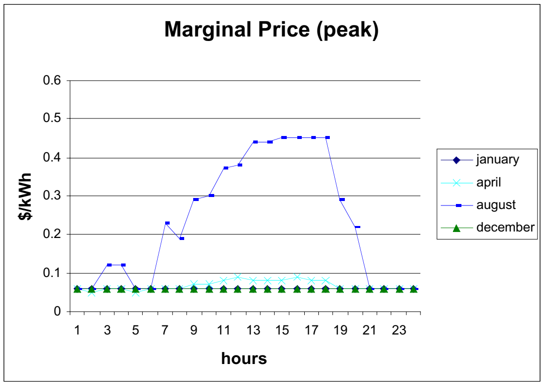

Figure 88. Grocery Low Natural Gas Prices Marginal Price (peak)

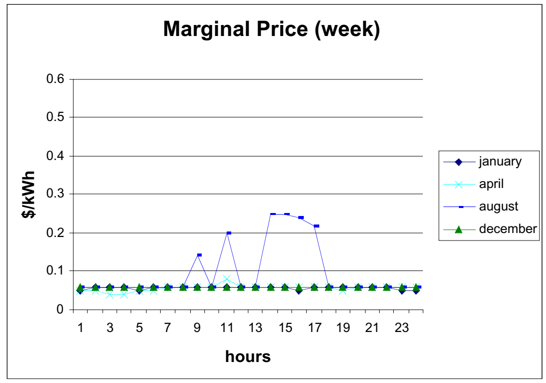

Figure 89. Grocery Low Natural Gas Prices Marginal Price (week)

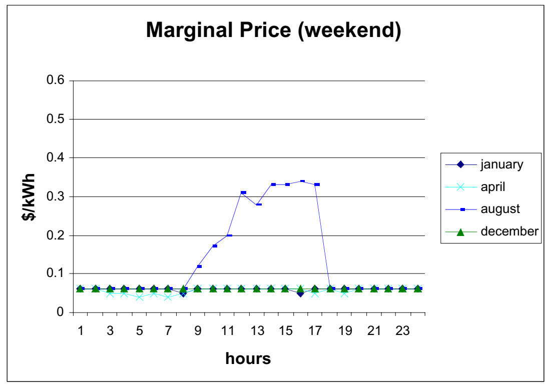

Figure 90. Grocery Low Natural Gas Prices Marginal Price (weekend)

7.3.10 PXRN with Year 1999 Prices

In order to determine the effect that low and relatively stable 1999 prices would have on DER-CAM results, this scenario replaces 2000 IEM prices with 1999 PX ones. Somewhat surprisingly, Dangerway is content, in this case, to purchase all of its electricity from the open market, thereby realizing total cost savings of almost 30% over the IERN case. In addition, if PXRN 1999 marginal prices (see Figure 97 through Figure 99) are compared to those for the do-nothing-IERN case (see Figure 13 through Figure 15), the differences in 1999 PX and 2000 IEM prices become apparent; the former are low and stable whereas the latter are high and volatile. Hence, the grocery's rational response is to install on-site generation in the latter case and to purchase from the market in the former. Therefore, this sensitivity proves quite illuminating, with the stark result that 2000 IEM prices lead to significant DER adoption while 1999 PX prices lead to none. And these are not extreme, alternative inputs, just the real-world California experience in back-to-back years.

Table 18. Breakdown of Electricity Purchase Costs for the PXRN 1999 Sensitivity

Total Supply Cost (k$)	113.037
PX Energy Purchases (k$)	113.037
Self-Generation Investment Costs (k$)	0
Self-Generation Variable Costs (k$)	0
Sales at the PX Price (k$)	0
Fraction of Consumed Energy Self-Generated	0%
Installed DER Capacity as a Percentage of Peak Load	0%
Average Price (¢/kWh)	6.62
Installed Capacity (kW)	0
Technologies	None

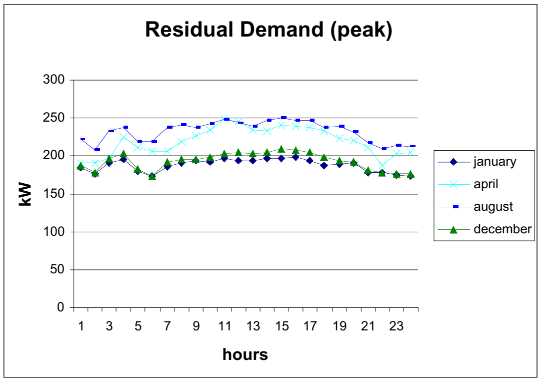

Figure 91. Grocery PXRN 1999 Prices Residual Demand (peak)

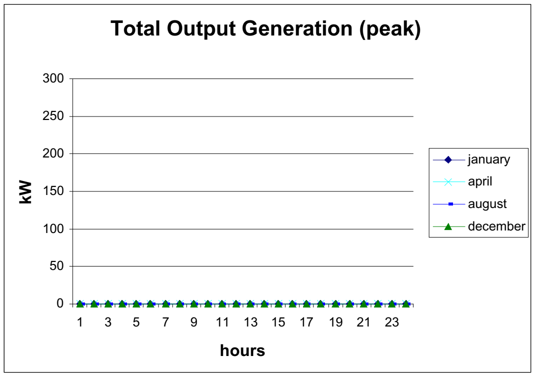

Figure 92. Grocery PXRN 1999 Prices Total Output Generation (peak)

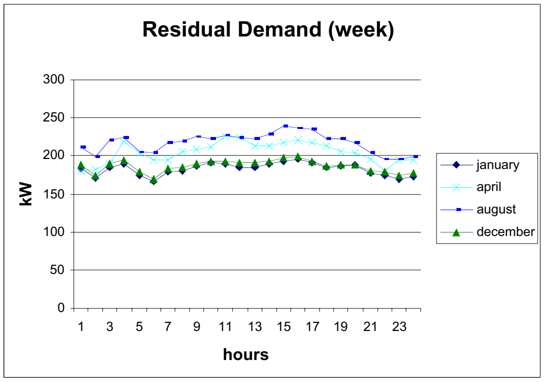

Figure 93. Grocery PXRN 1999 Prices Residual Demand (week)

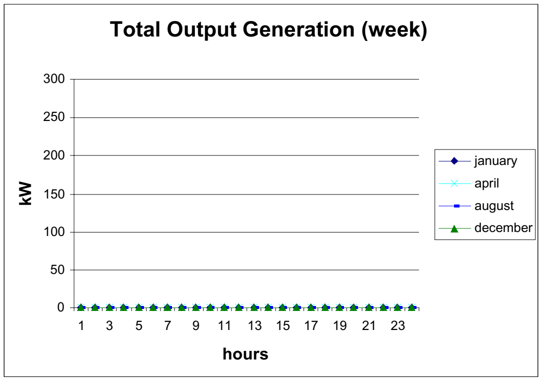

Figure 94. Grocery PXRN 1999 Prices Total Output Generation (week)

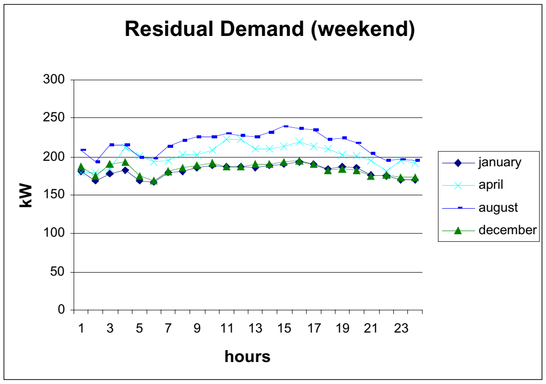

Figure 95. Grocery PXRN 1999 Prices Residual Demand (weekend)

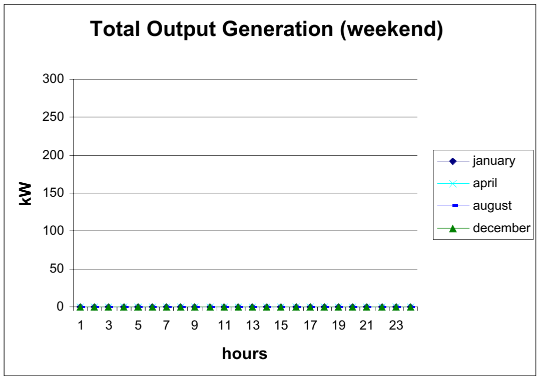

Figure 96. Grocery PXRN 1999 Prices Total Output Generation (weekend)

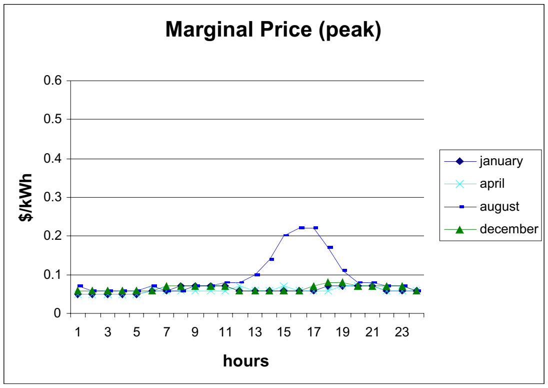

Figure 97. Grocery PXRN 1999 Prices Marginal Price (peak)

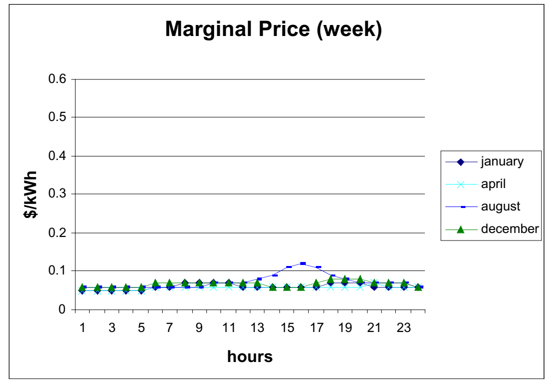

Figure 98. Grocery PXRN 1999 Prices Marginal Price (week)

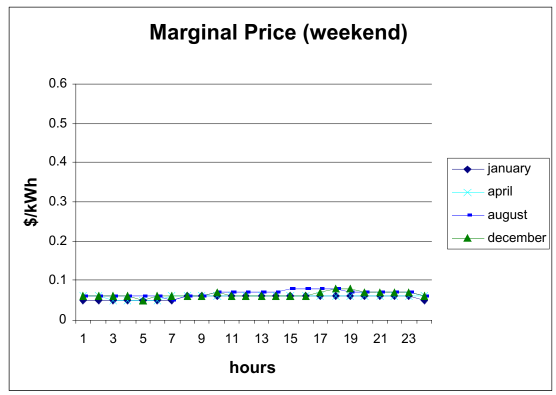

Figure 99. Grocery PXRN 1999 Prices Marginal Price (weekend)

7.3.11 Summary Of Results

This section briefly summarizes of all results of this study. For each customer (grocery, restaurant, deli, department store, fast food restaurant, office, retail store, warehouse store, and the Microgrid Oaks) and for every scenario, the adopted technologies, the total savings, and the power and energy coverage of DER are presented.

7.3.11.1 Adopted Technologies

The following tables summarize the capacity installed in all cases. Although the technologies adopted vary across customers and their circumstances, we find that if customers join together to form a µGrid, then the pattern of adopted technologies is more stable than if customers act separately. For example, the µGrid usually selects two gas back-up generators or diesel generators whereas customers acting on their own select a medley of technologies. This result implies that customers acting as a µGrid would be more robust in various market environments than individual customers would. Intuitively, this seems plausible because a larger customer is able to pool its resources in order to capitalize upon the economies of scale inherent in many DER technologies. Microgrid Oaks clearly purchases larger units, the 500-kW natural-gas generator. The

500-kW diesel replaces the natural gas model in the relaxed diesel constraint cases. Also the adopted 100-kW PV systems of the 75% PV subsidy case suggest that more economical large systems may have penetrated the 50% case.

Table 19. Technologies Adopted (Grocery and Restaurant)

Scenario	Grocery (Dangerway)	Restaurant (Nan Hideaway)
PXRN 1999	None	None
Low Natural Gas Prices	3 MT-AS-75	1 MT-AS-75
IERN Sales 2000	100 MTL-C-30 / 100 MTH-C-30 100 MT-AS-75 / 100 GA-K-25 100 GA-K-55 / 100 GA-K-100 100 GA-K-215 / 100 GA-K-500	100 GA-K-500 / 100 GA-K-215 100 GA-K-100 / 100 GA-K-55 100 GA-K-25 / 100 MT-AS-75 100 MTH-C-30 / 100 MTL-C-30
IERN 2000	3 MT-AS-75	1 MT-AS-75
IERN 2010	1 PEM-BA-250	2 GA-K-55
High DiscoER	3 MT-AS-75	1 MT-AS-75
Do-Nothing IERN	None	None
Diesel 8,760 Hours	1 DE-C-200 / 4 DE-C-7	1 DE-C-100
Diesel 4,052 Hours	1 DE-C-200 / 4 DE-C-7	1 DE-C-100
Diesel 3,052 Hours	1 DE-C-500	1 DE-C-100
Diesel 2,052 Hours	1 DE-C-500	1 DE-C-200
Diesel 1,052 Hours	1 GA-K-55 / 1 DE-C-500	2 DE-C-7 / 1 MT-AS-75
75% PV Subsidy	2 PV-100 / 2 GA-K-55 1 MT-AS-75	1 PV-50 / 1 PV-20 / 1 MT-AS-75
50% PV Subsidy	3 MT-AS-75	1 MT-AS-75

Table 20. Technologies Adopted (Deli and Department Store)

Scenario	Deli (Sub Safe Harbor)	Department Store (Spacy s)
PXRN 1999	None	None
Low Natural Gas Prices	1 GA-K-55	1 GA-K-55 / 3 MT-AS-75
IERN Sales 2000	100 GA-K-500 / 100 GA-K-215 100 GA-K-100 / 100 GA-K-55 100 GA-K-25 / 100 MT-AS-75 100 MTH-C-30 / 100 MTL-C-30	100 GA-K-500 / 100 GA-K-215 100 GA-K-100 / 100 GA-K-55 100 GA-K-25 / 100 MT-AS-75 100 MTH-C-30 / 100 MTL-C-30
IERN 2000	1 GA-K-55	2 GA-K-55 / 2 MT-AS-75
IERN 2010	1 GA-K-55	1 PEM-BA-250
High DiscoER	1 GA-K-55	1 GA-K-55 / 3 MT-AS-75
Do-Nothing IERN	None	None
Diesel 8,760 Hours	6 DE-C-7	1 DE-C-500
Diesel 4,052 Hours	6 DE-C-7	1 DE-C-500
Diesel 3,052 Hours	6 DE-C-7	1 DE-C-500
Diesel 2,052 Hours	7 DE-C-7	1 DE-C-500
Diesel 1,052 Hours	1 GA-K-55	1 GA-K-55 / 1 DE-C-500
75% PV Subsidy	1 PV-20 / 1 GA-K-55	2 PV-100 / 1 PV-50 / 2 MT-AS-75
50% PV Subsidy	1 GA-K-55	2 GA-K-55 / 2 MT-AS-75

Table 21. Technologies Adopted (Fast Food Restaurant and Office)

Scenario	Fast Food Restaurant (Burger Queen)	Office (Great Vistas Real Estate)
PXRN 1999	None	None
Low Natural Gas Prices	1 MT-AS-75	None
IERN Sales 2000	100 GA-K-500 / 100 GA-K-215 100 GA-K-100 / 100 GA-K-55 100 GA-K-25 / 100 MT-AS-75 100 MTH-C-30 / 100 MTL-C-30	100 GA-K-500 / 100 GA-K-215 100 GA-K-100 / 100 GA-K-55 100 GA-K-25 / 100 MT-AS-75 100 MTH-C-30 / 100 MTL-C-30
IERN 2000	1 MT-AS-75	None
IERN 2010	1 GA-K-55	None
High DiscoER	1 MT-AS-75	None
Do-Nothing IERN	None	None
Diesel 8,760 Hours	11 DE-C-7	2 DE-C-7
Diesel 4,052 Hours	11 DE-C-7	2 DE-C-7
Diesel 3,052 Hours	11 DE-C-7	2 DE-C-7
Diesel 2,052 Hours	1 DE-C-100	2 DE-C-7
Diesel 1,052 Hours	1 DE-C-7 / 1 MT-AS-75	2 DE-C-7
75% PV Subsidy	1 PV-50 / 1 PV-20 / 1 GA-K-55	2 PV-5
50% PV Subsidy	1 MT-AS-75	None

Table 22. Technologies Adopted (Retail and Warehouse Store)

Scenario	Retail Store (Drum Buster Stereo)	Warehouse Store (Ram s Club)
PXRN 1999	None	None
Low Natural Gas Prices	1 GA-K-55	1 GA-K-55 / 3 MT-AS-75
IERN Sales 2000	100 GA-K-500 / 100 GA-K-215 100 GA-K-100 / 100 GA-K-55 100 GA-K-25 / 100 MT-AS-75 100 MTH-C-30 / 100 MTL-C-30	100 GA-K-500 / 100 GA-K-215 100 GA-K-100 / 100 GA-K-55 100 GA-K-25 / 100 MT-AS-75 100 MTH-C-30 / 100 MTL-C-30
IERN 2000	1 GA-K-55	2 GA-K-55 / 2 MT-AS-75
IERN 2010	1 GA-K-55	1 PEM-BA-250
High DiscoER	1 MT-AS-75	1 GA-K-55 / 3 MT-AS-75
Do-Nothing IERN	None	None
Diesel 8,760 Hours	8 DE-C-7	1 DE-C-500
Diesel 4,052 Hours	8 DE-C-7	1 DE-C-500
Diesel 3,052 Hours	8 DE-C-7	1 DE-C-500
Diesel 2,052 Hours	9 DE-C-7	1 DE-C-500
Diesel 1,052 Hours	1 GA-K-55 / 1 DE-C-7	1 GA-K-55 / 1 DE-C-500
75% PV Subsidy	1 PV-50 / 1 GA-K-55	2 PV-100 / 1 GA-K-55 / 2 MT-AS-75
50% PV Subsidy	1 GA-K-55	1 GA-K-55 / 3 MT-AS-75

Table 23. Technologies Adopted (μGrid)

Scenario	μGrid (Microgrid Oaks)
PXRN 1999	None
Low Natural Gas Prices	2 GA-K-500 / 1 MT-AS-75
IERN Sales 2000	100 GA-K-500 / 100 GA-K-215 100 GA-K-100 / 100 GA-K-55 100 GA-K-25 / 100 MT-AS-75 100 MTH-C-30 / 100 MTL-C-30
IERN 2000	2 GA-K-500 / 1 MT-AS-75
IERN 2010	4 PEM-BA-250
High DiscoER	1 GA-K-500 / 8 MT-AS-75
Do-Nothing IERN	None
Diesel 8,760 Hours	2 DE-C-500 / 7 DE-C-7
Diesel 4,052 Hours	2 DE-C-500 / 7 DE-C-7
Diesel 3,052 Hours	2 DE-C-500 / 1 DE-C-200
Diesel 2,052 Hours	3 DE-C-500
Diesel 1,052 Hours	1 GA-K-500 / 2 DE-C-500
75% PV Subsidy	9 PV-100 / 1 GA-K-500 / 3 MT-AS-75
50% PV Subsidy	2 GA-K-500 / 1 MT-AS-75

7.3.11.2 Savings

We see from Figure 100 that installation of DER generation capacity results in significant savings over the do-nothing-IERN scenario. As discussed previously, customers acting together as Microgrid Oaks are able to realize greater savings because they can take advantage of economies of scale. In particular, it can be noted that customers with higher load factors (i.e., flatter loads) are able to achieve greater percentage cost savings. This is because they need not install additional capacity or purchase from the IEM to meet peaking loads that are uneconomic to self-provide. Figure 101 indicates that this relationship is indeed a strong one.

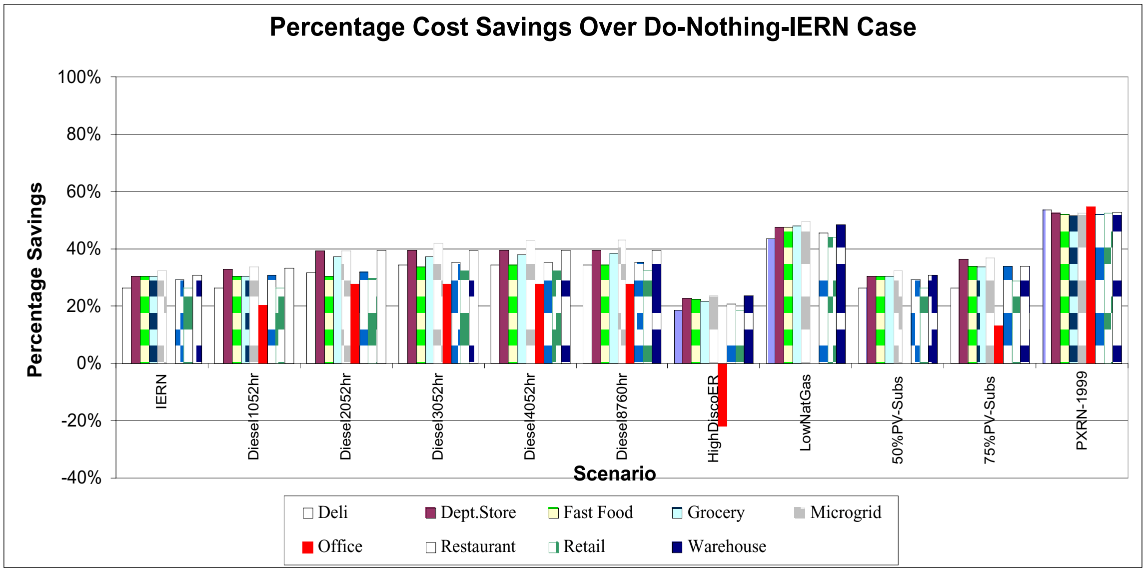

Figure 100. Savings Per Scenario/Activity Over Do-Nothing-IERN Case

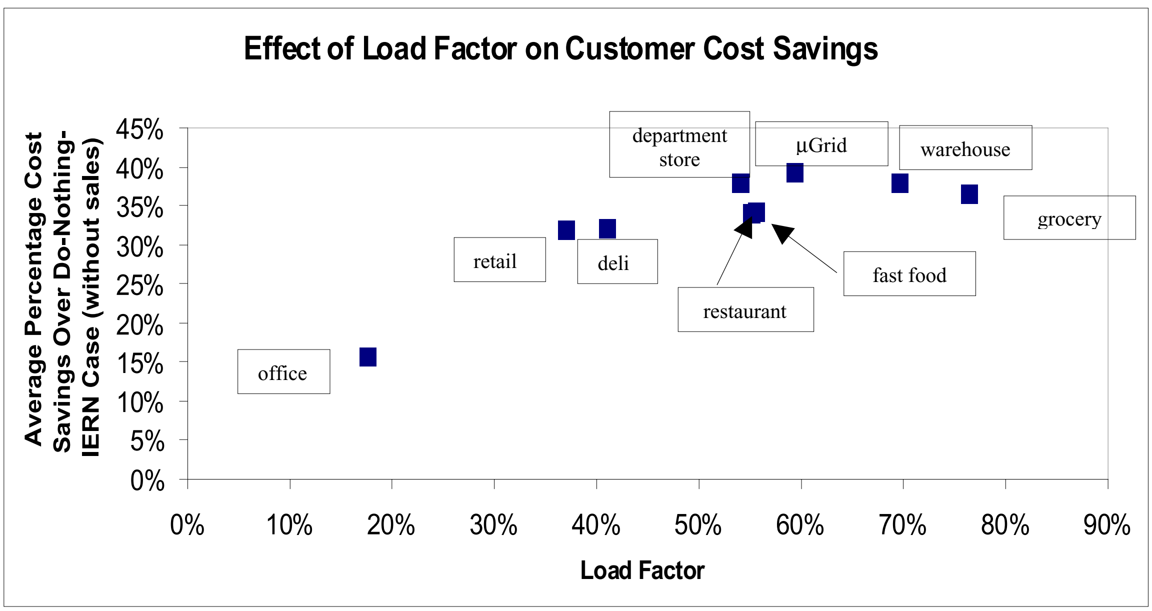

Figure 101. Effect of Load Factor on Customer Cost Savings

7.3.11.3 Power and Energy Coverage

Figure 102 and Figure 103 show that customers typically cover most of their peak demand and about half of their energy needs through installed capacity. The load factor again determines these results as the customers with lower load factors (e.g., the office, retail store, and deli) have relatively high peaks and install comparatively less capacity than other customers. Hence, they necessarily cover smaller fractions of their peak demand through installed capacity.

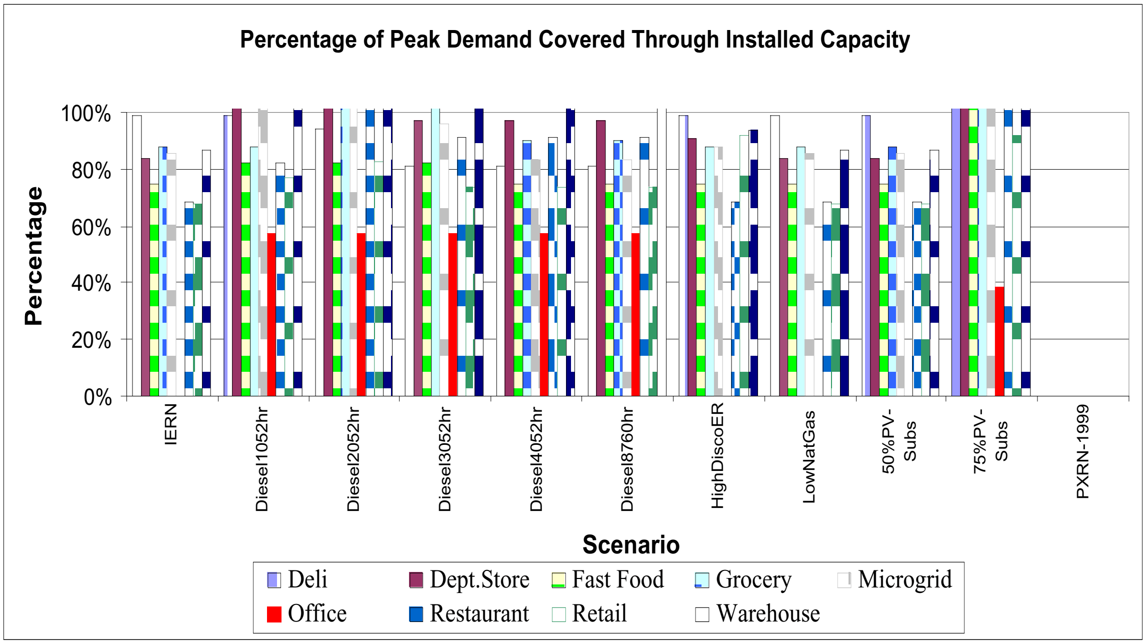

Figure 102. Percent Coverage of Peak Demand through Installed Capacity

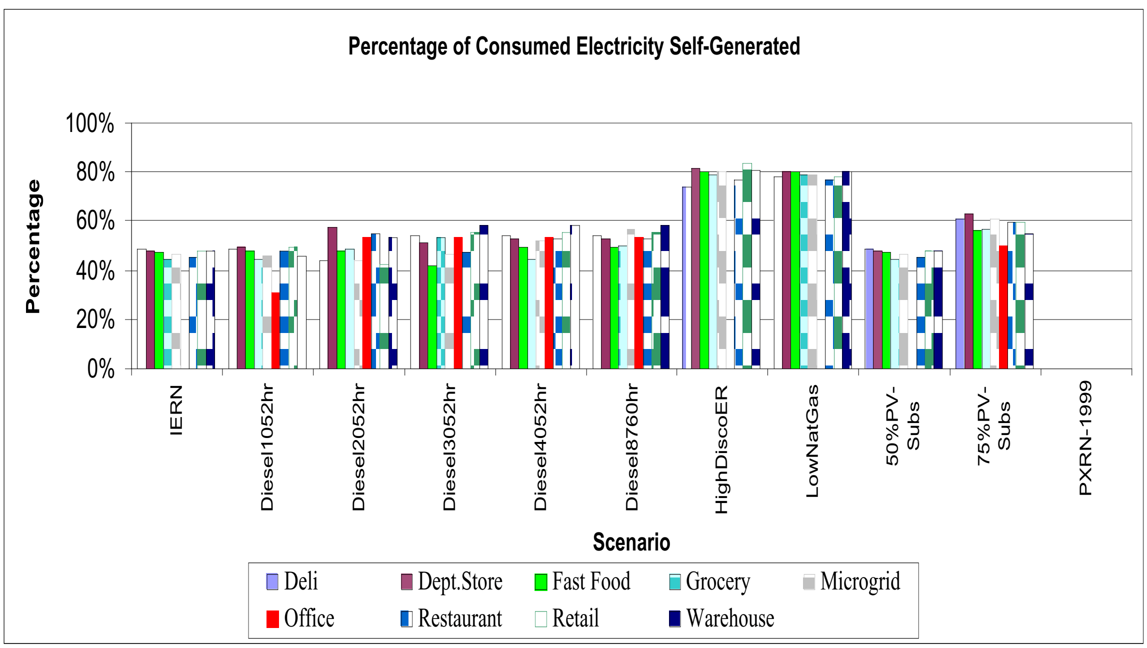

Figure 103. Percent Coverage of Consumed Energy through Installed Capacity

7.3.11.4 Comparison of Grocery with Microgrid Oaks

In this section, the advantages of belonging to a μGrid over isolated on-site generation are illustrated. The benefits of joining a μGrid arise from the fact that customers are better able to coordinate their activities. By sharing load information with other members of Microgrid Oaks, a typical customer benefits from the installation of on-site generation that realizes economies of scale. This allows for both greater flexibility in self-generation and some insulation from the potentially negative effects of high IEM prices. In effect, a typical customer gains most from the diversification of risks that is afforded by belonging to a μGrid.

Table 24. Comparison of Technologies Adopted (Grocery and μGrid)

Scenario	Grocery (Dangerway)	Microgrid Oaks
PXRN 1999	None	None
Low Natural Gas Prices	3 MT-AS-75	2 GA-K-500 / 1 MT-AS-75
IERN Sales 2000	100 MTL-C-30 / 100 MTH-C-30 100 MT-AS-75 / 100 GA-K-25 100 GA-K-55 / 100 GA-K-100 100 GA-K-215 / 100 GA-K-500	100 GA-K-500 / 100 GA-K-215 100 GA-K-100 / 100 GA-K-55 100 GA-K-25 / 100 MT-AS-75 100 MTH-C-30 / 100 MTL-C-30
IERN 2000	3 MT-AS-75	2 GA-K-500 / 1 MT-AS-75
IERN 2010	1 PEM-BA-250	4 PEM-BA-250
High DiscoER	3 MT-AS-75	1 GA-K-500 / 8 MT-AS-75
Do-Nothing IERN	None	None
Diesel 8,760 Hours	1 DE-C-200 / 4 DE-C-7	2 DE-C-500 / 7 DE-C-7
Diesel 4,052 Hours	1 DE-C-200 / 4 DE-C-7	2 DE-C-500 / 7 DE-C-7
Diesel 3,052 Hours	1 DE-C-500	2 DE-C-500 / 1 DE-C-200
Diesel 2,052 Hours	1 DE-C-500	3 DE-C-500
Diesel 1,052 Hours	1 GA-K-55 / 1 DE-C-500	1 GA-K-500 / 2 DE-C-500
75% PV Subsidy	2 PV-100 / 2 GA-K-55 1 MT-AS-75	9 PV-100 / 1 GA-K-500 / 3 MT-AS-75
50% PV Subsidy	3 MT-AS-75	2 GA-K-500 / 1 MT-AS-75

In Table 24, the technologies adopted by the grocery and μGrid are compared. Because of its larger load, the μGrid installs more onsite generation except in the perverse IERN-Sales-2000 scenario. It is of note that the DER technologies chosen for the grocery are also selected by the μGrid. Furthermore, the total capacity installed by the customers acting individually is less than the total capacity of the corresponding μGrid scenario. This reflects the economy of scale aspect of the model: the μGrid is able to install larger generators that produce cheaper energy per kWh than a set of smaller generators would.

In Figure 104 and Figure 105, the installed capacities and peak loads for the grocery and μGrid, respectively, are presented. In each case, the PXRN-1999 scenario discourages any onsite installation whereas both the Diesel-2,052-hour and 75%-PV-Subs scenarios encourage installation of diesel and PV technologies, respectively. The μGrid's ability to capture economies of scales is illustrated in the other three scenarios. In particular, the μGrid installs larger-capacity units (greater than 500 kW each) to meet its base load, and smaller capacity units (such as the 75-kW microturbine) to cover some of its peak load.

In contrast, the grocery usually installs several units of the smaller capacity generators to meet its base load. Only in the Diesel-4,052-hour scenario is the grocery able to install a generator specifically to cover its peak load. Hence, this implies that the µGrid realizes cost savings by installing generators that have specific purposes, e.g., to cover peak load. Because of its smaller size and lack of coordination with other market participants, the grocery is unable specialize. Consequently, it is often forced to meet its peak load needs through the IEM, a potentially negative market exposure that the µGrid is able to avoid. Also, the lumpiness of technology favors the larger install action. This shows up in the diesel-2,052-hour scenario, which results in a much more extreme overinvestment for Dangerway than for Microgrid Oaks.

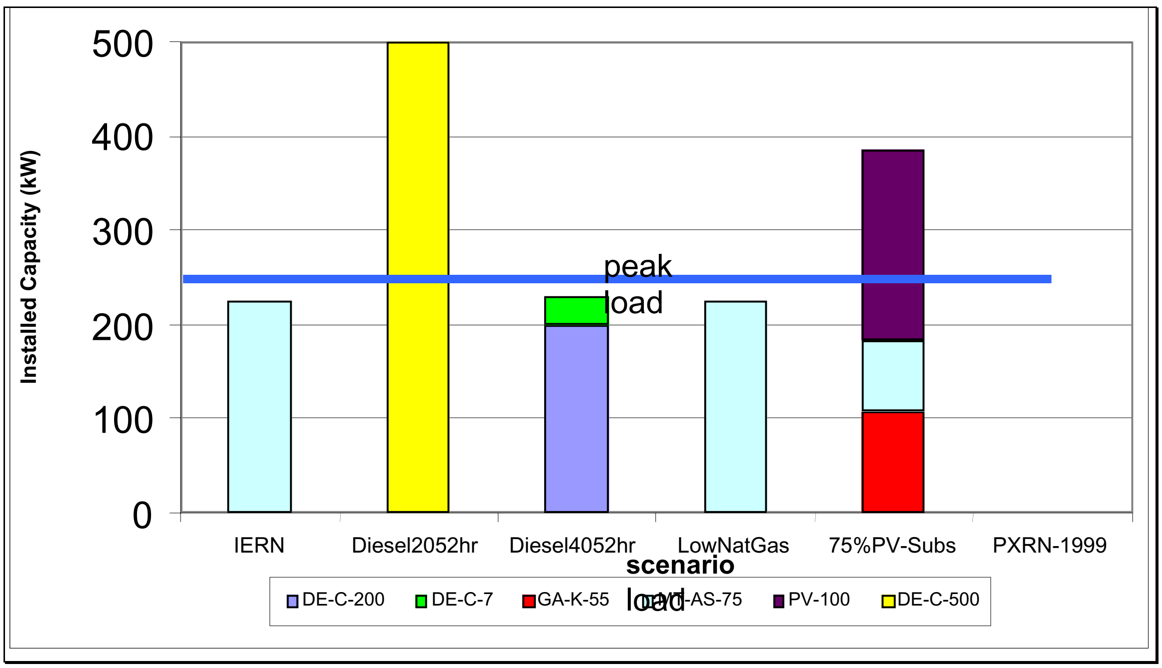

Figure 104. Installed Capacity and Peak Load for Grocery

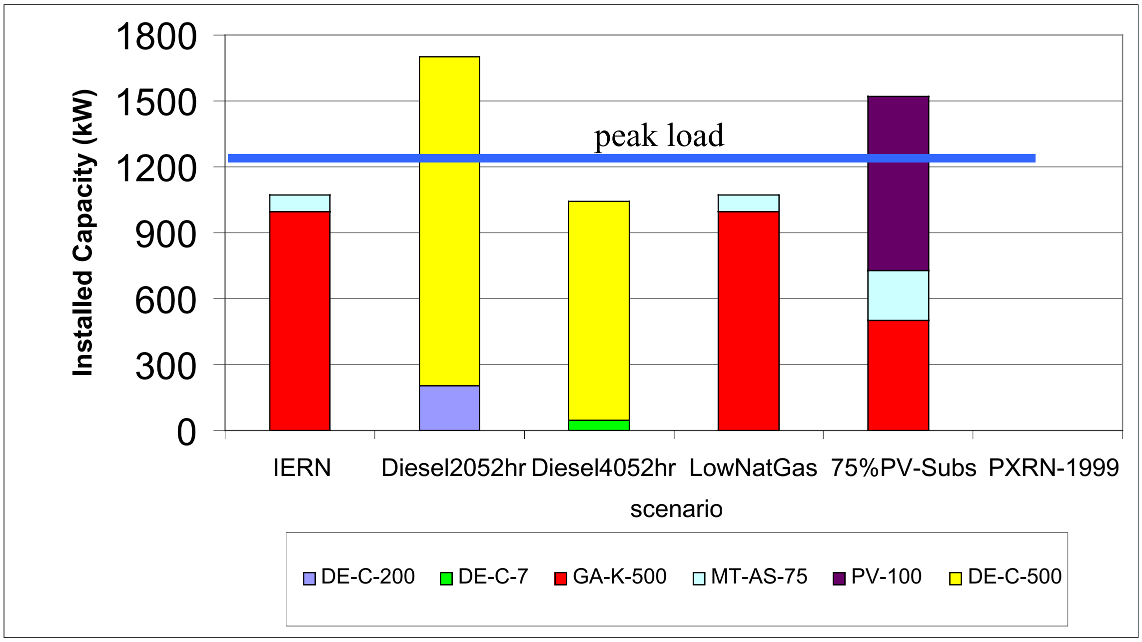

Figure 105. Installed Capacity and Peak Load for µGrid

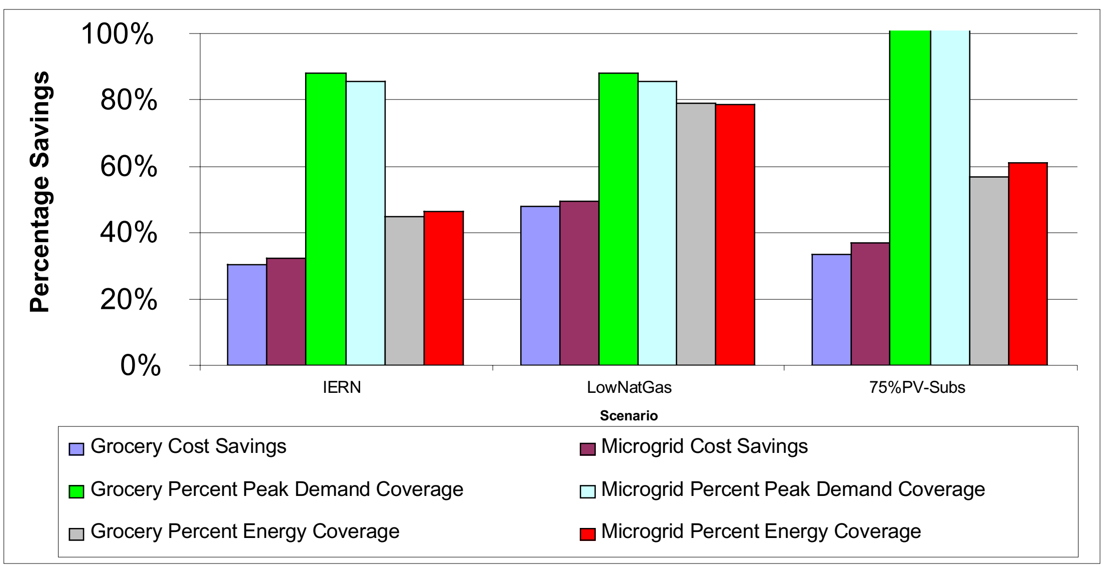

Figure 106. Comparison of Results for Grocery and µGrid

From Figure 106, it is evident that the µGrid realizes greater cost savings than the grocery does. Again, the µGrid's ability to install specialized machines and to coordinate the actions of the market participants appear to contribute to its lower costs. Indeed, across all scenarios, the grocery installs more capacity (as a percentage of its peak demand) than does the µGrid. Nevertheless, the µGrid usually covers more of its energy needs with this reduced installed capacity than does the grocery. This result is an illustration of the gains in efficiency that can be achieved through the strategic coordination that the µGrid enables.

7.4 Conclusions

In general, we find that installation of generation capacity is attractive to customers under a variety of circumstances. Only in the case with low and stable 1999 PX prices is it unattractive for the grocery to install any capacity. Although this installed capacity is used to generate a significant proportion of the customer s energy (more than 50% in most cases), there are no scenarios, given the set of IEM prices, in which the customer opts to disconnect fully from the grid (see Figure 103).

A comparison of the results for the µGrid and the grocery indicate that the µGrid is able to make more efficient use of its installed capacity. This is because of its ability to coordinate the actions of the various customers in order to realize economies of scale and install specialized on-site equipment. The customers in a µGrid, therefore, are able to diversify their risks by insulating themselves from the negative effects of high IEM prices or other external factors.

8. Summary, Conclusions, and Future Work

This report describes work recently completed for the CEC at the Berkeley Lab under the CERTS DERI project. Work has focused on the continued development and application of DER-CAM, an economic model of customer adoption of DER, implemented in the GAMS optimization software. DER-CAM finds the cost-minimizing combination of on-site generation that a customer could have had installed during a test year, the year 2000 for this study. The contrast between the early and late parts of the year and the high and volatile prices created provide an excellent opportunity to exercise DER-CAM.

Work focused on two areas: first, the acquisition of somewhat more accurate data than previously used for on DER technologies, including the development of methods for forecasting cost reductions for these technologies; and, second, the creation of a credible California example µGrid that can be applied in this study and in future work.

Data were collected from diverse sources to form a data set containing reasonable cost and performance parameters for about 30 DER options available for installation today. The data set includes two microturbines, a commercial FC, small wind and PV systems, and a wide range of reciprocating engines burning both diesel and natural gas fuel. Installation costs for these technologies were estimated using a standard engineering handbook. A data set representing possible equivalent data for 2010 was also developed, with some emphasis on forecasting of FC costs for that year. Consequently, the 2010 data set includes two additional FC technologies and an FCV. Costs for these technologies were estimated using a combination of experience curves and literature review.

DER-CAM makes these technologies available to a group of eight customers in a hypothetical strip mall in San Diego called Microgrid Oaks. The businesses that make up this mall are a supermarket, an office, a department store, a warehouse store, a smaller store, and three restaurants. These fictitious businesses have electricity loads that are based on actual end-use metering of southern California commercial buildings. In the scenarios reported below, each of the customers was individually offered the same options to self-generate electricity. Additionally, Microgrid Oaks, formed as the consolidation of its member customer loads, is also run through DER-CAM to find the optimal combination for the mall as a whole.

DER-CAM was run for the businesses in Microgrid Oaks individually and for the mall as a whole under 13 different scenarios. In the base, IERN, scenario, customers buy electricity at the IEM price and cannot sell electricity; natural gas costs 8.25 $/GJ, and diesel fuel costs 8.46 $/GJ. Use of diesel generators is restricted for air quality reasons to 52 h/a. Customers who install DER significantly lower their electricity costs over a do-nothing scenario, in the case of the grocery from 13.6 to 9.4 ¢/kWh. Microturbines are the most attractive technology to customers with high load factors, and gas-fired reciprocating engines appear in the choices of Microgrid Oaks as a whole and of several individual customers. In the case of Microgrid Oaks, a large (500-kW) natural gas engine is chosen because it offers noticeable economies of scale.

When the constraints on use of diesel engines are relaxed, diesel generators prove to be highly attractive, and, economies of scale make bigger machines more desirable. It appears that improvement in the environmental performance of these machines (resulting in looser permit conditions) could make them highly attractive, from a regulatory viewpoint, for self-generation.

When PV systems are heavily subsidized, they become an attractive option. Interestingly, because PV power is only available in daylight hours, gas engines and microturbines are typically installed as well, yielding the interesting result that, when PV is selected as part of a customer s DER mix, most customers individually and Microgrid Oaks as a whole install more generating capacity than their own peak demand, an outcome rare elsewhere. In this case therefore, Microgrid Oaks would be able to sell power, even at the time of its own peak demand. Unfortunately, sales to the grid could not be allowed in this study because the IEM price was so high relative to the fuel price that generation became enormously profitable and Microgrid Oaks would essentially be turned from a retail mall into a power generating station, a perverse result. In future work, however, the phenomenon of PV resulting in higher capacity installation could prove very interesting because it permits Microgrid Oaks to readily participate in interruptible load markets.

In most of the reasonable scenarios, customers save 20 to 40% on their 2000 electricity bills by self-generating, and higher-load-factor and larger customers do better. Joining customers together in the µGrid both raises load factor and increases overall size, so customers do gain by forming the µGrid although not enormously. However, to restore perspective, the PXRN assumptions, which replace the 2000 IEM prices with the 1999 PX prices, result in no DER adoption at all, and customers still save about 50% on their bills relative to the IERN case.

Although installed capacities for the year 2000 are quite high in this study, almost always between 60 and 100 % of peak demand, shares of energy self-provided are much lower, typically 40 to 60% of consumption. Naturally, self-provision is uneven during the year, there is less in the low-price first few months than during the high-price periods of the latter part of the year.

Future work will progress in several directions. The first and most important improvement to DER-CAM will be, the incorporation of CHP technology and the joint optimization of electricity and heat (in the case of California, invariably natural gas) consumption.. The use of waste heat on site could be one of DER s strongest attractions, and evaluating this size of this potential benefit for California s moderate climate will significantly improve the value of DER-CAM s results. To this end, data on CHP technologies are being collected, estimates of heat load shapes for Microgrid Oaks that were, not available in the original data set are being made, and DER-CAM is being extended to accommodate these data. The second imminent enhancement to DER-CAM will be the incorporation of interruptible load market participation into the µGrid s economic opportunities. Another economic benefit of on-site generation stems from the opportunity it creates to offer load shedding to grid operators. In California, this would most likely be in the form of participation in a program akin to the CAISO s Demand Response Program (DRP). In this program, customers receive a fixed capacity payment during the summer months for offering to shed load in response to CAISO requests and also receive an energy payment equivalent to the IEM price for the unserved energy. A µGrid could readily participate in such a market by employing its on-site generation to displace a fraction of its load at times that it would otherwise not expect to be self-providing. Although it may seem that the times of CAISO interest in invoking the DRP are likely to also be times of high electricity prices so that the µGrid would likely already be self-providing and could not reduce load, in fact DRP has been lucrative even when capacity prices were high enough to possibly stimulate the installation of higher DER capacities. One of the keys to analyzing this problem correctly is enhancing the model to account for the random nature of calls for load shedding.

Beyond these issues, numerous other improvements to DER-CAM are on the agenda, including simulation of forced equipment outages and optimization over longer time periods, so that the effect of improving technology can be directly addressed, along with joint optimization of loads and generation.

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