LBNL-62869

ERNEST ORLANDO LAWRENCE BERKELEY NATIONAL LABORATORY

Distributed Generation Dispatch Optimization under Various Electricity Tariffs

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June 2007

http://eetd.lbl.gov/ea/EMS/EMS_pubs.html

accepted to be published in the International Journal of Electronic Business Management Vol. 5, No. 3 (2007).

This research builds on prior energy manager work coordinated by the Consortium for Electric Reliability Technology Solutions and funded by the California Energy Commission, Public Interest Energy Research Program, under Work for Others Contract No. BG 99-396 (00). The Assistant Secretary of Energy Efficiency and Renewable Energy, former Distributed Energy Program of the U.S. Department of Energy (under contract) and the California Public Utilities Commission, Division of Ratepayer Advocates have also provided support on related work.

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DISTRIBUTED GENERATION DISPATCH OPTIMIZATION UNDER VARIOUS ELECTRICITY TARIFFS

Prepared for the

Office of Electricity Delivery and Energy Reliability

U.S. Department of Energy

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Acronyms and Abbreviations

CAISO	California Independent System Operator
CHP	combined heat and power
COP	coefficient of performance
CPP	critical peak pricing
DG	distributed generation
EIA	U.S. Department of Energy's Energy Information Administration
HHV	higher heating value
kWh	kilowatt hour
MILP	mixed integer linear program
P&DC	USPS Processing and Distribution Center
PV	photovoltaics
RT-OPTICOM	Real Time Optimal Control Model
RTP	real time pricing
SDG&E	San Diego Gas and Electric
TOU	time of use
USPS	United States Postal Service

Acknowledgements

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The authors would also like to thank:

- Bill Golove and Joe Vandenberg for their help and permission to access data for the San Diego P&DC,
- Russel Seibert for providing an extensive site tour of the San Diego P&DC,
- Todd Cahill for providing historic SDG&E tariff data, and
- Owen Bailey, Alex Farrell, Karl Magnus Maribu, Afzal Siddiqui, and Michael Stadler for input at various stages of this project.

Abstract

The on-site generation of electricity can offer building owners and occupiers financial benefits as well as social benefits such as reduced grid congestion, improved energy efficiency, and reduced greenhouse gas emissions. Combined heat and power (CHP), or cogeneration, systems make use of the waste heat from the generator for site heating needs. Real-time optimal dispatch of CHP systems is difficult to determine because of complicated electricity tariffs and uncertainty in CHP equipment availability, energy prices, and system loads. Typically, CHP systems use simple heuristic control strategies. This paper describes a method of determining optimal control in real-time and applies it to a light industrial site in San Diego, California, to examine: 1) the added benefit of optimal over heuristic controls, 2) the price elasticity of the system, and 3) the site-attributable greenhouse gas emissions, all under three different tariff structures. Results suggest that heuristic controls are adequate under the current tariff structure and relatively high electricity prices, capturing 97% of the value of the distributed generation system. Even more value could be captured by simply not running the CHP system during times of unusually high natural gas prices. Under hypothetical real-time pricing of electricity, heuristic controls would capture only 70% of the value of distributed generation.

Distributed Generation Dispatch Optimization Under Various Electricity Tariffs

1. Introduction

The on-site generation of electricity can offer building owners and occupiers financial benefits as well as social benefits, such as reduced grid congestion, improved energy efficiency, and reduced greenhouse gas emissions. Combined heat and power (CHP), or cogeneration, systems make use of the waste heat from the generator for site heating needs. Heat can also be used to provide cooling using a heat-activated chiller or to reduce electric cooling loads using a desiccant dehumidifier. CHP applications are typically what make on-site fossil-fired thermal generation both economic and energy and carbon efficient.

This distributed generation (DG) of electricity is becoming economically attractive for more, varied, and smaller commercial and industrial sites. While the economics of DG have become compelling in many cases, there are often significant and even insurmountable barriers to adoption. Many of these barriers are identified in [1] and categorized as:

- **technical** – utility requirements that may be redundant to DG system equipment capabilities,
- **business practice** – contractual and procedural requirements of the utility for interconnection, and identification of people within the utility with knowledge of the technology and the authorization to act on the utility's behalf, and
- **regulatory** – tariff structures specific to DG customers may burden the customers with excessive fixed costs or penalties.

An additional barrier to DG adoption is institutional, as described in a business case study of an industrial DG site [13]. The barrier consists of 1) the need within an institution for an individual or individuals to champion an activity that departs from the status quo (both within the institution and the industry, and 2) the risk to reputation and status that championing brings with it.

These barriers are being weakened as DG becomes more prevalent. While DG has traditionally been adopted by large (> 1-2 MW) industrial and commercial sites, reduced barriers, along with reduced equipment costs, public incentives, and increased public awareness, have made DG accessible to smaller, less sophisticated owners.

The optimal dispatch of a DG system is the least-cost solution to the supply of a site's energy demand by utility purchase, DG, or a combination of the two. Optimality requires minimizing a complicated cost function dependent on a non-linear electricity tariff, fuel prices that are changing over time, and stochastic site energy loads, equipment availability, and, in some cases, real-time electricity prices. Smaller DG installers typically rely on heuristic control strategies devised when the system was installed because custom-designed, intelligent controls were unavailable or prohibitively expensive.

Complicating matters is debate over appropriate electricity tariff structures. The marginal cost of central electricity production and delivery is time and location dependent. Traditional electricity tariffs have not efficiently passed such price fluctuations on to customers. Recent deregulation and improvements in metering capabilities are enabling tariff design that more accurately reflects the true costs of providing electricity.

Distributed Generation Dispatch Optimization Under Various Electricity Tariffs

This analysis quantifies the value of intelligent DG dispatch controls for a light industrial site in southern California. This is done by comparing energy costs and DG dispatch resulting from optimal and heuristic control strategies under three different tariff structures. The patterns of consumption under optimal control are also examined. Finally, the trade-off between cost-minimization and carbon-minimization is evaluated.

2. BACKGROUND

Optimal dispatch of a DG installation at each time-step depends on current site loads, energy prices, and DG system availability, as well as the actual structure of tariffs and uncertain forecasts of these parameters at future time-steps. This section describes common electricity tariff components and structures and recent research on DG dispatch optimization.

2.1 Electricity Tariff Structure

Unlike most goods, whose prices are set in open markets, the end-use supply of electricity is considered a natural monopoly good whose price is regulated on a cost-of-service basis. Utilities and their regulators typically set tariff elements to cover three kinds of costs:

- **Fixed** charges are invariant $/month prices. These are intended to recoup the infrastructure costs of supply and delivery that are incurred by the customer regardless of its energy consumption.
- **Volumetric** charges are proportional to the amount of energy consumed. They are expressed in $/kWh and may vary by time of day or by monthly consumption. Volumetric rates are intended to cover the variable costs of producing electricity, such as fuel and variable labor requirements.
- **Demand** charges are expressed in $/kW and levied on the maximum power consumption during a specified time range (such as the on-peak hours of the month), regardless of the duration or frequency of that level of power consumption. Demand charges are intended to collect the fixed costs of infrastructure shared with other customers by raising revenue in proportion to the amount of power required by the customer when assets are stressed.

Volumetric charges for large customers typically have a time-of-use (TOU) structure: electricity is priced differently for pre-specified on-peak and off-peak hours (or for a greater number of time slices). However, TOU rates do not reflect the dynamic nature of deregulated energy markets. Market volatility and the potential for exercise of market power are stoked by consumption behavior that does not respond to market clearing prices: regular consumption during irregularly high or low prices keeps prices irregular, whereas consumption that responds inversely to price changes stabilizes prices [5].

Real-time pricing tariffs (RTP), which pass market clearing prices directly to customers, have become optional or mandatory in some U.S. jurisdictions. Critics of real-time pricing argue that consumers are unlikely to be diligent “energy brokers,” continuously responding to variations in price, but could be responsive to occasional large price spikes during times of severe system shortages. This is the rationale behind critical peak pricing (CPP), which uses a TOU structure punctuated by very high price spikes during anticipated critical episodes. The economic efficiency of RTP tariffs is demonstrated in simulation in [4], which also qualitatively shows that CPP tariffs would capture much of the efficiency improvements over flat rate tariffs, while TOU tariffs would not capture much. This paper does not specifically consider consumers with on-site generation, whose demand elasticity could be much greater than consumers without on-site generation because of the ability to switch between utility purchase and self-generation without reducing site demand. Recent utility experience with RTP tariffs is described in 3.

2.2 Distributed Generation Optimization

Common DG devices are reciprocating engines, gas turbines, microturbines, and fuel cells. For prime-power applications (as opposed to back-up power) in the United States, these devices are typically fueled by natural gas, biogas, or propane. In CHP applications, the heat generated by these devices is harnessed for application to site space, water, and process heating needs or to satisfy cooling loads using a heat activated chiller. Wind power or solar energy harvested by photovoltaics and/or solar thermal collectors are also options.

In addition to engineering constraints on DG system performance, regulators may impose constraints for environmental or other reasons. For example, in California, DG systems must maintain an annual average system efficiency of 60% to be eligible for certain subsidies. California has also recently mandated reductions in its greenhouse gas emissions; this may result in explicit carbon constraints on power production.

The economically optimal control of DG systems is complicated by uncertainty, nonlinearities, and intertemporal constraints. End-use loads, energy prices, and equipment availability are all uncertain; demand charges are nonlinear; and constraints such as annual minimum efficiency and emissions limits are inter-temporal. These conditions require that, at a given time, optimal scheduling must include not only dispatch for the current time, but also an optimal strategy for all points in the future.

A threshold control strategy for CHP dispatch optimization in the presence of demand charges is proposed in [8]. The authors assume deterministic loads and 100% reliable equipment. Prior to the start of each month, monthly system operation and costs are simulated under varying threshold levels. The threshold level with least-cost results is selected. For several Ontario, Canada, buildings examined, this paper illustrates that using threshold control, rather than control based solely on volumetric price ($/kWh), can lower the payback period of a CHP system investment by 2 to 3 years. This is one of the few papers to identify the dependency of DG system value on control strategy, particularly under the influence of demand charges. The authors also discuss excessive start-stop cycles as a practical concern of analytic dispatch optimization strategies.

The concept of a real-time, automated energy manager that receives relevant information about a building energy system (loads, costs, and equipment performance) and makes optimal dispatch decisions is discussed in [12]. Dispatch decisions might also include limited load curtailment or rescheduling opportunities. This concept is realized in an actual mathematical program described [11] in which it is used to evaluate the value of integrating a limited, voluntary electricity curtailment program into a building energy system that has already installed DG.

The model described in [11] is used in this work to determine the optimal dispatch for a case-study site. This optimal dispatch and resulting energy cost is compared to the current, heuristic control strategy employed at the site under three different tariff structures: TOU, CPP, and RTP. Section 3 describes the dispatch optimization model. Section 4 introduces the case-study site, a light industrial site in San Diego, California. Data collection procedures are described in Section 5. Section 6 describes the methods used in the analysis, and results of the optimization are presented in Section 7. Finally, Section 8 discusses these results and offers conclusions.

3. DISPATCH OPTIMIZATION MODEL

The Real-Time Optimal Control Model (RT-OPTICOM) described in [11] is used to determine the optimal dispatch of a DG system with limited curtailment opportunities subject to uncertainty in energy loads, energy prices, and DG equipment availability. RT-OPTICOM is a mixed integer linear program (MILP), for which various robust commercial solvers are available

.

In order to be expressed as a MILP, randomly generated scenarios are used to represent stochastic parameters. Each scenario contains randomly generated values of energy loads (non-cooling electric, electric, and heating), electricity prices, DG availability, and solar insolation. The optimization problem is discretized into time-steps in the range of minutes to an hour. It is solved sequentially at each time-step, although dispatch decisions made at each time-step must be made for the current time-step as well as for all future time-steps. All future dispatch decisions are conditional on future conditions; i.e., there is a separate decision for each scenario at each future time-step. Future optimization, or a strategy, is necessary because 1) electricity demand charges are non-additive, but rather are determined by the maximum over all time-steps in the month and 2) there are inter-temporal (annual) constraints such as regulatory limits on system efficiency and emissions.

RT-OPTICOM can be used for two purposes: real-time dispatch optimization and system simulation. For real-time dispatch optimization, past and current information is the actual information about the energy system (loads, equipment availability, prices), whereas for system simulation, the "actual values" are an additional randomly generated scenario or set of historic actual values. For either purpose, "actual values" for a particular time-step are not revealed to RT-OPTICOM until that time-step.

Figure 1 illustrates the parameters and variables at time-step *i* of timespan length *T*. Rows are different parameter or variables types. Columns are time-steps. Each box in the figure represents a set of data or variables for a particular time-step, *t*. The actual parameter values for all past and the current time-step ($0 \le t \le i$) are known and sent to RT-OPTICOM. For future time-steps ($t > i$), sets of stochastic possible parameter values are also sent to RT-OPTICOM. Finally, all previous dispatch decisions are sent to RT-OPTICOM. The program then determines the actual dispatch for the current time-step, *i*, and a set of dispatch plans, contingent on future parameter values, for all scenarios 1,...,*n* at all future times *i*+1,…,*T*.

		timestep,t 1	2	…	i	…	T
actual parameters	AP_t	parameters sent to RT-OPTICOM				unknown	
stochastic parameters	$SP_{1,t}$	unnecessary				parameters	
	$SP_{2,t}$					sent to	
	⋮					RT-OPTICOM	
	$SP_{n,t}$						
actual dispatch	AD_t	parameters sent to RT-OPTICOM				unknown	
dispatch strategy	$DS_{1,t}$	unnecessary				variables	
	$DS_{2,t}$					determined	
	⋮					in RT-OPTICOM	
	$DS_{n,t}$						

Figure 1. parameters and variables at time-step i of RT-OPTICOM

Figure 1 is explained mathematically in equation (1).

$$AD_i = argmin\left(E\left(cost\begin{pmatrix} AP_1,\ldots, AP_i, \\ SP_{1it+1},\ldots SP_{n,i+1},\ldots, SP_{1,T},\ldots, SP_{n,T}, \\ AD_1,\ldots, AD_{i-1}, AD_i, \\ DS_{1,i+1},\ldots DS_{n,i+1},\ldots, DS_{1,T},\ldots, DS_{n,T}, \end{pmatrix}\right)\right) \tag{1}$$

where

- i is the current time-step
- T is the last time-step of the timespan
- $E(cost())$ is the expected energy costs for the timespan 1 to T
- AD_t is the actual dispatch at time-step t (a parameter for $t < i$, a variable for $t = i$)
- AP_t is the actual scenario parameter values (known for $t \leq i$)
- $SP_{j,t}$ is the randomly generated parameter values for stochastic scenario j at time-step t (known for all t, but replaced by AP_t for all $t \leq i$)
- $DS_{j,i}$ is the planned dispatch for stochastic scenario j at time t (a variable for all j and for all $t > i$)

4. CASE STUDY – SAN DIEGO, CALIFORNIA, INDUSTRIAL SITE

In order to examine optimal control and the effects of tariff structure on system control and performance, the United States Postal Service's (USPS) Margaret L. Sellers Processing and Distribution Center (P&DC) in San Diego, California, was selected as a case study. This site sorts and routes all outgoing mail from the San Diego region, and receives and routes all incoming mail to the region. In all, it handles approximately 12 million pieces of mail daily. Energy consumption patterns are conducive to DG. Due to the schedule of mail collection and sorting, the site has a nighttime peak electricity load of approximately 2.5 MW. Loads are dominated by the large mail-handling machines, which in turn necessitate a significant cooling load. The year-round moderate climate and consistent machine loads result in a year-round cooling demand.

A DG system was recently installed at the site consisting of a 1.5 MW natural gas fired reciprocating engine coupled to a 1 MW (280 ton) absorption chiller. At rated capacity, the absorption chiller offsets 250 kW of electric load from the compression chillers. Additionally, 12 kW of PV are installed at the site.

The CHP equipment is owned and operated by a third party. Electricity and heat are provided at lower cost than the electricity and natural gas utility provides. The system uses a load-following control; i.e., the generator is run as high as possible at all times.

For this research, the cogeneration owner and the P&DC site are treated as a single entity; i.e., the structure of transactions between the two parties is not considered here. This is realistic because the utility bills of both parties are additive, and any payments between them are internal transactions that do not affect the total paid to the local utility.

This research examines the economic efficiency of this load-following control strategy by comparing energy costs from a load-following strategy to those from an optimal dispatch control strategy. Additionally, it examines the optimal control results under other tariff structures. Critical peak pricing (CPP) tariffs are already offered as an optional tariff by the utility. Real-time pricing (RTP) could possibly be offered or imposed in the future.

5. DATA COLLECTION

This section summarizes the data collection process. The appendix describes the stochastic models of energy demand, DG availability, energy prices, and solar insolation that are based on these data.

5.1 Energy Loads

Utility electricity consumption data at the site were available electronically from December 2002 until the present. Detailed chiller logs and total electricity consumption were available from a similar P&DC site in Redlands, California [2]; from these data, the correlation of cooling loads to total electric loads was determined separately for daytime and nighttime periods in each month and applied to the San Diego site, thus developing a cooling load model. Redlands heating loads were scaled to the size of the San Diego site; these loads are minor relative to the electric loads at the site.

Figure 2 and Figure 3 show electric loads, disaggregated by non-cooling and cooling loads, for typical weekdays in January and July respectively. Non-cooling electric loads include the mail handling machinery, lighting, and office equipment. The magnitude of these loads varies by day of week and time of year, primarily because of variations in mail volume. Cooling loads are present at all hours of the day, during all months because the heat given off by the machinery must be removed from the building. Cooling loads are correlated to non-cooling loads, and also outside temperature. From these figures, the sites' night-time peaking load can be observed – most mail sorting (i.e. machinery running) is done at night because mail is collected during the day.

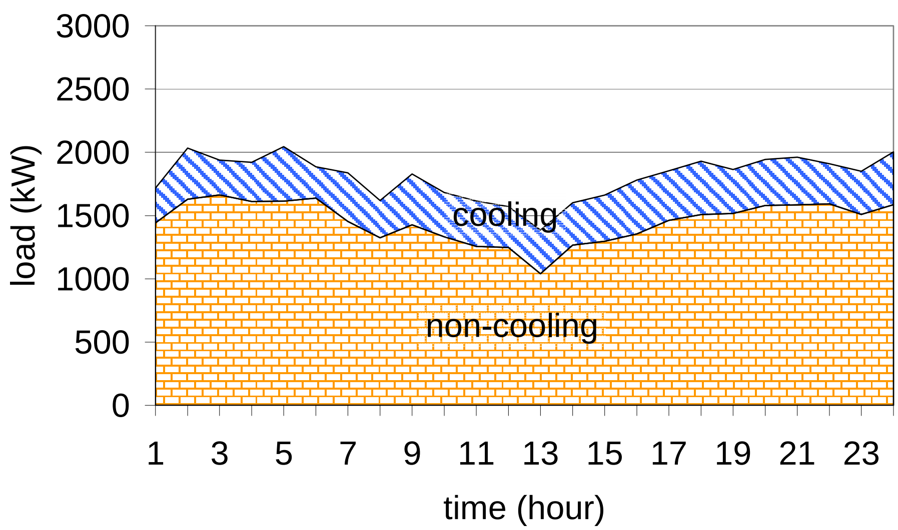


Figure 2. electric loads for a typical weekday in January

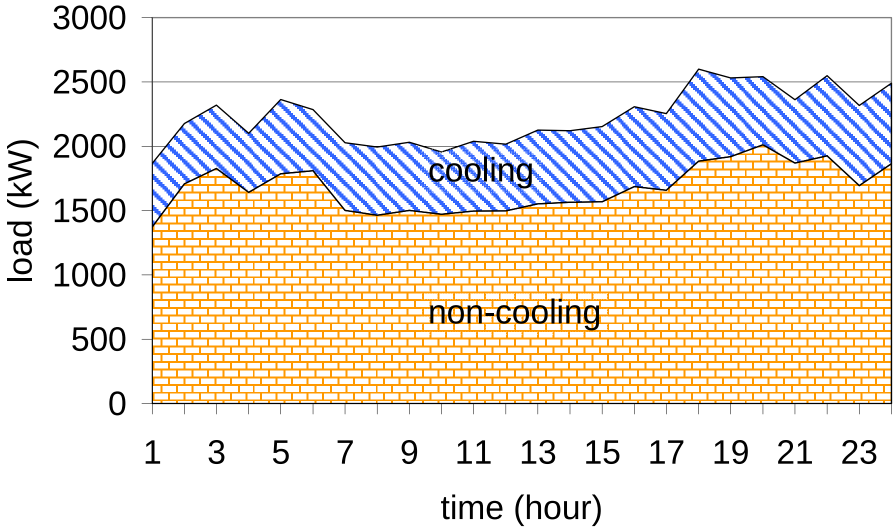


Figure 3. electric loads for a typical weekday in July

5.2 Energy System Characteristic

Details of the CHP system were obtained through interviews with relevant managers and operators at the site, and manufacturer specifications. The generator has an electrical efficiency of 36% (higher heating value) at rated capacity, and the absorption chiller has a coefficient of performance (COP) of 0.7. System availability was estimated from the site's electric load data by observing the times since the CHP installation that an offset in utility consumption was not present. An availability of 98% was used for this research. The electric chillers at the site have a COP of 4. The photovoltaic system output is assumed to be proportional to solar insolation.

5.3 Energy Prices

Electricity prices were collected from San Diego Gas and Electric (SDG&E) for the years 2004 to 2006 [14] and [17]. The default tariff for this site is a TOU structure with an optional CPP tariff also available.

A hypothetical RTP tariff was constructed because the utility does not currently offer one. Demand charges and the delivery portion of volumetric charges from the reported TOU tariff were used. In the place of the TOU rates for electricity supply, however, the actual spot market clearing prices for the San Diego region, SP15, from January 2004 through December 2006 [6] were used. These prices were correlated to the month of the year, hour of the day, and day-type (weekday or weekend) to develop a model of clearing prices, including stochastic terms.
It should be noted that in the models developed, the site energy loads were not correlated to spot market clearing prices, other than through monthly variation in the load and clearing price models. In reality, these two variables are strongly correlated for many customers, particularly during hot weather, when air conditioners raise site loads and (often) clearing prices. Similarly, in regions with significant amount of electric heating, very cold weather can have the same

effect. However, for this particular site, the omission probably does not have a large effect: San Diego has a very mild year-round climate and the site's loads, including peak loads, are dominated by mail handling machinery, not by air-conditioning. Furthermore, significant air conditioning loads are always present (see Figure 2 and Figure 3); the incremental increase in cooling loads because of hot weather is not as dramatic as for a typical customer.

Table 1 summarizes 2005 electricity prices for TOU and CPP. The CPP tariff has a TOU structure with exaggerated on-peak costs during CAISO determined critical event days. The tariff limits the number of critical event days to 6 per month, 12 per year. From 12 p.m. to 3 p.m. on a critical event day, on-peak prices are 2.3 times higher than the on-peak TOU rate. From 3 p.m. to 6 p.m., on-peak prices are 5.9 times higher than the on-peak TOU rate. In exchange for this price increase, on- and mid-peak rates during noncritical days are reduced by 10% over the TOU rates. Real-time clearing prices for zone SP15 in the first weeks of January and July 2005 are shown in Figure 4 and Figure 5. A distribution charge of $0.015/kWh is added to the clearing prices to complete the hypothetical RTP volumetric charge.

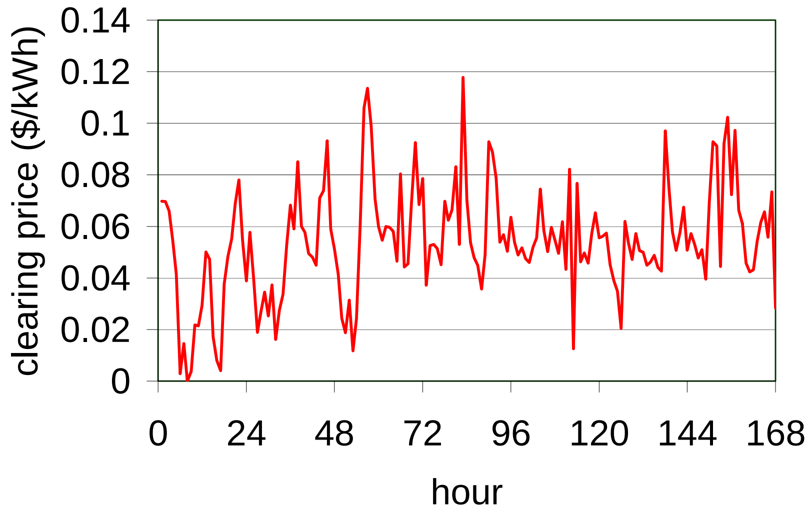
Table 1. TOU and CPP rates for SGD&E small industrial customers, 2005

source: CAISO (2006)

2005 TOU electricity prices			
		summer	winter
fixed ($/month)		335	
volumetric ($/kWh)	**on-peak**	0.119	n/a
	mid-peak	0.076	0.083
	off-peak	0.066	0.068
demand ($/kW)	**on-peak**	18.11	n/a
	mid-peak	2.5	n/a
	off-peak	0	n/a
	all hours	7.56	

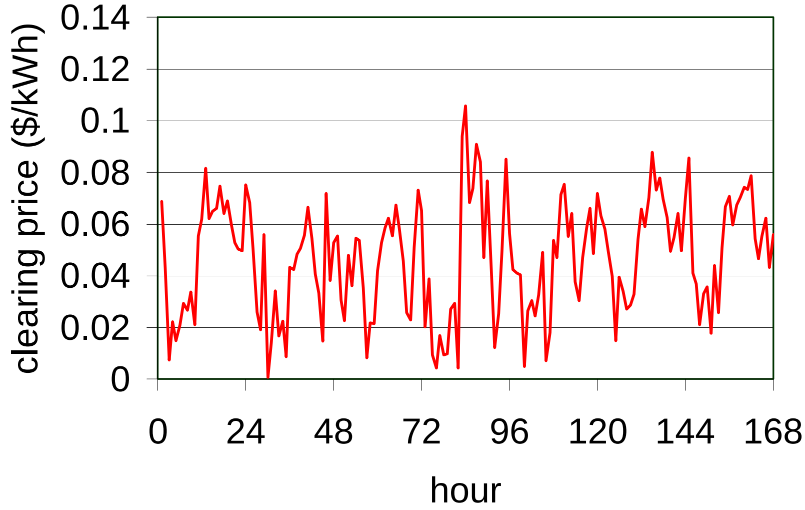
2005 ratio of CPP to TOU volumetric prices	
	ratio
noncritical on-peak hours	0.9
noncritical mid-peak hours	0.9
noncritical off-peak hours	1
critical moderate peak***	2.3
critical high peak****	5.9

**there is a maximum of six critical episodes per month*
***there is a maximum of 12 critical episodes per year*
**** moderate peak is from 12:00 PM to 3:00 PM*
***** high peak is from 3:00 PM to 6:00 PM*



source: CAISO (2006)

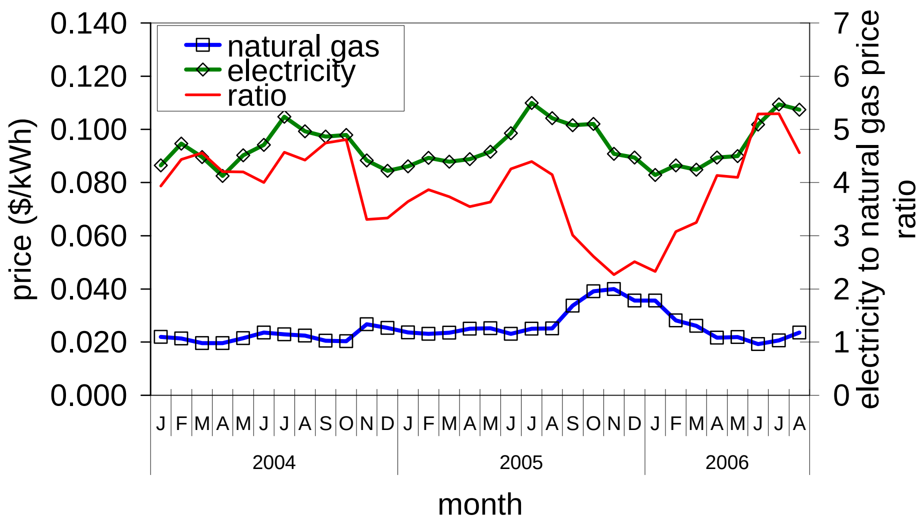
Figure 4. Zone SP15 spot market clearing prices for January 1-7, 2005



source: CAISO (2006)

Figure 5. Zone SP15 spot market clearing prices for July 1-7, 2005

Current natural gas prices were collected from SDG&E. Data from the U.S. Energy Information Administration (EIA) for city gate natural gas prices in California were added to current distribution costs to estimate historic natural gas prices. For each month long simulation/optimization, the price of natural gas was assumed to be constant and deterministic. These prices for 2004 through 2006 are plotted in Figure 6, along with the average California retail industrial electricity price, as reported by the EIA. The ratio of electricity to natural gas price is also plotted to illustrate the volatility of this ratio, or spark spread, which has ranged from 2.3 to 5.3 in less than three years. Given that DG converts natural gas to electricity, optimal dispatch must be responsive to the relative fluctuations in these two commodities' prices.



source: EIA

Figure 6. electricity and natural gas prices for January 2004 to August 2006 and the ratio of electricity to natural gas price

5.4 Solar Insolation

Historic solar insolation data were collected from [16].

5.5 Carbon Emissions

The average marginal rate of carbon emissions for SDGE reported in [15], 0.181 kgC/kWh, was used to determine site specific carbon emissions from utility electricity consumption. The carbon intensity of natural gas is 0.052 kgC/kWh; this is the higher heating value (HHV).

6. METHOD

Simulations of site energy demand and production were performed in order to determine optimal dispatch and compare optimal performance to performance under heuristic control. Energy performance at the site was simulated for each of the 36 months from January 2004 to December 2006 (estimates of energy prices were used for October, November, and December 2006). Simulations were repeated for three different tariff structures (TOU, CPP, and RTP) and for four control strategies:

- **optimal dispatch** – The full optimization program is used to make dispatch decisions.
- **load-following** – The generator is run as much as possible, mimicking the site's current strategy.

- **no-DG** – The generator and absorption chiller are not run, showing site behavior prior to DG installation.
- **heat-following** – The generator is dispatched to run at a level for which all recovered heat will be useful to the absorption chiller.

The simulation was carried out separately for each combination of tariff structure and control strategy. The same stochastic load, equipment availability, and solar insolation data were used for each combination of tariff structure and control strategy. Although not used directly for pricing, the same RTP prices were used in the CPP simulations to identify critical periods for the CPP tariff that were aligned with the critical periods in the RTP simulations. By using the same parameter values for each combination of tariff structure and control strategy, the true performance comparison of different control strategies and different tariff structures was possible.

For the optimal control strategy, each month-long simulation iteratively applied the optimal dispatch algorithm described above to each successive hour of the month. For non-optimal control strategies (load-follow, no-DG, and heat-follow), dispatch was constrained to follow the specified control strategy.

7. RESULTS

Monthly energy costs (electricity and natural gas) for the site are plotted in Figure 7 through Figure 9. Each figure plots these costs under each control strategy for a single tariff structure. Heat-follow results have been omitted from these figures and all subsequent results because they are nearly identical to the load-follow results; i.e., the cooling load is large enough and consistent enough that there is always a use (the absorption chiller) for any heat the generator produces. For TOU and CPP structures, optimal dispatch and load-following result in nearly identical costs for all but a few months in 2005 and 2006. These are months of relatively high natural gas prices. These graphs illustrate that load-following results in near-optimal energy costs for most months. However, these graphs also show that during months of particularly high natural gas prices (September 2005 – January 2006) it is more expensive to run the DG as much as possible than not at all. For the RTP tariff structure, the costs under optimal control are lower than under either load-follow or no-DG, suggesting that a more sophisticated control strategy is justified.

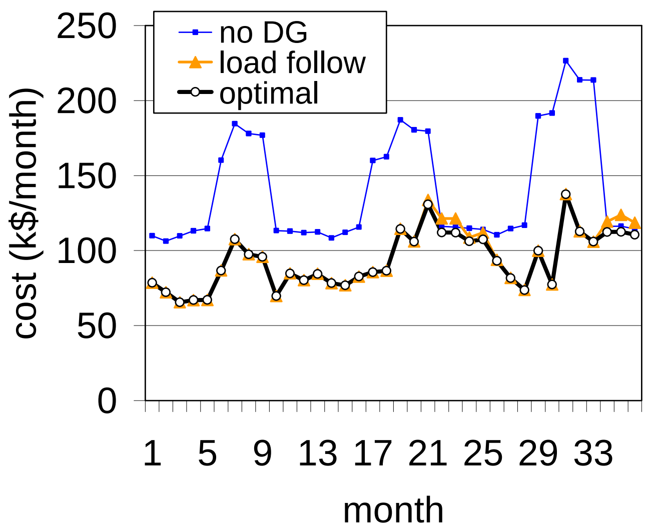


Figure 7. monthly costs under TOU tariff and three control strategies from 2004 to 2006

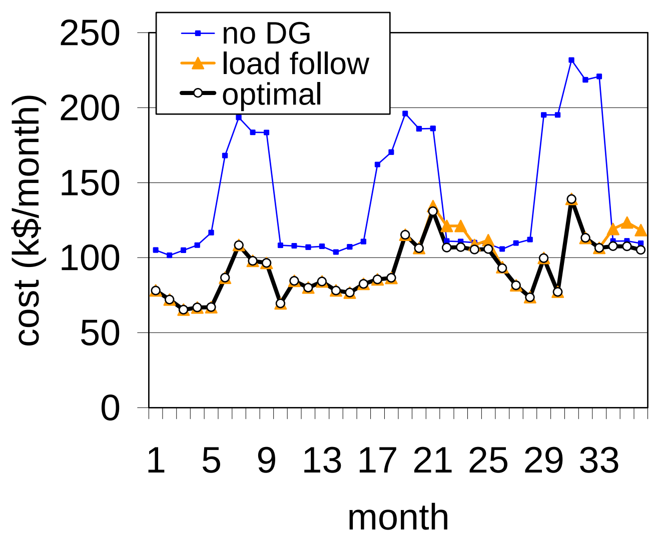


Figure 8. monthly costs under CPP tariff and three control strategies from 2004 to 2006

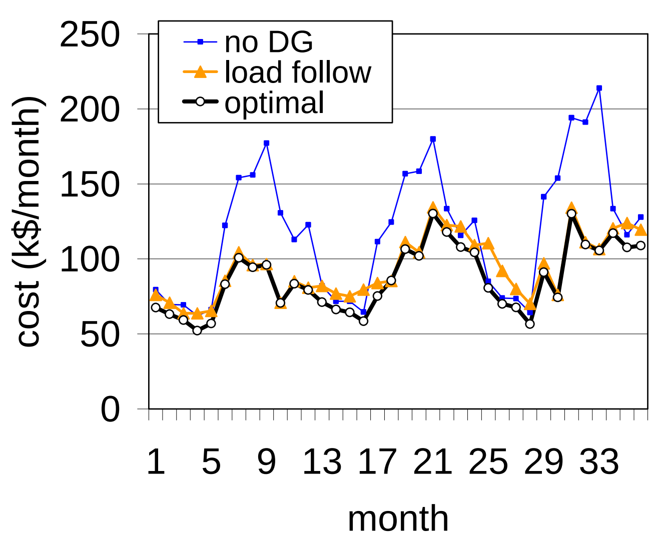


Figure 9. monthly costs under RTP tariff and three control strategies from 2004 to 2006

Figure 10 through Figure 15 summarize the annual energy costs and energy cost savings (over no-DG dispatch) for the three years considered under each of the three tariff structures. For a site considering DG, these values could be used to determine if the investment in DG is economic, given the cost of a proposed DG system. From these figures, the added benefit of optimal control over load-follow control is observed: for TOU, the average annual added benefit is $19,000, for CPP, it is $28,000, and for RTP, it is $90,000.

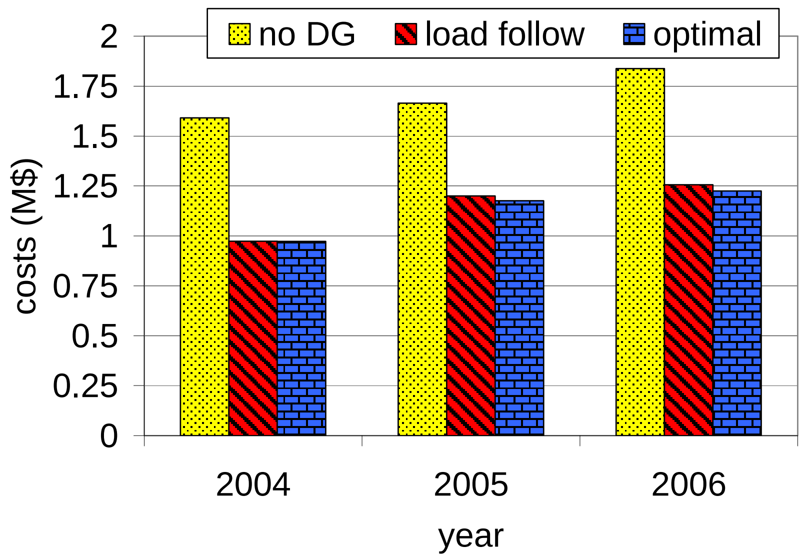


Figure 10. annual energy costs under TOU tariff and three control strategies

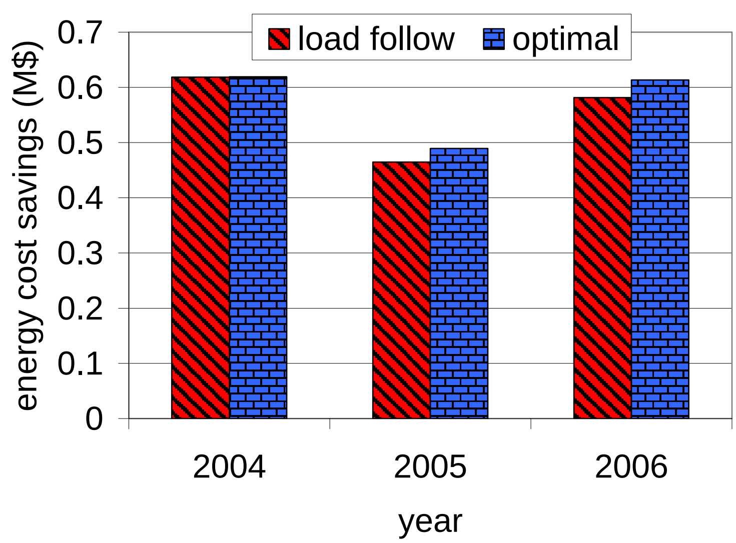


Figure 11. annual energy cost savings over do-nothing control strategy under TOU tariff

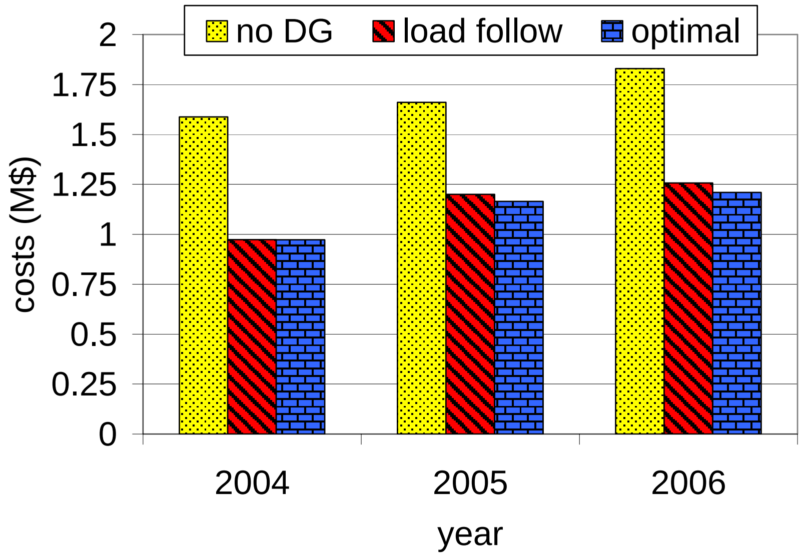


Figure 12. annual energy costs under CPP tariff and three control strategies

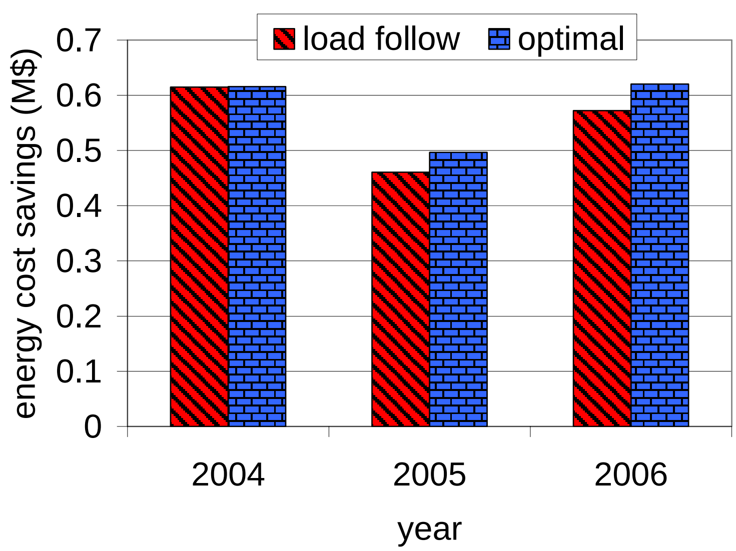


Figure 13. annual energy cost savings over do-nothing control strategy under CPP tariff

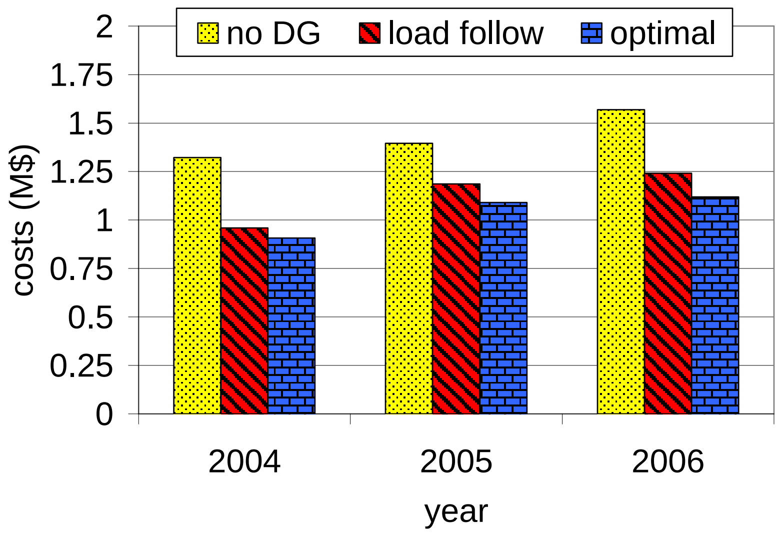


Figure 14. annual energy costs under RTP tariff and three control strategies

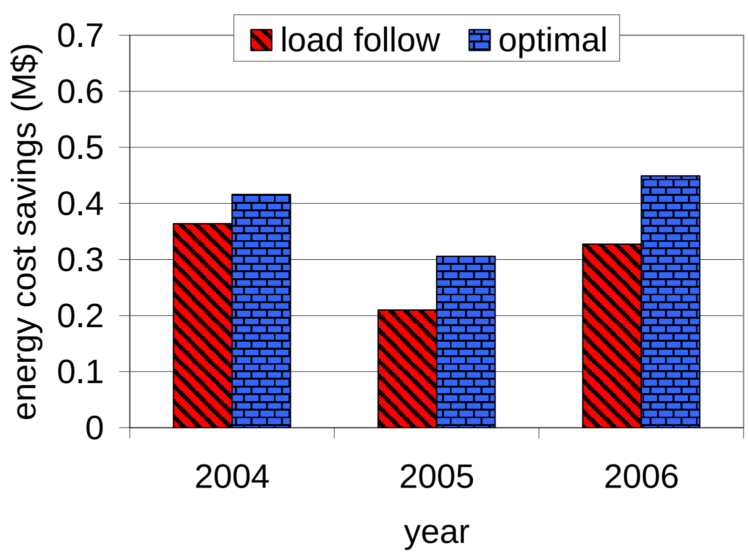


Figure 15. annual energy cost savings over do-nothing control strategy under RTP tariff

Figure 17 through Figure 21 show how electricity demand is met by utility purchase and site equipment for the first full weeks (Monday – Sunday) of January 2004 and July 2004 under each of the tariff structures and optimal control. Where DG generation goes from significant to zero indicates a generator outage. These figures suggest that optimal control under TOU and CPP tariffs is simply load-following. Optimal control under RTP is more complicated and clearly responsive to market clearing prices.

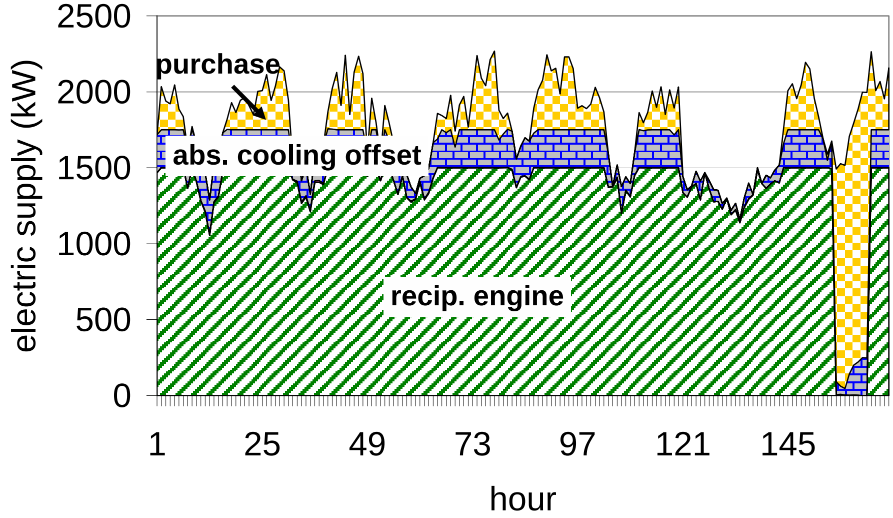


Figure 16. optimal electric supply under TOU tariff for the first full week of January 2004

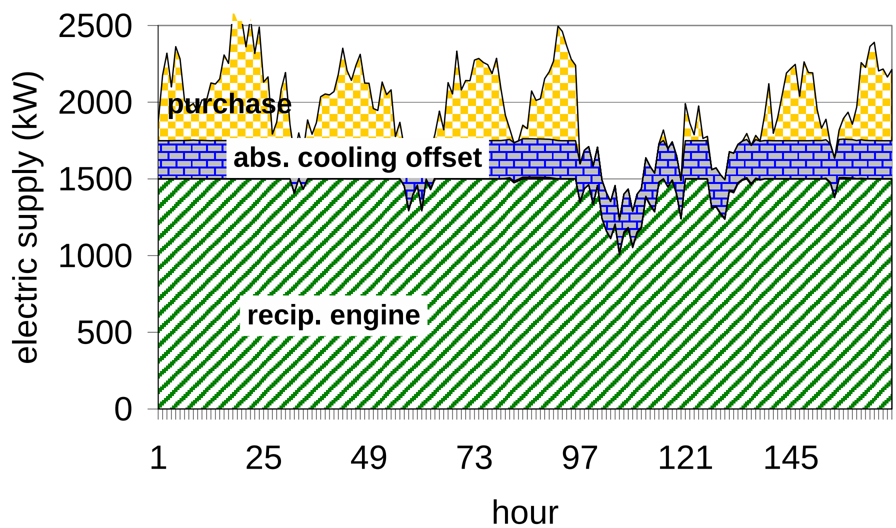


Figure 17. optimal electric supply under TOU tariff for the first full week of July 2004

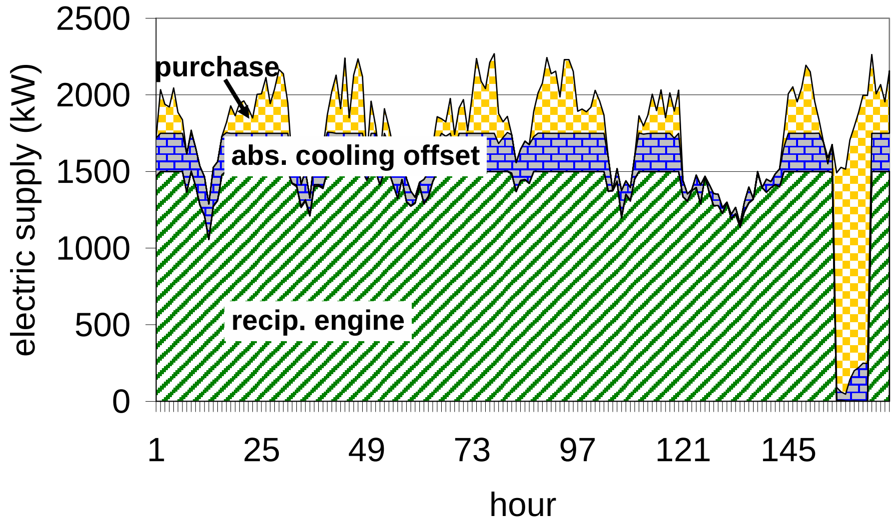


Figure 18. optimal electric supply under CPP tariff for the first full week of January 2004

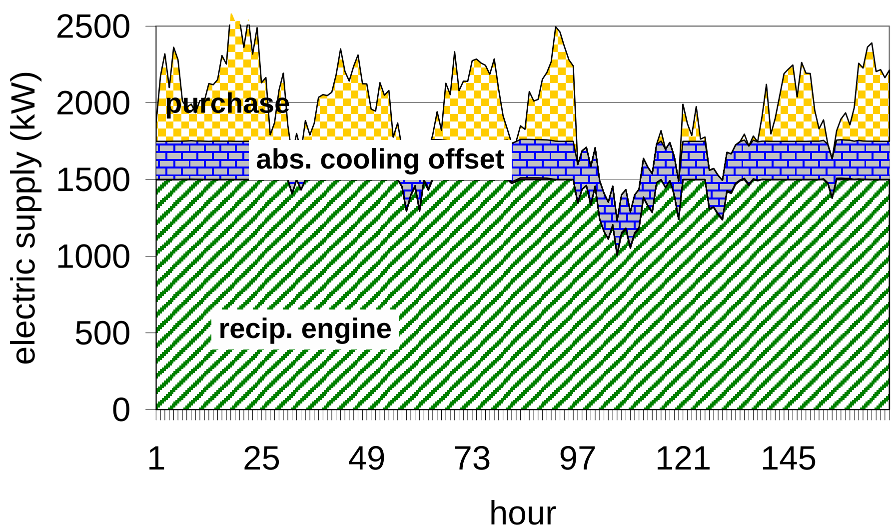


Figure 19. optimal electric supply under CPP tariff for the first full week of July 2004

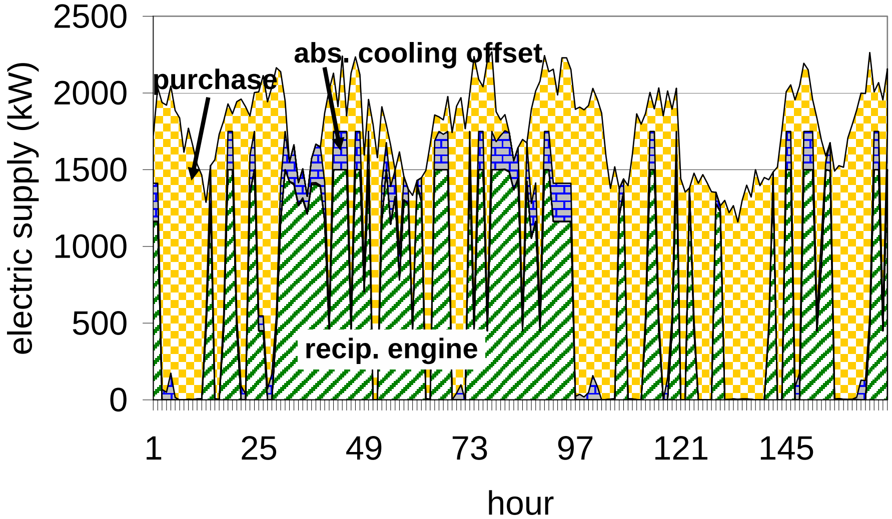


Figure 20. optimal electric supply under RTP tariff for the first full week of January 2004

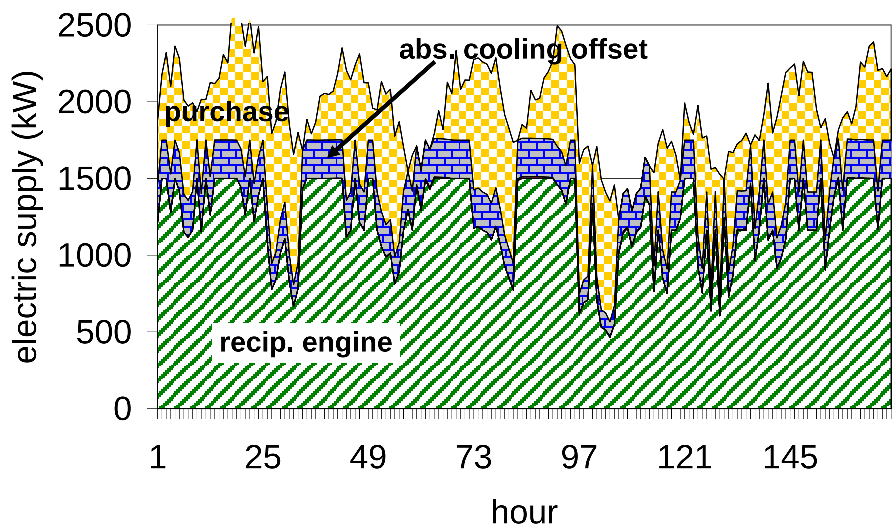


Figure 21. optimal electric supply under RTP tariff for the first full week of July 2004

A very different result is obtained in November 2005 during a natural gas price spike. Figure 22 through Figure 24 show how electricity demand is met by utility purchase and site equipment for the first full week of this month. These figures suggest that optimal control under TOU and CPP tariffs is simply the no-DG control strategy. Under the RTP tariff, however, there are still opportune times to dispatch the DG.

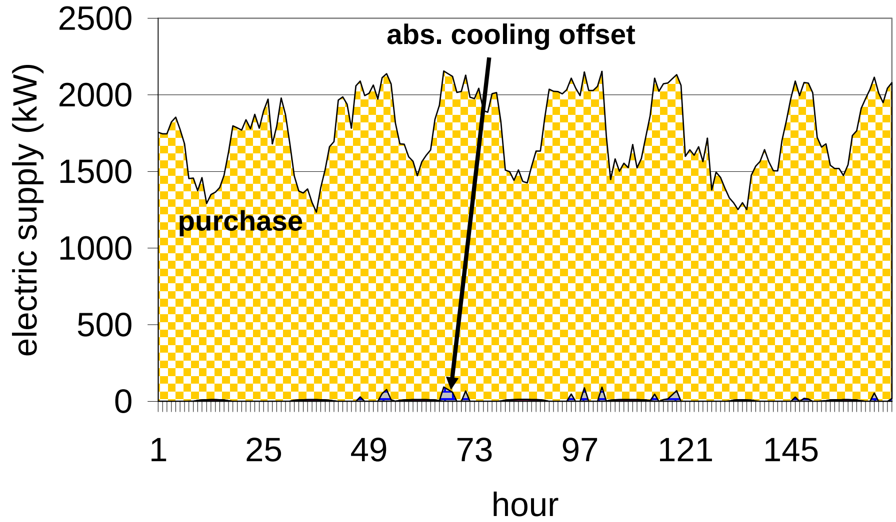


Figure 22. optimal electric supply under TOU tariff for the first full week of November 2005

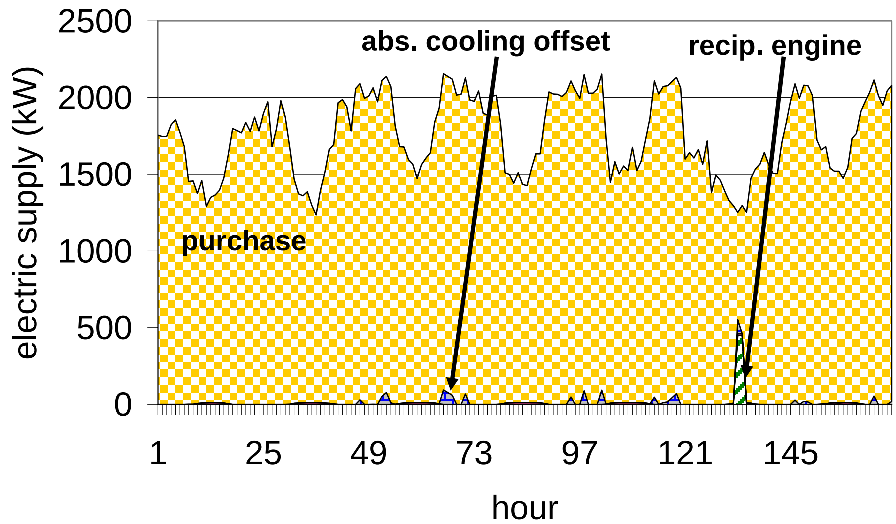


Figure 23. optimal electric supply under CPP tariff for the first full week of November 2005

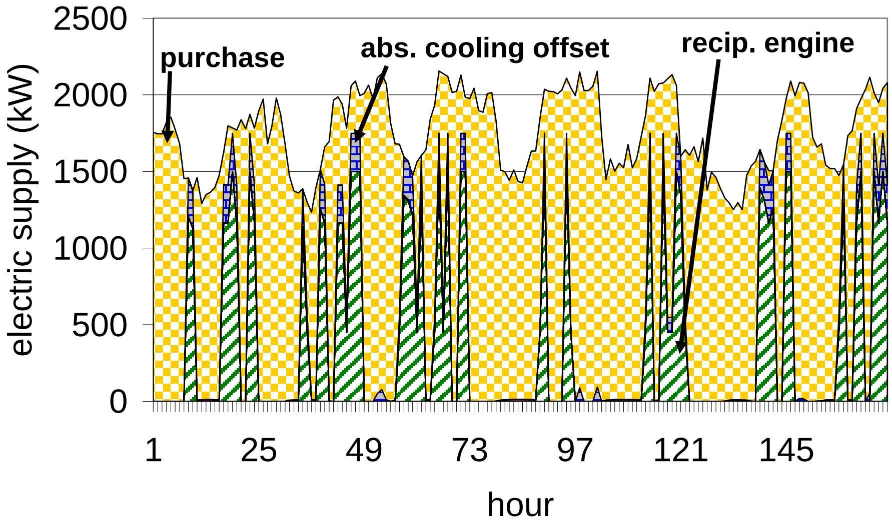


Figure 24. optimal electric supply under RTP tariff for the first full week of November 2005

Under RTP, the site is responding to the fluctuations in price and is more price responsive. Figure 25 through Figure 27 illustrate this demand elasticity. In these figures, the hours of the month are sorted by the real-time price and plotted on the right vertical axis. The offset of utility electricity purchase achieved through DG and absorption chilling for this same ordering of hours is plotted on the left vertical axis. In other words, drawing a vertical line through one of the plots illustrates how much electricity the site chooses not to purchase from the utility at a given spot-market clearing price. The lines showing electricity offsets have been smoothed by using 20-hour rolling averages, rather than the actual sorted data. This has been done for visual clarity; oscillations in the actual sorted data are due to factors besides the clearing price of electricity that affect dispatch: generator availability, electricity prices not reflecting the clearing price, etc. The gradual increase in offsets under RTP tariff in all three months as clearing prices increase clearly illustrates the price responsiveness possible under RTP. Also illustrated is the indifference to market clearing prices under TOU and CPP tariffs.

It should be noted that the extreme price responsiveness of the optimal control under RTP tariff may be unrealistic, as constant variation in generator load might make maintenance costs undesirable or prohibitively expensive. A smoother (but still fluctuating) consumption pattern would be seen if limits were placed on the amount of load variation. It should also be noted that RTP tariffs in general incent less generation than do TOU or CPP tariffs. This in turn causes site carbon emissions to be greater under RTP tariff than the other tariffs because DG is more carbon efficient than the central grid when waste-heat is useful. This result in particular is specific to areas with relatively high electricity prices, such as California, where distributed generation is often cost- and carbon-efficient.

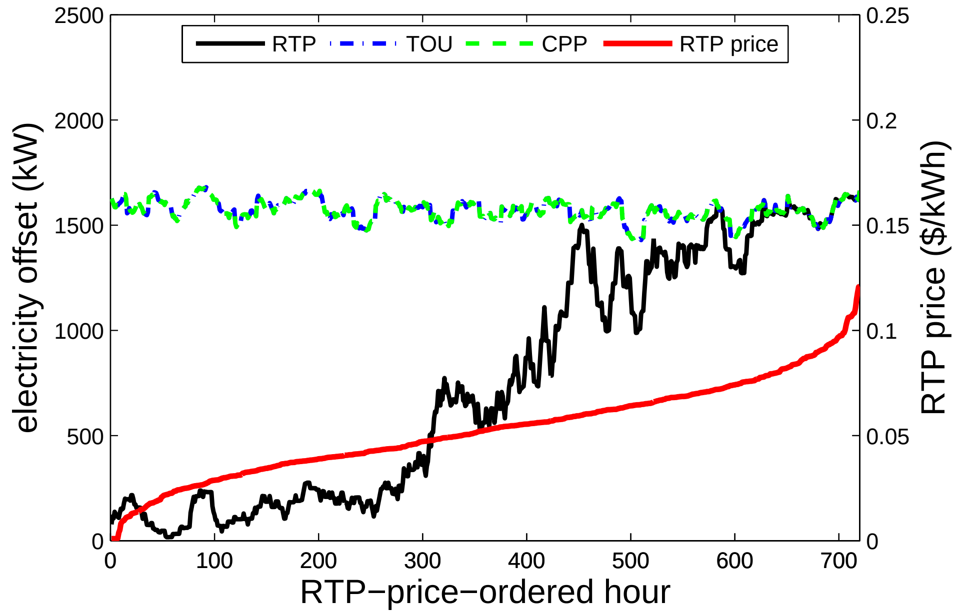


Figure 25. electrical load offset ordered by spot market clearing price under all tariffs in January 2004 – 20-hour rolling average

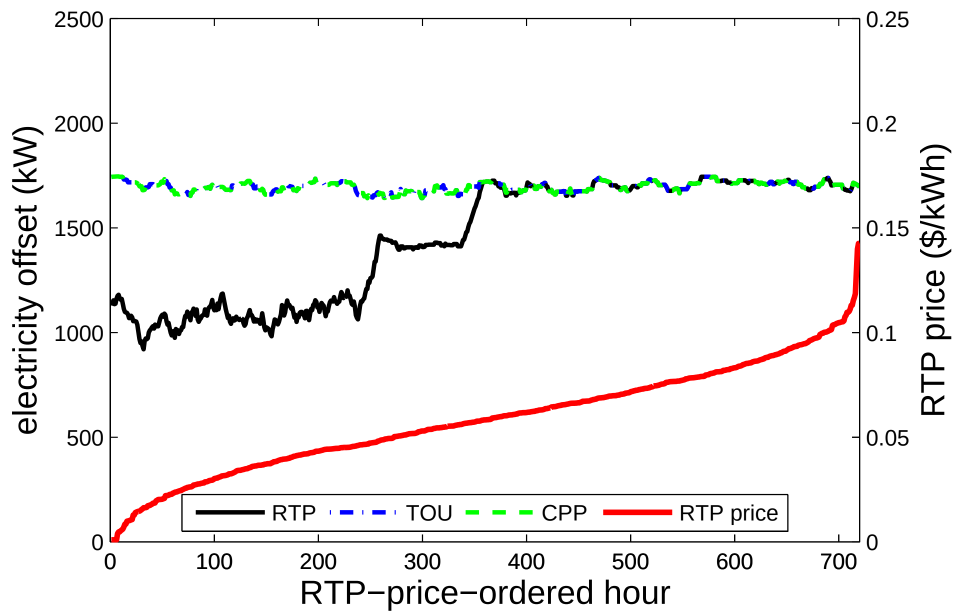


Figure 26. electrical load offset ordered by spot market clearing price under all tariffs in July 2004 – 20-hour rolling average

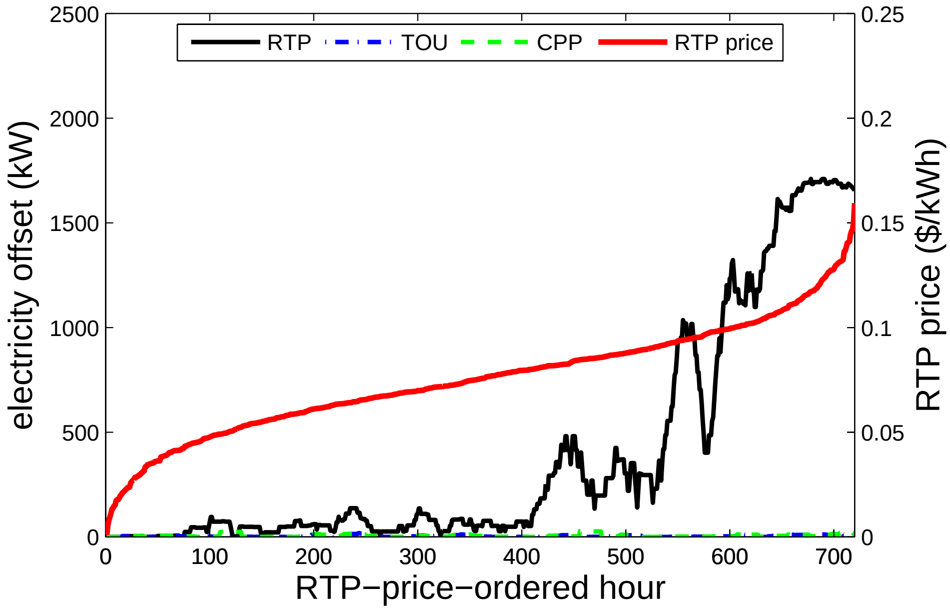


Figure 27. electrical load offset ordered by spot market clearing price under all tariffs in November 2005 – 20-hour rolling average

The final experiment was to examine the effect of site-attributable carbon emissions constraints on energy costs under optimal control and the three different tariffs. Site-attributable carbon emissions are the sum of emission from grid electricity and on-site natural gas consumption. One constraint in the optimization model is a ceiling on the amount of site-attributable carbon emissions in each month. For this experiment, for the 12 months of 2005, the simulation under optimal control and each of the three tariffs was rerun for a series of carbon constraint levels. The set of costs and carbon emissions levels from these runs were then analyzed to obtain an estimate of the cost/carbon trade-off under each tariff structure. The results are plotted in Figure 28 with carbon emissions on the horizontal axis and the corresponding minimum possible annual energy cost on the vertical axis. The maximum and minimum points on these curves are reported in Table 2. All points on Figure 28 and in Table 2 are determined through a separate optimization problem that finds the least-cost combination of monthly carbon constrained results for the year. These least-cost values could not be obtained in practice because they assume perfect foresight for the year in natural gas prices and general trends in electricity prices; however, they do provide an estimate of the cost/carbon trade-off.

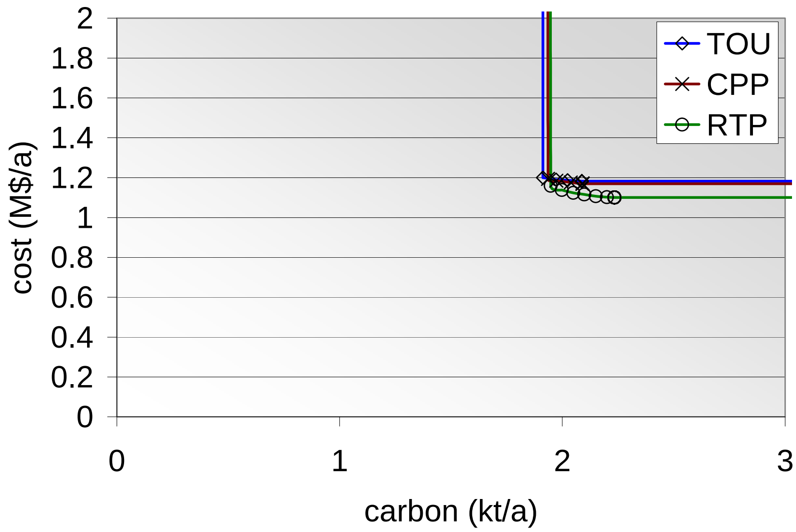


Figure 28. cost/carbon Pareto curve

Table 2. Pareto curve maximum and minimum points

	TOU		*CPP*		*RTP*	
	cost (M$)	**carbon (kTon)**	**cost (M$)**	**carbon (kTon)**	**cost (M$)**	**carbon (kTon)**
@best cost	1.2	2.1	1.2	2.1	1.1	2.2
@best carbon	1.2	1.9	1.2	1.9	1.2	1.9
% difference from best	1%	9%	2%	8%	5%	15%

The relatively sharp right-angles of the plots reveal that, for this site, least-cost dispatch is roughly least-carbon dispatch. The rounder angle of the RTP plot shows that the economic incentives not to run the DG at times are a disincentive to minimize carbon emissions.
Table 3 summarizes the carbon intensities of various energy practices at the site. From this table, it is clear that using DG is less carbon intensive than direct utility supply, even when there is no use for recovered heat.

Table 3. carbon intensity of electric load offset from grid and on-site sources

	carbon intensity of load offset (kgC/kWh)
central grid for electricity	0.18
DG for electricity, no recovered heat	0.15
DG for electricity and absorption chilling	0.12
central grid for compression chilling	0.18
natural gas for absorption chilling	0.30

8. CONCLUSIONS

At the San Diego P&DC site, optimal controls could add 4%, 5%, or 30% value to a DG system for TOU, CPP, and RTP tariffs respectively, relative to a load-follow control system. Based on these results, heuristic control strategies appear adequate for TOU, CPP tariff structures for a site such as the San Diego P&DC. These heuristics, however, should identify days or months in which it is not profitable to run the DG system. RTP tariffs would make DG less profitable under simple load-follow control, yet optimal dispatch control could improve the profitability and possibly make the case for installing DG. Because the cost of these controls would be largely invariant to DG system size, this would be a regressive barrier to DG adoption, i.e. a larger barrier to smaller systems.

While TOU and CPP tariffs would be more convenient and profitable for customers with DG, these tariffs do not incent self-generation that helps to stabilize the spot market. The CPP tariff does not incent any different DG behavior than the TOU tariff; generators are already running at on-peak times. RTP tariffs, however, do incent self-generation behavior that would mitigate price volatility in the spot market: more generation during times of high clearing price and less generation during times of low clearing price.

While RTP tariff structures do incent desirable market behavior, they incent higher site-attributable carbon emissions than TOU or CPP tariffs. Carbon emissions under TOU and CPP tariffs and cost minimizing control are 8% to 9% greater than under carbon minimizing controls. However, for the RTP tariffs, emissions are 15% greater than under carbon minimizing controls. This is because DG dispatch, which is always more carbon efficient than grid purchases, is less frequently the least-cost option under RTP than under TOU or CPP. Regulators should note that with current energy prices in San Diego, price responsiveness and carbon emissions reductions are opposing objectives. This would not be the case if carbon emissions were taxed directly, rather than treated as an externality.

9. FUTURE WORK

The results of this research suggest that at this site, optimal control may not be worth the cost of implementation, particularly under common simple tariffs such as TOU or CPP. In such cases, simulation using optimal control algorithms can be used to identify heuristics for determining dispatch schedules. However, this may not be the case for different building types, or in different regions, which would experience different heating/cooling loads and different energy prices. Immediate further research will examine several P&DC sites across the Unites States.

The optimal dispatch algorithm used in this paper is particularly useful for integrated systems, which can dispatch curtailment and rescheduling opportunities as well as distributed generation. This algorithm has been used in [11] to determine the value of curtailment programs to sites that already had distributed generation. This type of analysis would be useful for the P&DC sites being studied to determine the cost incentive of demand response under tariffs that may or may not directly incent demand response.

Intermittent renewables (in larger quantities than the PV considered in this case study) add an additional complexity, for which this optimization algorithm is particularly useful. Optimizing curtailment opportunities under significant uncertainties in self-generation availability and energy prices could prove to be valuable and must be examined.

Finally, greenhouse gas emissions reductions initiatives, such as the recent legislation in California and in several northeastern states, will change some or all of the parameters in the optimization problem in yet unknown ways. Having a tool such as this optimization algorithm will be useful for identifying new control strategies in response to these changes.

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APPENDIX: MODELS

This appendix describes the models of energy system characteristics, stochastic loads, electricity prices, and weather conditions that were necessary for this research.

Energy System Characteristics

Electrical Efficiency

Generator efficiency is modeled indirectly by the linear function

$$FuelConsumptionRate = m * OutputPower + b \quad (2)$$

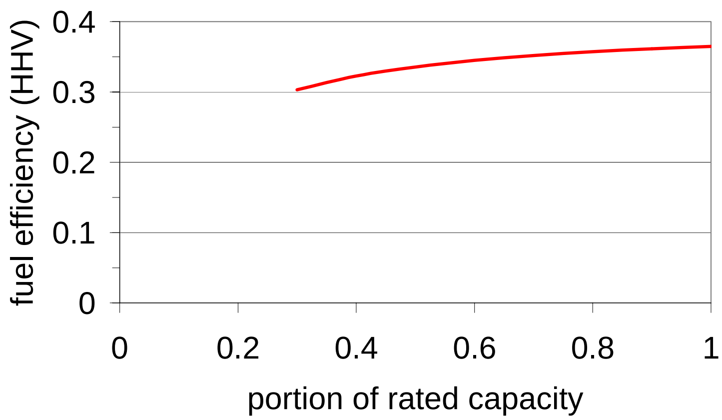

Figure 29. generator part-load electrical efficiency

Based on manufacturer's specifications of part-load efficiency for this generator, the m and b values of 2.5 and 0.24 respectively were obtained. Figure 29 shows the resulting efficiency (OutputPower/FuelConsumptionRate) for the allowable output range of the generator.

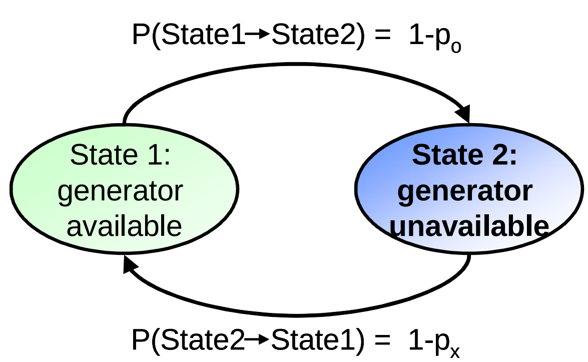

Figure 30. Two-state Markov model of generator availability

DG equipment availability is modeled as a two-state Markov process. The two states are simply "available" and "unavailable," with p_i the probability of remaining in state *i* at the current time-step if in state *i* at the previous time-step. This two-state process models the actual situation, in

which generators available at one time-step are likely to remain available at the next time-step, and generators unavailable at one time-step are likely to remain unavailable.
At each hour there is a probability p_o that the generator will remain available if it was available at the prior hour, and a different probability 1-p_x that the generator will become available if it was not available at the prior hour. The subscripts *o* and *x* refer to the "available" and "unavailable" states, respectively. Figure 30 illustrates this. For the Markov model, p_o and p_x can be derived from commonly cited parameters: expected availability (portion of hours generator is available), *A*, and expected outage length, E_x. These expressions are show in equations (3) and (4).

$$p_x = \frac{E_x}{1 + E_x} \tag{3}$$

$$p_o = \frac{AEx}{1 - A + AE_x} \tag{4}$$

Energy Loads

Electricity

The site provided access to several years of hourly electricity consumption data. From this data, hourly loads were categorized by month, day-type (either non-Sunday or Sunday), and hour of day. From this an average for each unique combination of month, day-type, and hour, *load(month,day-type,hour)* was determined.

A stochastic model of actual electricity loads was assumed for each day of simulation:

$$\begin{aligned} &load(m,h) = \\ &\alpha_{load}(day_h) * \overline{load}(m, dt_h, dh_h) + \beta_{load}(m,h) \end{aligned} \tag{5}$$

where
- *m* is the month {1,…,12}
- *h* is the hour of the month {1,…,720}
- day_h is the day of the month that hour *h* is in {1,…,30}
- d_{th} is the day-type of dayh {weekday,Sunday}
- d_{hh} is the hour of the day of hour *h* {1,…,24}
- *load(m,h)* is the electricity load in month *m* at hour *h*
- $\alpha_{load}(day_h)$ is a daily random variable that follows a normal distribution
- $\beta_{load}(m,h)$ is an hourly random variable that follows a normal distribution
- $\overline{load}(m, dt_h, dh_h)$ is the average hourly electricity load at hour d_{hh} of day-type d_{th}.

α is a daily scaling factor, that is, larger on busy days and smaller on quiet days. *β* represents hourly variation in electric loads due to the intermittent use of various equipment. By design, α has mean value of 1, *β* has a mean value of 0. The variance, maximum value, and minimum value of α and β were determined through analysis of the electric load data provided. The variance of β is assumed to be independent of the hour of the day. Knowing the hourly average values and the statistical description of α and β, loads for each hour in each scenario were generated, starting with the generation of random α (one per day) and β (one per hour) values. Randomly generated values of α and β are truncated to be within the minimum and maximum values observed.

Cooling

The share of electricity use due to cooling loads was more difficult to determine because detailed records were not available. Fortunately, detailed electricity and cooling load data were available from [2] of a similar P&DC facility in Redlands, California. Cooling loads are dominated by equipment waste heat; the cooling load is correlated with the electric load and with outside temperature. This relationship for each month was determined for the Redlands site and applied to San Diego site.

Electricity Prices

A hypothetical RTP tariff was constructed because the utility does not currently offer one. Demand charges and the delivery portion of volumetric charges from the reported TOU tariff were used. In the place of the TOU rates for electricity supply however, the spot market clearing prices for the San Diego region, SP15, were used [6].

A stochastic model of clearing prices was assumed in the same format as electric loads:

$$\begin{aligned} &price(m,h) = \\ &\quad \alpha_{price}(dt_h, day_h) * \overline{price}(m, dt_h, dh_h) \\ &\quad + \beta_{price}(m,h) \end{aligned} \tag{6}$$

where

- all indices are the same as in Eq. (5) except that here day-types, d_{th} are either weekday (Monday through Friday) or weekend (Saturday and Sunday).
- $\alpha_{price}(day_h)$ is a daily random variable that follows a normal distribution
- $\beta_{price}(m,h)$ is an hourly random variable that follows a normal distribution
- $price(m,h)$ is the clearing price of electricity at hour h in zone SP15
- $\overline{price}(m, dt_h, dh_h)$ is the average hourly electricity clearing price at hour d_{hh} of day-type d_{th}

The variance of α and β are determined from the clearing price data. Randomly generated values of α and β are truncated to be within the minimum and maximum values observed. The same values of $\alpha_{price}(day_h)$ that were used in the RTP simulations were used indirectly in the CPP simulations to identify days with critical episodes, i.e. $\alpha_{price}(day_h)$ above a threshold value.

Solar Insolation

Historic solar insolation data were collected from [16]. The stochastic model of solar radiation from which scenario values were generated is similar to the electric load and spot market price models except that there are no day-types (weather is indifferent to weekends):

$$SolRad(m,h) = \alpha_{SolRad}(day_h) * \overline{SolRad}(m,dh_h) + \beta_{SolRad}(m,h) \tag{7}$$

where

- all indices are the same as in Eq. (5)
- $\alpha_{SolRad}(day_h)$ is a daily random variable that follows a normal distribution
- $\beta_{SolRad}(m,h)$ is an hourly random variable that follows a normal distribution
- $SolRad(m,h)$ is the solar radiation (kW/m^2) of electricity at hour h in the inland San Diego region
- $\overline{SolRad}(m,dh_h)$ is the average hourly solar radiation at hour d_{hh} of the day

As with the previous models, the variance, minimum, and maximum values of α and β are determined from the historical data available and used to generate random solar radiation values for each hour in each scenario.