On-Site Generation Simulation with EnergyPlus for Commercial Buildings¹

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ABSTRACT

Building energy simulation software (e.g. EnergyPlus) is a powerful tool used widely by designers and researchers. However, current software is limited in modeling distributed generation (DG), including DG with heat recovery applied to building end-use, i.e. combined heat and power (CHP). Concurrently, DG investment and dispatch optimization software has been developed, yet has not been linked to a building energy simulation program for accurate assessment of DG designs, particularly under uncertainty in future end-use loads and equipment availability. CHP is a proven approach to cost effective reductions in primary fuel consumption and CO_2 emissions. Integrating DG system design and controls into building energy simulation is an important step towards popular DG acceptance.

We propose to extend the existing building energy simulation program, EnergyPlus (E+), to enable the simulation of various DG modules and associated control strategies in order to achieve more accurate and holistic analysis of DG technologies. Extension of EnergyPlus is conveniently facilitated by SPARK, a program capable of modeling building equipment and controls as individual modules. These modules can be automatically integrated with EnergyPlus building models. Candidate DG systems can be selected from the DG investment optimization program, Distributed Energy Resources Customer Adoption Model (DER-CAM). The dispatch of the modeled DG system can be determined by a novel dispatch optimization algorithm, the Energy Manager, that accounts for uncertainty in future load and DG availability, as well as curtailment options. DG equipment and controls can modeled in SPARK and integrated into EnergyPlus building models. The way to this holistic approach will be described in this paper.

Introduction

Researchers at the Lawrence Berkeley National Laboratory (LBNL) have developed several powerful tools for the design and analysis of building energy systems. EnergyPlus (E+) is a building energy analysis tool with thousands of users worldwide, capable of assessing the energy demand of buildings given their envelope design, heating ventilation and air conditioning (HVAC) system design and controls, and climate and occupancy data.

In separate efforts at LBNL, DER-CAM (Distributed Energy Resources Customer Adoption Model) has been developed as a DG investment and operation planning optimization tool. Analysis using DER-CAM has demonstrated the cost effectiveness of CHP at improving site energy efficiency and reducing carbon emissions. The economically optimal investment is a complicated problem, dependent on a particular site's end-use load profiles, electricity and natural gas tariff structure and rates, DG investment options, and regulatory constraints.

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While DER-CAM determines economic candidate systems and a preliminary optimal dispatch, it is not capable of handling the stochastic nature of loads and equipment outages, nor has it considered the integrated dispatch of DG and curtailment (e.g. demand response) a strategy for minimizing costs associated with peak consumption, i.e. demand charges.

On the other hand the Energy Manager is an algorithm that has been developed to pick up where DER-CAM leaves off, determining this optimal real-time dispatch of DG and curtailment options under the uncertainties mentioned above.

DG adoption has been limited, in part, by designers' unfamiliarity with system design tradeoffs and performance. Enabling a proven design tool such as E+ with DG modelling capabilities would facilitate the process of gaining the trust and comfort of system designers.

However, while the DER-CAM model as well as the Energy Manager algorithm have been designed they have yet to be implemented into E+. Therefore, the primary part of this paper focuses on the description of the basic determination of the DER candidate systems - with the DER-CAM model - and the description of the Energy Manager algorithm.

EnergyPlus

EnergyPlus (Crawley et al. 2004) is a recently-developed whole-building energy analysis program that builds on the best capabilities of BLAST and DOE-2. Some key capabilities of E+ include configurable modular systems integrated with heat balance-based zone simulation, a variable time stepping scheme for the HVAC simulation, and flexible HVAC system configuration. The simultaneous solution of the building loads and the HVAC systems offers the numerical framework necessary to accurately describe the operation of a DG system in a simulation tool.

The fluid loops and HVAC components support a "manager-interface" simulation protocol that allows for the independent simulation of subsystems, each possibly using a customized solution procedure. Thus, the E+ program structure allows the solution to a particular subsystem to be computed without affecting the solution schemes used for the other subsystems. This fundamental requirement enables the integration of new models in the E+ building systems simulation.

SPARK

SPARK (Curtil 2003 and Sowell et al. 2004) is a generic differential-algebraic equation (DAE) solver for constructing and solving models of complex HVAC components. In a typical application, the user provides inverse C++ functions that solve for variables in the equations of interest. In this way, the user builds a modular system of equations describing the dynamics and configuration of the overall physical system of interest. SPARK then employs graph-theoretic methods to decompose the problem into independent subsystems, and to identify the smallest subset of variables that need to be solved iteratively by re-ordering the equations in each subsystem. The solution sequence generated by this pre-processing step produces a mathematical system of equations that is faster to solve than the full, original system, thus making SPARK an extremely fast DAE solver.

The SPARK and E+ programs have been linked to construct detailed models of systems and system components - with emphasis on advanced control strategies and new energy

technologies - that can be run within E+. The equation-oriented approach in SPARK makes it a natural platform to generate robust and efficient simulators for individual component models, allowing the user to focus on the mathematical representation of the physical model. This relieves the user of the burden of developing an efficient solution algorithm. The resulting self-contained simulators for the individual components can then be evaluated as part of a larger system – in this case EnergyPlus – that does not have to be aware of the solution algorithm used in the SPARK model. For each SPARK model, the data mapping between the E+ and SPARK variables must be specified to support the data exchange mechanism at runtime. Then at every time step, the SPARK link acts as a driver for the individual SPARK models within the context of the E+ simulation. It is possible to drive a SPARK model either at the HVAC system time scale or at the zone time scale, depending on the desired level of interaction with the envelope and/or HVAC calculations.

Because SPARK implements a state persistency mechanism for saving and restoring the internal state of a SPARK model at runtime, the SPARK link is able to handle stateful models. This capability facilitates the integration of dynamic models or models depending on past history (e.g., the Energy Manager) within E+. Furthermore, as the SPARK link ensures systematic synchronization with the E+ clock, along with the required state management, the dynamic SPARK models (i.e., models with integrators) can actually be simulated at a time step smaller than the E+ time step, even allowing for variable time stepping methods to enforce local integration error control. This improves the E+ capability to model short time scale processes (i.e., smaller than the HVAC time step of typically one minute), such as the ones occurring with digital controls relying on high sampling frequency or physical models with faster dynamics.

Finally, as part of integrating the SPARK models into E+, the EnergyPlus Input Definition Dictionary is typically extended to present the input values specific to the SPARK models using the native E+ formalism based on the Input Definition File. Similarly, the reports for the variables computed by the SPARK models are declared as native E+ reports or meters. Thus, a typical E+ user running a building model consisting of linked SPARK components need not be familiar with the SPARK simulation tool as the SPARK component models appear as native E+ components with regard to the input/output formalism.

The SPARK tool provides an ideal prototyping environment for developing and testing new DG component models, as well as the Energy Manager. The SPARK link offers an elegant, minimally intrusive and efficient approach to extending E+ modeling capabilities, which satisfies the functional requirements for DG simulation. At the present time, it should be noted that, although there is no inherent software limitation regarding the Linux/UNIX-based platforms, the SPARK/E+ link capability is only available with the Windows release of E+.

The Deterministic View of the Future - DER-CAM²

DER-CAM (Siddiqui et al. 2003) is a Mixed Integer Linear Optimization Program (MILP) written and executed in the General Algebraic Modeling System (GAMS). The objective is to minimize annual energy costs for the modeled site, including utility electricity and natural gas costs, amortized capital costs for DG investments, and maintenance costs for installed DG equipment.

² DER-CAM has been developed as a flexible tool capable of modelling a wide variety of commercial and industrial sites.

Site specific inputs to the model are end-use energy loads³, electricity and natural gas tariff structure and rates, and DG investment options. The following technologies are considered:

- Natural gas-fired reciprocating engines, gas turbines, microturbines, and fuel cells⁴;
- Photovoltaics and solar thermal collectors;
- Heat exchangers for application of solar thermal and recovered heat to end-use loads; and
- Heat-driven absorption chillers.

A key constraint is a limit on the acceptable simple payback period, which mimics typical investment decision made in practice; that is, only investment options with a payback period less than that specified as an input model parameter are considered.

Figure 1 shows a high-level schematic of the energy flow modeled in DER-CAM. Possible energy inputs to the site are solar insolation, utility electricity and natural gas. For a given DG investment decision, DER-CAM selects the optimal combination of utility purchase and on-site generation required to meet the site's end-use loads at each time step.

- Electricity-only loads (e.g. lighting and office equipment) can only be met by electricity.
- Cooling loads can be met either by electricity or by heat (via absorption chiller)⁵.
- Hot water and space heating loads can be met either by recovered heat or by natural gas.
- Natural gas-only loads (e.g. mostly cooking) can only be met by natural gas.

Figure 1. Schematic of the Energy Flow Model Used in DER-CAM



The outputs of DER-CAM include the optimal DG adoption and an hourly operating schedule, as well as the resulting costs, fuel consumption, and carbon emissions.

⁴ DER-CAM is technology neutral and can also consider other systems.

³ Three different day-long profiles are used to represent the set of daily profiles for each month: weekday, peak day, and weekend day. DER-CAM assumes that three weekdays of each month are peak days.

⁵ Cooling loads in DER-CAM are expressed in units of electric energy required to meet the load.

Optimal DER Equipment for a Large Healthcare Facility in San Francisco

To demonstrate DER-CAM's capabilities, an analysis of a generic large hospital in San Francisco is presented. The end-use load profiles for the site are shown in Figure 2 and Figure 3⁶. Throughout the year, during the expensive mid- and on-peak hours for electricity consumption, there is significant space and water heating demand, as well as cooling loads which can be met thermally. This coincident use for the electricity and heat provided by DG, combined with high energy prices (Table 1) in San Francisco, suggest that this site is a prime candidate for DG investment.

Figure 2. Electricity Only and Cooling Loads for a Large Healthcare Facility in San Francisco (Jan. and Sept. Weekday)





Table 1. 2004 San Francisco Utility Electricity & Natural Gas Costs for the GenericFacility

		Summer (June - Sept.) Winter			nter (Oct	er (Oct May)		
		on peak*	mid peak**	off peak***	on peak	mid peak	off peak	
	fixed (\$/month)	175						
FIECTFICITY	energy (\$/kWh)	0.1647	0.1	0.0881	0.1083	0.1083	0.0891	
	demand charge (\$/kW month)	11.8	2.65	0	0	2.65	0	
	non-coincident demand charge (\$/kW month)	2.55						
I Natural das	fixed (\$/month)	100						
	energy (\$/kWh)	0.029 - 0.032						

* on peak: for summer months from 12pm to 6pm, for all days of a week.

** mid peak: summer months from 9am to 12pm and 6pm to 10pm, for all days of a week.

** mid peak: winter months from 9am to 12pm for all days of a week.

*** all other hours

Source: LBNL Tariff Analysis Project

Demand charges are a significant component of the electricity tariff. They are proportional to the maximum *rate* of electricity consumption (regardless of the duration or frequency of such consumption). DER-CAM includes the potential for five types of demand charges, assessed either on a daily (as in New York) or monthly (more common) basis:

⁶ The load profiles are gathered from DOE-2. In the future these load profiles should be taken from the enhanced E+.

⁷ Please note that the DER-CAM demand window is arbitrary and that e.g. also a 15 or 30 minute demand window would be possible. However, smaller time frames result in longer optimization times.

- Non-coincident: based on the maximum consumption in any hour;
- On-peak: based only on on-peak hours;
- Mid-peak: based only on mid-peak hours;
- Off-peak: based only on off-peak hours; and
- Coincident: based only on the hour of peak system-wide consumption.

A large part of the value of DER investment can be to mitigate the costs of demand charges.

Without any DER investment, DER-CAM determines the annual energy costs to be US\$870,000 and the peak electricity demand to be 1.1GW. With investment, and subject to a six year maximum payback period, the DER-CAM optimal solution is the purchase of two 500 kW reciprocating engines, one with heat recovery and an absorption chiller. The annual energy costs (including amortized capital costs) is reduced by 19% to US\$707,000. Figure 4 and figure 5 show the sources of electric and thermal energy supply over the course of a typical January weekday. The CHP unit is run throughout the day to meet the base electric load, the heating load, and to offset the electric cooling load via absorption chilling. The electricity-only unit is dispatched during the high priced peak hours of the day. Because of the usage of CHP enabled technologies the overall system efficiency⁸ increases from 40% prior to DG investment to 48%. Recovered heat satisfies the entire heating demand and 74% of the annual cooling demand.





Figure 5. Nat. Gas Supply Structure in the DER Invest Case for the Large Healthcare Facility in San Francisco (Jan. Weekday)



The Energy Manager

As DER-CAM has shown, increasing energy costs and decreasing self-generation capital costs have made DG a profitable investment in an increasing number and variety of settings. With the adoption of DG and potential for restricting and/or rescheduling consumption, commercial and industrial electricity consumers can and are shifting from captive price takers towards active participants in the energy market.

The entire system of energy sources (on-site generation, storage, and utility supply) and sinks (end-use loads and storage) in a building can be viewed as a single, Integrated Energy

⁸ Efficiency = $\frac{AnnualUsefulEnergy}{AnnualFuelConsumption}$ using AnnualFuelConsumption = $\frac{ElectricityPurchase_{Annual}}{Efficiency_{Macrogrid}} + AnnualNaturalGasPurchase_{DG}$

⁺ AnnualNaturalGasPurchase $_{NonDG}$ and AnnualUsefulEnergy = \sum_{i} EnduseLoad $_{i}$

System (IES). From this perspective, coordination between the operation of the various equipments and the dispatch of flexible loads can be used to minimize the economic and/or environmental costs of energy consumption. For a more detailed discussion of this topic, see Firestone et al. 2005.

However, a site with central command over a variety of energy supply, storage, and consumption devices will find it challenging to determine the optimal dispatch of this integrated system in real time. Optimal dispatch must be in response to *non-deterministic* site energy loads, equipment outages, and price signals. The computation required for this requires an automated energy manager, which can make optimal dispatch decisions for an integrated system of energy supply and curtailment/rescheduling options.

Dispatch Optimization Problem

Given the decision variables of the IES, such as DG operation levels and flexible load dispatch, an optimal decision must be made in real-time, on the order of every five minutes to one hour. Optimal dispatch must take into consideration the current state of the system, historical state information, and predicted future states of the system, as well as operation constraints and the site's energy objectives. Dispatch to the IES must be within any specified constraints, such as minimum CHP efficiency (often imposed by regulators in exchange for subsidy), operational constraints on DG equipment, limits on emissions and noise, planned outage scheduling for DG devices, and limitations on load flexibility such as magnitude, duration, and frequency.

In situations where DG is more expensive than volumetric electricity rates, DG may still be economic if it can mitigate demand charges. However, because of uncertainty in the availability of DG equipment, there is no guarantee that the DG equipment will be available at the times required to mitigate demand charges. If the duration and frequency of peak consumption are small, the probability of DG being available in all of those hours may be high enough to warrant running DG as an effective demand charge reduction strategy.

The dispatch of DSM can improve the mitigation potential of DG by reducing load during the infrequent occasions when there is a DG outage at an inopportune time.

Smaller customers, for whom custom controls are prohibitively expensive, will benefit from generic algorithms that could be applied to a variety of sites and could respond to changes in IES configuration and utility tariff structure and rates. The Energy Manager could be an autonomous controller or an advisory system.

Dispatch Optimization Algorithm

This section describes a simple IES dispatch optimization algorithm that considers a finite number of possible future scenarios as an approximation of the future. Scenarios are generated randomly; each scenario contains values for each stochastic parameter at each time step. Because of the similarity of days in a month, a relatively small number of scenarios can be used to represent the most probable future conditions. The dispatch problem, then, is to select a dispatch decision for the current time-step and a dispatch strategy for all future time steps, given historic load and dispatch information.

This algorithm considers a site with a CHP system comprised of one generator with heat recovery and with limited curtailment options. Two dispatch decisions are considered: the set point of the generator in the CHP system and a curtailment command.

Indices:

d	days {1D}
dd	dispatch decisions {generation level, curtail}
h	hours {1N}
h-off	subset of off-peak hours
h-on	subset of on-peak hours
scen	stochastic scenarios {1S}
sp	stochastic parameter {electric load, generation availability}
tou	time of use {on-peak, off-peak}

Parameters:

AS (sp,h)	actual scenario stochastic parameter values
CurrentHour	current hour of month
Curt	magnitude (kW) of curtailed load
CurtFreq	maximum number of curtailment hours allowed per month
DailyHeatLoad (d)	daily total space and water heating (kWh) requirement
DCost (tou)	demand cost (\$/kW peak) for electricity by time of use
DGCapacity	electric capacity (kW) of on-site generation (kW)
DGVarCost	variable maintenance cost (\$/kWh) of on-site generation
Efixed	monthly fixed cost (\$) of utility electricity service
EnergyCost (TOU)	volumetric cost (\$/kWh) of electricity by time of use
FtoHeffic	efficiency of converting fuel to heat via direct combustion
HistD (dd,h)	historical dispatch decisions
Ν	number of hours in month
NGCost	volumetric cost of natural gas (\$/kWh)
NGfixed	monthly fixed cost (\$) of utility natural gas service
S	number of stochastic scenarios considered
SP (scen, sp, h)	stochastic parameter values used for optimization problem (1 if the generator is available)
SV (scen, sp, h)	stochastic values from Monte Carlo simulation

Decision Variables:

Cost (scen)	total monthly cost (\$)
D (scen, dd, h)	dispatch decision (1 if the dispatch command is to curtail, 0 if no curtailment is
	dispatched)
EPurch (scen, h)	electricity purchased (kWh)
NGforDG (scen, h)	natural gas purchase (kWh) for DG
NGforHeat (scen,h)	natural gas purchase (kWh) for heating
RecHeat (scen,h)	useful recovered heat (kWh) from distributed generation

For all hours prior to and including the current hour, stochastic parameter values are all known and are equal to the actual scenario parameter values. $SP(scen, sp, h) = AS(sp, h) \quad \forall scen, sp, \forall h \leq CurrentHour$ (1)

For all hours beyond the current hour, the stochastic parameter values are the stochastic values *generated* for each scenario.

$$SP(scen, sp, h) = SV(scen, sp, h) \quad \forall scen, sp, \forall h > CurrentHour$$
⁽²⁾

Dispatch constraints. For all hours prior to the current hour, dispatch is known and is the historical dispatch of the system.

$$D(scen, dd, h) = HistD(dd, h) \quad \forall scen, dd, \forall h < CurrentHour$$
(3)

For the current hour, dispatch for each scenario must be equal, i.e. as there is only one actual scenario, there is only one actual dispatch.

 $D(i, dd, h) = D(j, dd, h) \quad \forall i, j \in scen, \forall dd, h = CurrentHour$ (4)

For all hours beyond the current hour, dispatch may vary by scenario. The set of dispatch decisions for all future hours for all scenarios represents a *dispatch strategy*.

Energy balance. Electricity loads must be met instantaneously by the sum of electricity purchase, on site generation, and curtailment.

SP(scen, "electric - load", h) = EPurch (scen, h) + D(scen, "generation - level", h)(5) + Curt * D(scen, "curtail", h) \forall scen, h

Heating loads must be met on a daily basis by the sum of direct combustion of natural gas and recovered heat from on-site electricity generation⁹.

 $DailyHeatLoad(d) = \sum_{h \in d} \{NGforHeat(scen,h) * FtoHeffic + RecHeat(scen,h)\} \quad \forall scen,d$ (6)

On site generation. On-site generation is only allowed when the DG system is available, and must be less than or equal to the capacity of the system^{10,11}.

 $D(scen, "generation - level", h) \le SP(scen, "generation - availability", h) * DGCapacity \forall scen, h$ (7)

(8)

(**A**)

Curtailment. The number of curtailment hours per month is constrained. $\sum_{h} D(scen, "curtail", h) \le CurtFreq \quad \forall scen$

Energy costs. Cost for each scenario is the sum of volumetric electricity and natural gas costs, time of use demand charges, volumetric natural gas costs, DG variable maintenance costs, and fixed monthly service fees for utility electricity and natural gas service.

$$Cost(scen) = \sum_{tou} \left(\sum_{\substack{h \in h - on, tou = on - peak \\ h \in h - off, tou = off - peak }} EPurch(scen, h) * ECost(tou) + \max_{\substack{h \in h - on, tou = on - peak \\ h \in h - off, tou = off - peak }} (EPurch(scen, h) * DCost(tou)) \right) + EFixed + NGFixed + \sum_{\substack{h \in h - off, tou = off - peak \\ h \in h - off, tou = off - peak }} (NGforDG(scen, h) + NGforHeat(scen, h)) * NGCost + \sum_{\substack{h \in h - off, tou = off - peak \\ h \in h - off, tou = off - peak }} (D(scen, h) * DGVarCost \quad \forall scen + \sum_{\substack{h \in h - off, tou = off - peak \\ h \in h - off, tou = off - peak }} (D(scen, h) * DGVarCost \quad \forall scen + \sum_{\substack{h \in h - off, tou = off - peak \\ h \in h - off, tou = off - peak }} (D(scen, h) * DGVarCost \quad \forall scen + \sum_{\substack{h \in h - off, tou = off - peak \\ h \in h - off, tou = off - peak }} (D(scen, h) * DGVarCost \quad \forall scen + \sum_{\substack{h \in h - off, tou = off - peak \\ h \in h - off, tou = off - peak }} (D(scen, h) * DGVarCost \quad \forall scen + \sum_{\substack{h \in h - off, tou = off - peak \\ h \in h - off, tou = off - peak }} (D(scen, h) * DGVarCost \quad \forall scen + \sum_{\substack{h \in h - off, tou = off - peak \\ h \in h - off, tou = off - peak }} (D(scen, h) * DGVarCost \quad \forall scen + \sum_{\substack{h \in h - off, tou = off - peak \\ h \in h - off, tou = off - peak }} (D(scen, h) * DGVarCost \quad \forall scen + \sum_{\substack{h \in h - off, tou = off - peak \\ h \in h - off, tou = off - peak }} (D(scen, h) * DGVarCost \quad \forall scen + \sum_{\substack{h \in h - off, tou = off - peak \\ h \in h - off, tou = off - peak }} (D(scen, h) * DGVarCost \quad \forall scen + \sum_{\substack{h \in h - off, tou = off - peak \\ h \in h - off, tou = off - peak }} (D(scen, h) * DGVarCost \quad \forall scen + \sum_{\substack{h \in h - off, tou = off - peak \\ h \in h - off, tou = off - peak }} (D(scen, h) * DGVarCost \quad \forall scen + \sum_{\substack{h \in h - off, tou = off - peak \\ h \in h - off, tou = off - peak }} (D(scen, h) * DGVarCost \quad \forall scen + \sum_{\substack{h \in h - off, tou = off - peak \\ h \in h - off, tou = off - peak }} (D(scen, h) * DGVarCost \quad \forall scen + \sum_{\substack{h \in h - off, tou = off - peak \\ h \in h - off, tou = off - peak }} (D(scen, h) * DGVarCost \quad \forall scen + \sum_{\substack{h \in h - off, tou = off - peak \\ h \in h - off, tou = off - peak }} (D(scen, h) * DGVarCost \quad \forall scen$$

Objective function. The objective is to minimize the expected monthly energy cost, where the expected cost is the average of costs from each scenario.

$$ExCost = \frac{\sum_{scen} Cost(scen)}{S}$$
(10)

The optimal dispatch for the current hour is contained in the solution to the minimized expected cost.

 $D(scen, dd, h) = \arg\min(ExCost(D))$ (11)

⁹ It is assumed that tank storage is adequate to support daily asynchrony in thermal supply and demand.

¹⁰ The natural gas requirements of on-site generation are proportional to the electricity production.

¹¹ The maximum amount of recovered heat from on-site generation is proportional to the amount of on-site generation.

Dispatch Optimization at a Boston Office Building

In this section, the algorithm proposed before is implemented in a mixed integer linear program and applied to the hourly simulation of an office building in Boston, Massachusetts. The most important reasons for selecting this site are:

- The volumetric (\$/kWh) cost of electricity is favorable to DG when waste heat is useful, and to the utility when waste heat is not useful;
- Heating loads at the site vary significantly by month, illustrating the range of DG uses, from peak shaving in summer months with high demand charges and low use for heat, to base-loading in winter months with high use for heat;
- Demand charges are extremely high (\$25/kW month in the summer), creating strong potential for dispatch coordinated to mitigate demand charges.

The energy load data for this hypothetical site are obtained from the building energy simulation program DOE-2. A typical weekday load profile is shown in Figure 6. Energy costs for 2005 were collected from Boston utilities NSTAR (NSTAR electricity rates) and Keyspan (KeySpan) and are shown in Table 2.

A hypothetical IES system comprised of a single-generator CHP system and limited curtailment opportunities is considered. Amortized capital costs of the system are not included in the energy costs reported here. The specifications of this IES system are listed in Table 3.

Figure 6. Typical January Weekday Loads



Table 2. 2005 Boston Utility Electricity and Natural
Gas Rates

			er (June - ept.)	Winter (Oct - May)			
		on peak off peak on peak off peak					
Electricity	fixed (\$/month)	350					
	energy (\$/kWh)	0.11	0.09	0.09	0.09		
	demand (\$/kW month)	25.28	0.00	11.69	0.00		
Natural gas	fixed (\$/month)	300 0.038062					
	energy (\$/kWh)						

Table 3: IES System Details

CHP system							
electrical capacity	700 kW						
electrical efficiency	33%						
availability	98.50%						
heat to electric ratio	1.5						
variable maintenance cost	\$0.01/kWh						
Curtailable load							
curtail magnitude	150 kW						
curtail duration	1 hour						
maximum curtail frequency	6 per month						

For each month, a simulated actual scenario and set of stochastic scenarios were considered. For each of these scenarios, a stochastic value for electricity load and DG availability was assigned to each hour. The algorithm was run iteratively from the first hour of the month to the last hour. At each iteration the next actual scenario values replaced the stochastic values. For each month, four cases were considered: no dispatch, DG only, curtailment only, and DG and curtailment. Monthly cost results for the 12 months and 4 cases considered are shown in Table 4.

	No									
	dispatch	DG only			Curtail only			DG and Curtail		
		Energy	Savings	Savings	Energy	Savings	Savings	Energy	Savings	Savings
Month		cost (\$)	(\$)	(%)	cost (\$)	(\$)	(%)	cost (\$)	(\$)	(%)
January	\$53,293	\$47,727	\$5,566	10.4%	\$53,023	\$270	0.5%	\$46,177	\$7,116	13.4%
February	\$51,590	\$46,114	\$5,476	10.6%	\$51,286	\$304	0.6%	\$44,458	\$7,132	13.8%
March	\$50,730	\$45,595	\$5,135	10.1%	\$50,272	\$458	0.9%	\$44,258	\$6,472	12.8%
April	\$50,335	\$45,652	\$4,683	9.3%	\$49,541	\$794	1.6%	\$44,028	\$6,307	12.5%
Мау	\$53,566	\$49,289	\$4,277	8.0%	\$52,668	\$898	1.7%	\$47,662	\$5,904	11.0%
June	\$79,693	\$72,381	\$7,312	9.2%	\$78,022	\$1,671	2.1%	\$69,124	\$10,569	13.3%
July	\$81,798	\$74,611	\$7,187	8.8%	\$80,329	\$1,469	1.8%	\$71,193	\$10,605	13.0%
August	\$80,831	\$74,031	\$6,800	8.4%	\$79,162	\$1,669	2.1%	\$70,989	\$9,842	12.2%
September	\$74,539	\$68,979	\$5,560	7.5%	\$72,874	\$1,665	2.2%	\$65,624	\$8,915	12.0%
October	\$50,875	\$48,986	\$1,889	3.7%	\$50,181	\$694	1.4%	\$47,424	\$3,451	6.8%
November	\$53,323	\$50,827	\$2,496	4.7%	\$52,718	\$605	1.1%	\$49,503	\$3,820	7.2%
December	\$57,461	\$56,273	\$1,188	2.1%	\$56,963	\$498	0.9%	\$54,607	\$2,854	5.0%
annual	\$738,034	\$680,465	\$57,569	7.8%	\$727,039	\$10,995	1.5%	\$655,047	\$82,987	11.2%

Table 4. Monthly Site Energy Costs

These energy costs reflect the increased electricity costs during summer months (June – September), as well as the increase in natural gas costs beginning in October. In the beginning of the year, DG can be used to reduce the volumetric costs of electricity because of the large use (and thus value) for waste heat. DG can also be used to mitigate moderate demand charges. During summer months - when there is less use for waste heat - DG is used to mitigate the large summer on-peak demand charges. Curtailment alone (0.2% of total monthly consumption) can be used to reduce energy costs by 2%. The most significant result in this table is the synergistic relationship between DG and curtailment: in every month, the combined savings from integrated dispatch of DG and curtailment is greater than the savings from either IES component used in isolation. Over the entire simulated year, dispatching the DG system alone leads to 7.8% energy cost savings over the no dispatch case; curtailment alone leads to 1.5% savings, and yet the savings from the integrated dispatch of both DG and curtailment is 11.2%.

Synthesis & Conclusions

Although DG can offer many economic and environmental benefits to commercial and industrial customers, it is often overlooked because of designers' and sites' unfamiliarity with it. Building energy simulation is a major component of modern building design and renovation; making an analysis tool available that includes DG equipment and controls options would greatly improve the accessibility of DG adoption. Coupling DG system design and dispatch with a complimentary program of curtailment and/or rescheduling could provide benefits greater than either of the two in isolation.

E+ is a popular, powerful building energy analysis tool that already has earned widespread acceptance in the building energy analysis community. The flexibility in system modelling capabilities enabled by SPARK makes E+ particularly powerful, as libraries of devices, equipment, and controls can be offered to designers without encumbering the E+ code. A library of SPARK DG equipment modules can be developed and made available with E+.

DER-CAM can be used to suggest site-specific candidate DG systems. Investigations performed with DER-CAM have shown that CHP enabled technologies, which increase the overall system efficiency, as seen in the DER-CAM example, are very important technologies and have to be considered in building simulations. Any DG system modelled in E+/SPARK will also require a controller. An optimization algorithm is required for this controller to optimize the

real-time dispatch of this DG system or of an entire IES. The algorithm proposed here serves such a purpose.

A beneficial feature of the modular nature of modelling in SPARK is the option to experiment with various IES control strategies. A complex optimization algorithm may prove too costly and questionably robust to warrant implementation beyond the design phase. Simpler, heuristic control strategies could be derived from the results of the original optimization algorithm to provide a robust, cost effective, near-optimal dispatch solution.

Developing this DG enabled E+/SPARK model is ongoing work at LBNL. The principal steps necessary for this effort are shown in Figure 7. Starting with the building parameters and the weather data, E+ calculates the load profiles for each energy end-use. DER-CAM then uses these load profiles, along with DG investment options and energy tariffs and rates, to determine candidate systems for the selected building. The final step is to return to the site's E+ model to include a candidate DG system and an energy manager. This provides the most accurate assessment of the site's energy consumption and economic and environmental implications. Figure 7 illustrates the process and Figure 8¹² illustrates the final product.



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¹² DER-CAM does not run synchronized with EnergyPlus. In other words, EnergyPlus generates - for a certain building – 'static' load profiles and feeds them back to DER-CAM (this can happen through a file which acts as a pipe). Then, the new E+ modules have to evaluate the static solution (given by DER-CAM) under 'dynamic' boundaries. However, there is no direct real-time link between DER-CAM and E+.

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