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Disclaimer

Integrated Energy System Dispatch Optimization

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Abstract **- On-site cogeneration of heat and electricity, thermal and electrical storage, and curtailing/rescheduling demand options are often cost-effective to commercial and industrial sites. This collection of equipment and responsive consumption can be viewed as an integrated energy system (IES). The IES can best meet the site's cost or environmental objectives when controlled in a coordinated manner. However, continuously determining this optimal IES dispatch is beyond the expectations for operators of smaller systems. A new algorithm is proposed in this paper to approximately solve the real-time dispatch optimization problem for a generic IES containing an on-site cogeneration system subject to random outages, limited curtailment opportunities, an intermittent renewable electricity source, and thermal storage. An example demonstrates how this algorithm can be used in simulation to estimate the value of IES components.**

I. INTRODUCTION

MODERN automation, power generation and energy storage technologies have enabled commercial and industrial buildings a large degree of flexibility regarding power consumption. Objectives that can be achieved by exploiting this flexibility include energy cost minimization and site energy efficiency maximization. Optimization of energy system controls, however, is a complex problem requiring integrated planning and dispatch of all energy options under uncertain, yet relevant future conditions.

This paper illustrates the value of dispatch informed by data collection and computation to individual customers and to society. The costs of energy production and consumption to suppliers, consumers, and society at large are described in Section II. Section III describes the particular energy options available to buildings. Section IV discusses the optimization problem that these options, coupled with the costs of energy consumption and uncertain future conditions, present. Section V proposes an algorithm for determining the near-optimal real-time dispatch of integrated energy systems. Results of the application of this algorithm to an illustrative site are presented in Section VI.

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II. ENERGY COSTS TO SUPPLIERS, CONSUMERS, AND SOCIETY

Commercial and industrial customers are billed for electricity in a manner that reflects the costs to suppliers. In the United States, the main components of their electricity bill are volumetric ($/kWh), demand ($/kW peak consumption per month), and fixed ($/month) costs. Volumetric costs cover variable costs to suppliers such as for fuel and disposal of byproducts. These rates may vary by time of day to reflect the higher cost of producing electricity during the peak hours of the day. Demand charges reflect the capacity costs incurred by the utility per MW of peak demand on the system, and include the infrastructure costs of power plants, transmission, and distribution systems, which must be sized to meet this peak demand. Fixed costs are incurred regardless of electricity demand quantities or rates, and cover maintenance costs and the administrative costs of metering and billing. Customers can reduce electricity costs by 1) shifting their electricity consumption to times of less expensive volumetric rates, 2) reducing their volume of consumption, or 3) reducing their peak demand.

Volumetric costs to society are incurred because of the consumption of finite resources (i.e. fossil fuels), the environmental and political costs of obtaining and processing fuels, and environmental cost of electricity byproducts, such as greenhouse gases, NO_x and particulate matter. Capacity costs are incurred because of the undesirability of siting new power plants and transmission lines.

This section illustrates that the pricing mechanism for consumers is 1) equitable because costs are incurred to individuals in proportion to the costs that suppliers incur and 2) is beneficial to society because it encourages reductions in both volume and peak demand.

III. DISTRIBUTED ENERGY RESOURCE OPTIONS TO COMMERCIAL AND INDUSTRIAL BUILDINGS

To reduce energy costs and/or to improve their environmental footprint, commercial and industrial buildings have several investment and implementation options. In addition to energy efficiency retrofitting, which requires no active controls, they can invest in on-site energy generation and storage devices, as well as programs to curtail or reschedule some of their power demand. Collectively, these actively controlled options are referred to as distributed energy resources (DER).

A. Distributed Generation

Buildings can invest in on-site electricity generation equipment (i.e. distributed generation (DG)) such as 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. The heat generated by these devices can be harnessed for application to site space, water, and process heating needs. Heat can also be used to satisfy cooling loads via an absorption chiller. Solar electricity (i.e. photovoltaics (PV)), solar thermal, and wind power devices are also options.

Typically, on-site electricity production is most economic when in parallel with utility electricity purchase. When the cost of producing electricity and heat on-site is less than the cost of purchasing electricity and heating fuel separately, on-site generation is dispatched to run. On-site generation can reduce both the volumetric and demand charges of electricity production, although unplanned outages often reduce the potential for demand charge mitigation.

This paper examines the problem of optimal real-time control of DG systems already installed. Much work has already been done by the authors and their research team on the optimal DG investment problem [1].

B. Storage

Thermal or electrical energy can be stored for use at a more opportune time. Typically, electrical storage is cost prohibitive for all but brief transition periods (on the order of milliseconds to minutes) and targeted loads (manufacturing or data processing). Thermal storage is more cost effective and can be in the form of tanks, the embodied heat retention of operating fluids in thermal loops, or the thermal mass of a building.

Storage can reduce energy costs by applying an abundant or inexpensive resource (e.g. recovered or solar heat, off-peak electricity) at one time to an energy demand at a less opportune time. The co-optimization of DG and thermal storage investments has been examined in [2].

C. Demand Side Management

Curtailment and rescheduling opportunities can be used to limit peak power consumption or shift energy consumption for cost savings. Typical curtailment measures include raising chiller setpoints and reducing lighting in hallways, garages, and other non-work areas. Rescheduling measures include time-shifting energy intensive processes or production schedules. These demand side management (DSM) measures can be characterized by their maximum demand reduction magnitude (kW), duration (e.g. minutes per episode), and frequency (e.g. times per month). There may be direct and/or indirect costs associated with DSM episodes, which must be weighed against their value.

DSM can reduce costs to buildings by lowering their peak demand for electricity, and by shifting some volumetric costs to lower priced times of the day. [3] provides a recent examination of fully-automated DSM opportunities.

IV. The Optimization Problem For Integrated Energy Systems

Dispatch to a site's DER options must be made continuously and includes the setpoints of generators, the charging or discharging of storage, and DSM commands. Typical constraints on the system include

- engineering constraints on equipment such as ramping rates and maximum and minimum operating levels;
- regulatory constraints on noise, operation hours, or overall DG system efficiency (i.e. utilization of waste heat); and
- magnitude, duration, and frequency constraints on DSM.

As with any set of decisions that affect a common objective, the dispatch decisions to all DER options can best meet site energy objectives if the decisions are coordinated. This introduces the concept of the integrated energy system (IES), a holistic view of all site energy options.

A common problem for DG systems is determining the proper level of demand charge mitigation. This arises when the volumetric costs of utility electricity and heating fuel are less than that of on-site production of electricity and heat, yet monthly utility demand charges tip the scale in favor of on-site generation. The situation is complicated by the stochastic nature of DG system failures, which can happen at inopportune times during the month and lead to surges in utility electricity demand. For this hedging problem, the optimal level of demand mitigation must be determined in light of energy costs, DG system reliability parameters, and hourly end-use load forecasts for the month. As the month progresses, the optimal demand hedge will change as any DG failures are incurred and as forecasts are updated.

Another common problem for a wider range of IES systems is making the best use of limited opportunities. Examples of limited opportunities include

- profitable DG systems that are operationally constrained by regulatory efficiency constraints (where there is only limited use for waste heat), maximum run-time regulations, or limited fuel supply, and
- DSM measures that a site's occupants will only accommodate a limited number of times.

Optimally exploiting limited opportunities is challenging because it is dependent on uncertain future conditions, such as DG intermittency (generator outages or variation in renewables output), end-use demand, and energy pricing.

The IES dispatch problem is to minimize, at each time step, the expected cost (or other site energy objective) of all energy consumption, given past system operation, present conditions, and forecasts of future conditions. This is done by simultaneously solving the unit commitment and setpoint level problems for the current timestep and all future timesteps, conditional on future conditions.

While prior research has considered dispatch optimization for IES systems comprised of DG, storage, and/or curtailment (e.g. [4]), a literature review revealed none that considered demand charges or stochastic DG outages. These, however, are exactly details of the IES problem that cause real-world results to deviate from design estimates.

V. An Algorithm for Optimization of Real-time IES Dispatch

Because of the complexity of the IES dispatch optimization problem and large number of timesteps to be solved over (ideally timesteps of several minutes over the course of a month or more), an exact solution to the problem, conditional on the statistical description of stochastic parameters, is infeasible. A feasible approach is to optimize the current dispatch and future dispatch strategy relative to a finite number of future scenarios.

This section describes a simple IES dispatch optimization algorithm from which more complicated, practical algorithms could be built upon. The algorithm 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 timestep. 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 optimization over the course of a month for a site with a DG system comprised of one generator with heat recovery for heating and absorption cooling, a photovoltaic (PV) system, and limited curtailment options. A limited amount of thermal storage is considered by relaxing the synchronous constraint on thermal demand. Two dispatch decisions are considered: the setpoint of the generator in the CHP system and a curtailment command.

A. Parameter Assignment

The best information about the stochastic parameters, SP (scen, sp,t), is a combination of actual (historic and current) scenario values, AS(sp,t), for all previous and current timesteps, and the set of S randomly generated parameter values, SV(scen,sp,t), for all future timesteps.

For all timesteps prior to and including the current timestep, stochastic parameter values are all known and are equal to the actual scenario parameter values.

$$SP(scen,sp,t) = AS(sp,t) \quad \forall\, scen, sp, \forall\, t \le CurrentTime \tag{1}$$

For all future timesteps, the stochastic parameter values are the stochastic values generated for each scenario.

$$SP(scen,sp,t) = SV(scen,sp,t) \quad \forall\, scen,\, sp,\, \forall t > CurrentTime \tag{2}$$

TABLE I
INDICES

Symbol	Description	Set
d	days	{1,…,D}
dd	dispatch decisions	{generation level, curtail}
scen	stochastic scenarios	{1,…,S}
sp	stochastic parameter	{electric load, generation availability, solar insolation}
t	timesteps	{1,…,T}
t-mid	subset of mid-peak timesteps	
t-off	subset of off-peak timesteps	
t-on	subs set of on peak hours	
TOU	time of use	{on-peak, mid-peak, off-peak}

TABLE II
PARAMETERS

Parameter	Description
AS (sp,t)	actual scenario stochastic parameter values
CurrentTime	current timestep of month
Curt	magnitude (kW) of curtailed load
CurtFreq	maximum number of curtailment timesteps allowed per month
DailyHeatLoad (d)	daily total space and water heating (kWh) requirement
DCost (TOU)	demand cost ($/kW peak) for electricity by time of use
DGCapacity	electric capacity (kW) of on-site generation
DGVarCost	variable maintenance costs ($/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,t)	historical dispatch decisions
HtoEgen	ratio of useful heat to electricity generation of DG
NGCost	volumetric cost of natural gas ($/kWh)
NGfixed	monthly fixed cost ($) of utility natural gas service
PVCapacity	electric capacity (kW peak production) of photovoltaics on-site
S	number of stochastic scenarios considered
SP (scen, sp, t)	stochastic parameter values used for optimization problem
SV (scen, sp, t)	stochastic values from Monte Carlo simulation
T	number of timesteps in month

TABLE III
DECISION VARIABLES

Variable	Description
AbsHeatLoad(scen,t)	heat required (kWh) for absorption chiller
AbsOffset(scen,t)	electric load (kWh) offset by absorption chiller
D (scen, dd, t)	dispatch decision
EPurch (scen, t)	electricity purchased (kWh)
ExCost	expected monthly energy cost, considering all scenarios
NGforDG (scen, t)	natural gas purchase (kWh) for DG
NGforHeat (scen,t)	natural gas purchase (kWh) for heating
RecHeat (scen,t)	useful recovered heat (kWh) from distributed generation

B. Dispatch Constraints

For all timesteps prior to the current timestep, dispatch is known and is the historical dispatch of the system.

$$D(scen, dd, t) = HistD(dd, t) \quad \forall\, scen, dd, \forall t < CurrentTime \tag{3}$$

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

$$D(i, dd, t) = D(j, dd, t) \quad \forall i,j \in scen, \forall dd, t = CurrentTime \tag{4}$$

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

C. Energy Balance:

Electricity loads must be met instantaneously by the sum of electricity purchase, on site generation (including PV generation), and electric chiller load offset by heat-driven absorption chiller, and curtailment.

$$\begin{aligned} &SP(scen,\text{"}electric-load\text{"}, t) \\ &= EPurch(scen,t) + D(scen,\text{"}generation-level\text{"}, t) \\ &+ PVCapacity * SP(scen,\text{"}solar-insolation\text{"}, t) \\ &+ AbsOffset(scen,t) + Curt * D(scen,\text{"}curtail\text{"}, t) \qquad \forall scen,t \end{aligned} \tag{5}$$

Heating loads, including that of the absorption chiller, must be met on a daily basis by the sum of direct combustion of natural gas and recovered heat from on-site electricity generation. It is assumed that tank storage is adequate to support daily asynchrony in thermal supply and demand.

$$\begin{aligned} &DailyHeatLoad(d) + \sum_{t \in d} AbsHeatLoad(scen,t) = \\ &\sum_{t \in d} NGforHeat(scen,t) * FtoHeffic + RecHeat(scen,t) \quad \forall scen,d \end{aligned} \tag{6}$$

D. 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. Availability at each timestep and for each scenario (*SP(scen, "generation-availability",t)*) is a binary variable equal to zero if the generator is unavailable and one if it is.

$$\begin{aligned} &D(scen,\text{"}generation-level\text{"}, t) \le \\ &SP(scen,\text{"}generation-availability\text{"}, t) * DGCapacity \\ &\forall scen,t \end{aligned} \tag{7}$$

E. Curtailment:

The number of curtailment timesteps per month is constrained.

$$\sum_t D(scen,\text{"}curtail\text{"}, t) \le CurtFreq \qquad \forall scen \tag{8}$$

F. 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 fees for electricity and natural gas service.

$$\begin{aligned} &Cost(scen) = \\ &\sum_{tou} \left(\begin{aligned} &\sum_{\substack{t \in t-on, tou=on-peak \\ t \in t-mid, tou=mid-peak \\ t \in t-off, tou=off-peak}} EPurch(scen,t) * EnergyCost(tou) \\ &+ \max_{\substack{t \in t-on, tou=on-peak \\ t \in t-mid, tou=mid-peak \\ t \in t-off, tou=off-peak}} \big(EPurch(scen,t) * DCost(tou)\big) \end{aligned} \right) \\ &+ \sum_h \big(NGforDG(scen,t) + NGforHeat(scen,t)\big) * NGCost \\ &+ \sum_t D(scen,\text{"}generation-level\text{"}, t) * DGVarCost \\ &+ EFixed + NGFixed \qquad \forall scen \end{aligned} \tag{9}$$

G. Objective Function:

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

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

For risk averse operators, the expected cost may exceed the average cost; a cost function that assigns disproportionate penalties to high cost scenarios would also be possible.

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

$$D(scen, dd, t) = \arg\min(ExCost(D)) \tag{11}$$

For this research, the optimization is formulated as a mixed integer linear program (MILP) and solved by the CPLEX™ solver. Integer variables are the on/off decision on DG equipment and curtailment options. As is typical for MILP, this problem is NP-hard: the number of discrete feasible solutions is exponential in time.

VI. Example: DSM Value When Coordinated with Intermittent DG

This section provides an example of a building energy simulation which uses the algorithm proposed in Section V. For the study, an area with high demand rates was desired to illustrate the value in mitigating demand charges. Southern California meets this criteria, with on-peak demand rates during the six summer months of the year are ~US$30/kW.

A prototype shopping center in the coastal regions of Southern California is considered, and based on data obtained from a prior case study [5] of a commercial building in Southern California covering 13,000 m^2 of floor-space and containing a large retail store, supermarket, food court, and other small businesses. The annual peak electricity load is 1,050 kW. Electricity and natural gas prices for the year April 2005 to March 2006 were obtained from the local utilities [6][7] and summarized in Table IV.

For each case and scenario, a building energy simulation for each month of the study year was performed using hour-long timesteps. Note that for real-time applications, smaller timesteps could be used. Uniform distributions were used for all stochastic parameters. Simulation entails

1) considering forecasts of each parameter value at each timestep for each of the S stochastic scenarios
2) determining the optimal dispatch for the current time step
3) executing the dispatch and recording the resulting system performance data
4) advancing to the next timestep

and continuing steps 2) – 4) until the last timestep of the month is reached. This simulates actual building operation where a decision is made at the first timestep of the month, and at each consecutive timestep until the end of the month.

The simulation used here is static: past dispatch decisions do not affect current energy loads. Integrating this IES dispatch optimization algorithm into a building energy simulation program such as EnergyPlus would provide more accurate, dynamic simulations by better estimating the energy demand of thermal equipment at varying load levels and the thermal response of the building to curtailment events. Work on this topic is underway by the authors [8].

Curtailment opportunities for the site were parameterized by their magnitude, frequency, and duration. The magnitude of curtailment considered ranged from 50 to 250 kW, the frequency ranged from 5 to 25 times/month, and the duration was always constrained to one hour at a time. For the simulation, it is assumed that any dispatched curtailment actually occurred (i.e. curtailment dispatch could not be overridden by building occupants).

Other IES components considered were 1) a DG system: 500 kW reciprocating engine with heat recovery and a 500 kW (capacity for heat removal) absorption chiller, and 2) a 200 kW photovoltaic system. To reflect current California incentives, the DG system was constrained to utilize 60% of input fuel energy in the form of electricity or useful thermal energy. The following cases were considered

1) curtailment only
2) DG and curtailment
3) PV and curtailment
4) DG, PV, and curtailment

For each case the forecasted and actual parameter values for each scenario (set of curtailment magnitude and frequency constraints) are constant; only the constraints on curtailment magnitude and frequency vary. The overall annual energy cost, including utility electricity, natural gas, and DG maintenance costs are summarized in Section VII.

VII. RESULTS

Table V summarizes the annual energy costs with no curtailment for each case. From the annual savings over Case 1 (no on-site generation), the net present value (NPV) of the DG and PV systems without curtailment is also reported. These values are based on a 20 year lifetime for DG systems, 30 year lifetime for PV systems, and a 5% discount rate. Fig. 1 shows how electrical loads are met for three days in July for a particular case and scenario. Fig. 2 through Fig. 5 show contour plots of the annual energy cost savings over the no-curtailment scenario for each case. These plots show the value of curtailment for each case, where value is defined as annual cost less annual cost with no curtailment.

Without on-site generation, feasible curtailment schemes could save this site US$20,000/year (Fig. 2), or about 3% of the annual energy cost without IES. Curtailment becomes more valuable at low curtailment magnitudes (50-100 kW, roughly 5-10% of peak load) in conjunction with DG (Fig. 3 and 5), which is a synergy between the two IES components. Increasing curtailment magnitude does not significantly increase the cost savings for these cases. Curtailment is less valuable when in conjunction with PV, suggesting some overlap in savings between the two IES components.

For the site considered, small, frequent curtailments are more effective than large, infrequent curtailments. If limited to 20 one-hour 50 kW (5% of peak load) curtailment episodes per month, curtailment alone can reduce site annual energy costs by 1.7% relative to site energy costs with no IES components. As a component in a more complex IES system, this value can increase to 3.1%. These results will depend heavily on the statistical distribution of site energy loads and DG intermittency patterns.

VIII. CONCLUSIONS

Optimal dispatch is a complex and challenging problem for IES in commercial and industrial buildings. An algorithm is proposed here which can make near-optimal dispatch decisions in real-time. The example and results presented in Sections VI and VII illustrate how this algorithm can be used in simulation to estimate the value of particular IES system configurations. Although this example should not be considered exemplary of the entire stock of U.S. buildings, it does illustrate how valuable IES components and systems can be in a location with significant demand charges.

This example suggests the proposed algorithm's usefulness as a screening and design tool for a wide variety of sites considering IES projects. For sites where this integrated approach suggests significant costs savings over current control strategies, this algorithm would be useful in the actual real-time dispatch of IES systems. Where this algorithm proves too complex to implement, heuristic control strategies derived from the results of this algorithm could be implemented. Implementation would require an energy management system capable of 1) collecting the sensed parameter values, 2) running the optimization program, and 3) dispatching the IES components.

Taking advantage of optimization opportunities with IES relies heavily on the information technology available to the site. Certainly computation is required at each time-step to execute an optimization. Additionally, an instrumented building can provide the detailed information necessary to identify least cost DSM opportunities. These technologies enable societal benefits of reduced energy consumption on two levels: the first is that they help optimize the volumetric and demand reductions that existing IES systems are capable of. The second is that they enhance the value of IES systems, which incents IES system adoption. This in turn leads to more energy savings.

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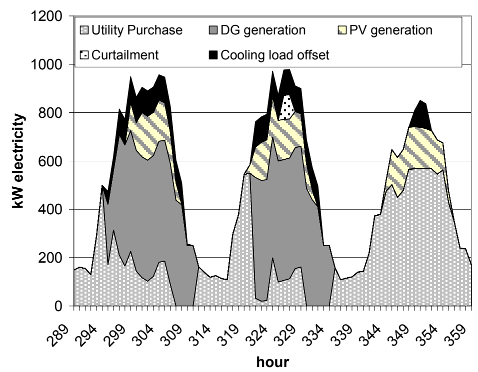

Fig. 1: How electricity loads are met for two weekdays and a weekend day in July. Results are from Case 4 (DG, PV, and curtailment) limited to 10 one-hour, 100 kW curtailment episodes per month.

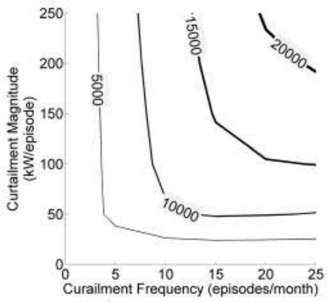

Fig. 2 Curtailment value (US$/year). Case 1: Curtailment Only

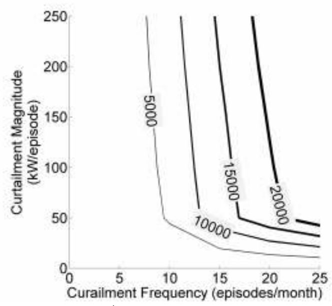

Fig. 3 Curtailment value (US$/year). Case 2: Curtailment and DG

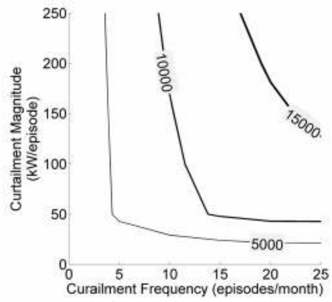

Fig. 4 Curtailment value (US$/year). Case 3: Curtailment and PV

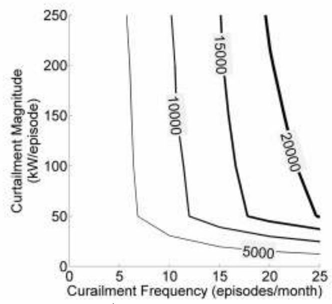

Fig. 5 Curtailment value (US$/year). Case 4: Curtailment, DG, and PV

TABLE IV
ENERGY PRICES

		summer (May – Oct)	winter (Nov – Apr)
Electricity Rates			
Fixed (US$/month)		288	
Volumetric (US$/kWh)	on-peak	0.157	n/a
	mid-peak	0.094	0.118
	off-peak	0.055	0.057
Demand (US$/kW-month)	all hours	8.75	8.75
	on-peak	20.51	n/a
	mid-peak	5.01	0.00
Natural Gas Rates			
Fixed (US$/month)		1022	
Volumetric (US$/kWh (US$/therm))		0.020- 0.38 (0.60 – 1.10)	

TABLE V
ANNUAL COST RESULTS PRIOR TO CURTAILMENT

Case	Energy cost without curtailment (US$/year)	Savings over no IES (US$/year)	NPV of generation equipment (US$/kW)
1: No on-site generation	$606,330	n/a	
2: DG only	$405,560	$200,770	$8800
3:PV only	$541,350	$64,985	$5000
4: DG and PV	$351,680	$254,650	