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OPTIMIZING MICROGRID ARCHITECTURE ON DEPARTMENT OF DEFENSE INSTALLATIONS

by

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September 2014

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Second Reader: Dashi Singham

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Energy managers are faced with the challenge of upgrading their installation microgrids in a tight fiscal environment, while meeting the challenges of incorporating higher percentages of renewable energy sources and providing better energy assurance during commercial grid failures.

Incorporating renewable sources of energy into a microgrid is challenging due to the intermittent nature of supply. Using historical solar data and simulated forecasts for wind data, we formulate and exercise a capital planning optimization model designed to choose the best subset of existing and potential energy sources to maximize microgrid islanding time. Islanding time is defined as the amount of time demands can be met without connection to the commercial power grid, and it is one measure of an installation's power resiliency.

Using sensitivity analysis, we show quantitatively how increases in the capital planning budget has a direct positive impact on islanding time. However, the model also identifies areas where large increases in budget yield proportionally smaller returns in islanding time. Additionally, energy storage can provide increases in islanding time, but there are diminishing returns as the storage capacity is increased. Finally, we quantitatively show that increasing reliance on renewable power decreases sensitivity to changes in the price of fuel.

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OPTIMIZING MICROGRID ARCHITECTURE ON DEPARTMENT OF DEFENSE INSTALLATIONS

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Submitted in partial fulfillment of the
requirements for the degree of

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LIST OF ACRONYMS AND ABBREVIATIONS

BTU	British thermal unit
DOD	Department of Defense
DRID	Department of Defense Reform Initiative Directive
EIA	U.S. Energy Information Administration
EMC	energy management center
ESM	energy surety microgrid
ExFOB	experimental forward operating base
GEFS/R	Global Ensemble Forecast System Reforecast
GHG	greenhouse gas
GWEC	Global Wind Energy Council
HEG	hybrid electric microgrid
HOMER	Hybrid Optimization Model for Electric Renewables
HRES	hybrid renewable energy system
JCTD	Joint Command Technology Development
kW	kilowatt
MCAGCC	Marine Corps air ground combat center
MCAS	Marine Corps air station
MGO	MicroGrid Optimizer
MILP	mixed integer linear program
MW	megawatt
NAVFAC	Naval Facilities Engineering Command
NDAA	National Defense Authorization Act
NOAA	National Oceanic and Atmospheric Administration
NREL	National Renewable Energy Laboratory
OUSD[AT&L]	Office of the Under Secretary of Defense for Acquisitions, Technology, and Logistics
OUSD[I&E]	Office of the Under Secretary of Defense for Installations and Environment
PPA	power purchase agreement
PV	photovoltaic
QDR	Quadrennial Defense Review
SNL	Sandia National Laboratory
SPIDERS	Smart Power Infrastructure Demonstration for Energy Reliability and Security

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EXECUTIVE SUMMARY

Energy managers are being faced with the challenge of upgrading their installation microgrids in a tight fiscal environment. They must meet the challenges of incorporating higher percentages of renewable energy sources and providing better energy assurance in the face of commercial grid failures.

Incorporating renewable sources of energy into a microgrid is challenging due to the intermittent nature of supply. Capital planning must be done to determine the best mix of energy sources for a given installation's microgrid architecture. Using historical solar data and simulated forecasts for wind data, we use an optimization model to choose the best subset of existing and potential energy sources to create a microgrid with the longest islanding time. Islanding time is defined as the amount of time demands can be met without use of the commercial power grid, and it is one measure of an installation's power resiliency. We utilize actual solar energy production numbers from the U.S. Army Garrison Presidio of Monterey. We also obtain wind forecasts for the same historic period of time from the National Oceanic and Atmospheric Administration's (NOAA) Global Ensemble Forecast System Reforecast (GEFS/R).

Our analysis shows that increasing the capital planning budget has a direct positive impact on islanding time. First, we show the value of simply having a microgrid to interconnect existing infrastructure. In one scenario we show that the combined islanding time increases by a net 384 hours, a 44% increase over a non-connected grid. Using renewable power in general increases islanding time by reducing the amount of power required from generators. The most drastic gain in the Presidio of Monterey case study shows that adding a wind turbine to a microgrid with the existing infrastructure would result in an additional 13 day and nine hours of islanding time for a total of 25 days, a 112% increase. However, not all scenarios are created equal. Results are highly dependent on the wind forecast, solar data, and demand. Our model enables analysts to identify combinations of renewable power and demand in which large monetary investments yield proportionally smaller returns in islanding time.

Energy storage can provide increases in islanding time, but there are diminishing returns as the storage capacity is increased. We describe a scenario in which a 700% increase in battery capacity has only a negligible impact on islanding time. However, it is important to recognize that storage capacity is also affected by the excess or lack of excess renewable power, and additional renewable production capabilities would likely result in a greater need for storage.

We also perform a sensitivity analysis in order to explore the effect of changing the number of times fuel-based generators can adjust their output. We find that islanding time can be increased by allowing more changes, but that after a certain number there is no longer any increasing benefit. The number will vary by scenario, and the model can help identify this number.

Finally, we employ our model to quantitatively demonstrate that increasing utilization of renewable power decreases our sensitivity to changes in the price of fuel, as defined by fuel cost per islanding hour. Using sensitivity analysis, we show that a generator-only microgrid has a fuel expense range of $76 to $152 per hour of islanding, for fuel prices of $4 and $8 per gallon, respectively. A microgrid with two 380 kW solar arrays, one 50-meter wind turbine, and 400 kW of total energy storage yields a new range of $46 to $92 per hour of islanding. This is a 39% reduction in the range, or stated otherwise, the sensitivity to fuel prices.

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I. INTRODUCTION

The topics of energy, clean energy, and energy independence are frequently debated and discussed in the U.S. The aging and oil-dependent infrastructure in the U.S. needs to be secure and to incorporate new sources of energy. One area of concern for the Department of Defense (DOD) is installation energy, much of which has been privatized.

Utility privatization on DOD installations allows commanders to focus on core missions by relieving them of activities done more efficiently by the commercial market. The Office of the Deputy Under Secretary of Defense Installations and Environment (OUSD[I&E]) has issued guidance to replace Department of Defense Reform Initiative Directive (DRID) #49 published 23 Dec 1998, again restating the directive requiring DOD installations to privatize every electric utility unless security concerns required federal ownership or it was uneconomical [1].

The U.S. commercial electric grid is fragile and a potential security risk. A recent article in the *Los Angeles Times* stated that "the vulnerability of the power grid has emerged as among the most pressing domestic security concerns" [2]. While this statement primarily stems from fears about cyber threats, in 2013, unidentified assailants launched a physical attack when they fired on a power station near San Jose, almost knocking out electricity to Silicon Valley [3].

Energy resiliency needs have not gone unnoticed by the DOD. The DOD Energy Policy, Directive 4180.01, issued by the Office of the Under Secretary of Defense for Acquisitions, Technology, and Logistics (OUSD[AT&L]) assigns the responsibilities for energy planning, use, and management. Specifically, OUSD[I&E] is, among other things, to ensure "cost-effective investments are made in facility infrastructure to reduce energy demand, increase on-site distribution (including renewables), and enhance the power resiliency of installations" [4]. Hybrid microgrids containing renewable energy sources are one potential solution.

Incorporating renewable sources of energy into a microgrid is challenging due to the intermittent nature of supply. It has been suggested that we can use day-ahead scheduling with weather forecasts to optimally operate a microgrid [5]. Capital planning must be done to determine the best mix of energy sources for a given installation's microgrid architecture.

One of the key components of energy security is an installation power grid's resiliency to commercial outages. Resiliency is often measured as islanding time. Islanding time is defined as the amount of time demands can be met without use of the commercial power grid. While energy security is recognized as a key challenge facing the DOD, to our knowledge, there exists no optimization-based capital planning model designed to maximize islanding time. This thesis creates an optimization model designed to choose the best subset of existing and potential energy sources to create a microgrid with the longest islanding time. Using historical solar data and simulated forecasts for wind data, we perform a sensitivity analysis to explore the impact that the capital planning budget has on power resiliency.

A. BACKGROUND

1. Strategic, Environmental, and Monetary Benefits

The DOD has pushed hard to remove utility management from the roles and responsibilities of the military commanders. That shift has created a security concern by transferring utility stability solely into the hands of a commercial market. Most DOD installations have tried to mitigate their risk by installing fossil fuel-based generators to provide power to critical operations in the event of power outages. This typically provides a range of a few hours to a few days of operations.

The *2014 Quadrennial Defense Review* (QDR) clearly states that "our actions to increase energy and water security, including investments in energy efficiency, new technologies, and renewable energy sources, will increase the resiliency of our installations and help mitigate these effects" [6]. This is in keeping with prior guidance that emphasizes that energy security is critical to national security. The challenge is to retain privatized utilities but the gain power resiliency that is critical to national security.

Although the majority of DOD energy consumption is for operational forces (see Figure 1), over a quarter of the energy need is land-based facilities, and microgrids can greatly reduce that consumption. In 2010, it was estimated that 26% of energy consumed by the DOD was at permanent military installations in the United States and abroad, at a cost of approximately $4 billion [7]. If the potential monetary savings is not sufficient justification for pursuing a solution, perhaps it is sufficient knowing that these installations contribute approximately 40% of the DOD's 73.2 million tons of CO_2 emissions [7].

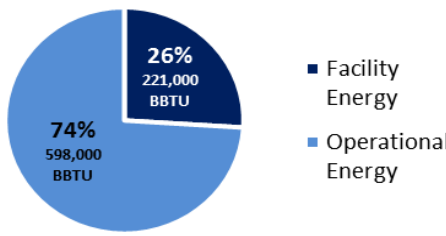


Figure 1. DOD Energy Use in FY 2010, after [7]

2. Policies and Directives

The list of reasons why renewable energy use is appealing is exhaustive. DOD leaders do not need to justify the use of renewable energy. They have already been directed to incorporate it. The 2007 National Defense Authorization Act (NDAA) set a goal that 25% of all DOD energy consumption should be satisfied by renewable energy [8]. In 2009, President Barack Obama signed Executive Order 13514, stating that government agencies must consider locally generated renewable energy [9].

In 2012, Secretary of Defense Leon Panetta and Secretary of the Interior Ken Salazar signed a Memorandum of Understanding that clearly recognizes the "significant proven or potential solar, wind, geothermal and biomass resources on or in the vicinity of DOD installations" [10]. More declaratively, "electrical power produced from these renewable resources, when combined with advanced microgrid and storage technologies, could support DOD needs for energy security and reduce the cost of energy" [10].

Each year, the U.S. Energy Information Administration (EIA) issues its *Annual Energy Outlook*. Its analysis projects out to 2040 and tries to predict trends in energy assuming current laws and regulations remain unchanged. Figure 2 shows how the total

U.S. energy projections are consistent with the direction that is being taken by the DOD. Renewables increase 25% and biofuels by 50%. More specifically, Figure 3 shows electricity generation. The EIA was estimated that renewable generation will grow "by an average of 1.9%/year from 2012 through 2040" [11]. The important take-away from this is that as energy needs increase in the U.S., they are increasingly being met with renewable sources.

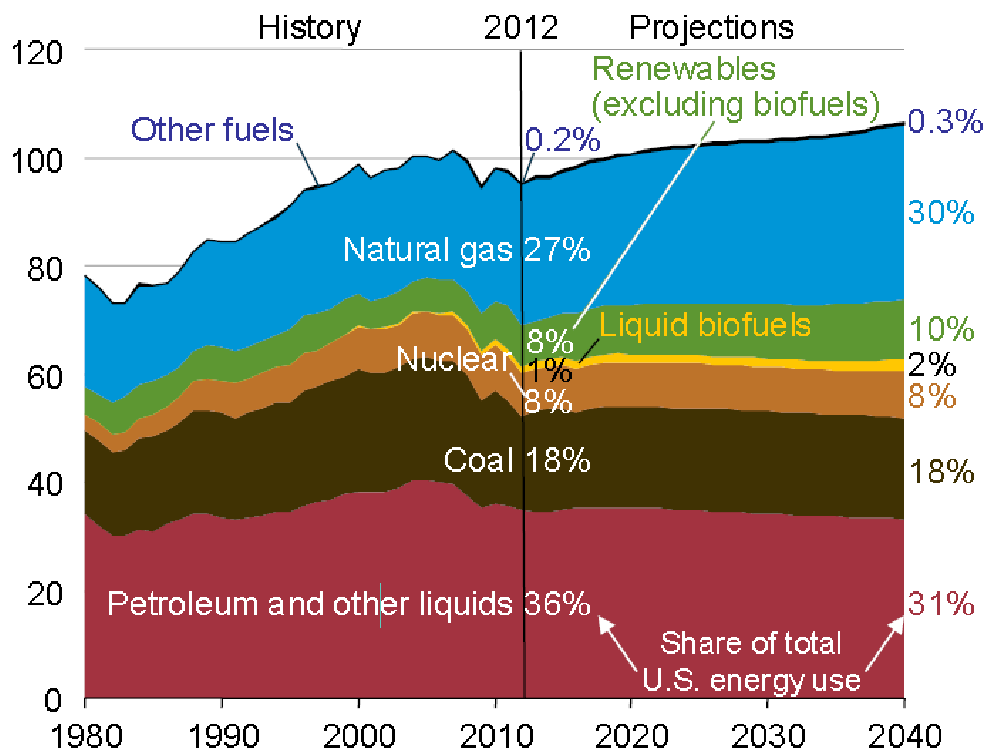


Figure 2. Primary energy use by fuel in quadrillion BTU, 1980–2040, from [11].

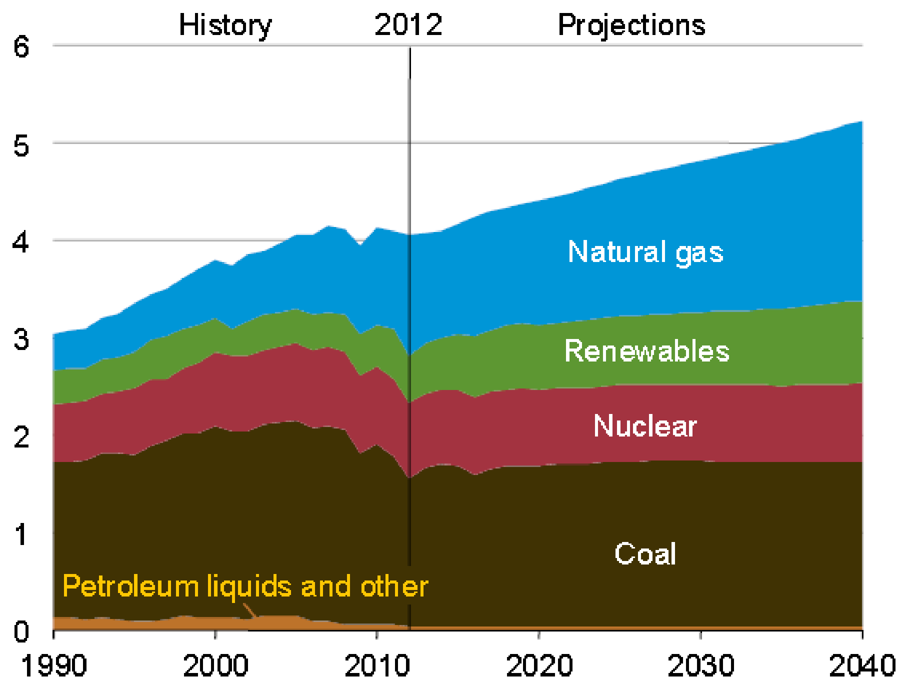


Figure 3. Electricity generation by fuel in trillion kilowatthours, from [11].

It is also interesting to see where the most growth in renewables has occurred. Figure 4 shows how non-hydro renewables outweigh the contribution of hydro power more each year. In 2012, 55% of renewable energy was hydro. By 2040, it is estimated that hydro will only be 35% of renewable energy [11]. This is not surprising since hydro power has limited potential for expansion.

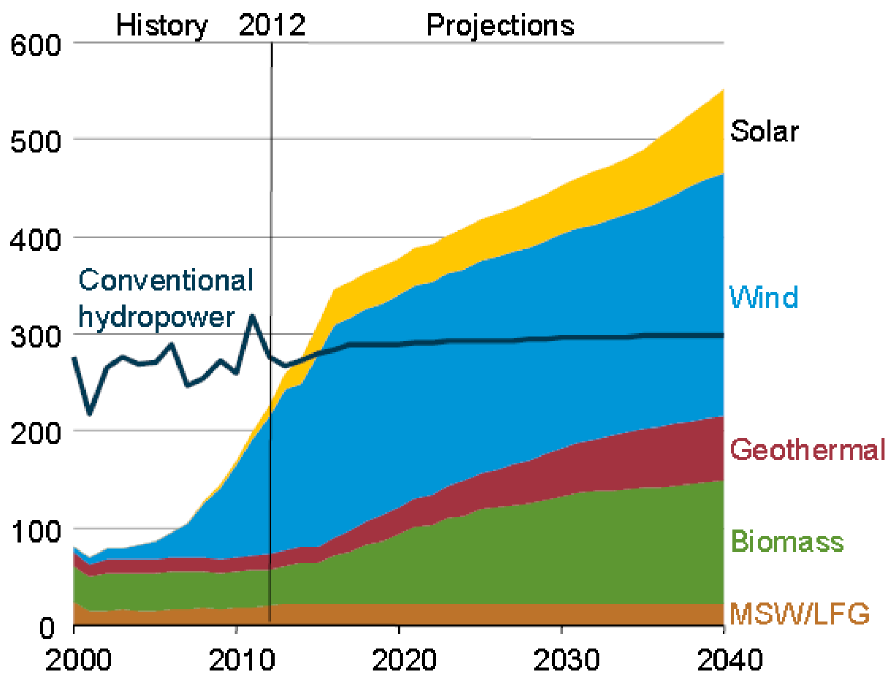


Figure 4. Renewable electricity generation by type, in billion kilowatthours, 2000-2040, from [11].

3. DOD Examples of Renewable Energy Use

The DOD has responded with great enthusiasm to promote the shift to more renewable sources of energy of all types. Projects have ranged from geothermal plants to photovoltaic (PV) cells on rooftops. Table 1 provides renewable energy production levels for FY2010, and these numbers have only increased due to the large number of initiatives began since this information was published.

At China Lake Naval Air Weapons Station, the 270-megawatt geothermal power plant annually provides an average of 1.4 million megawatt-hours of electricity to the power grid, according to the U.S. Navy. Further exploration into geothermal is underway at Naval Air Facility El Centro, Naval Air Station Fallon, Marine Corps Air Station Yuma, and Marine Corps Air Ground Combat Center (MCAGCC) Twenty-nine Palms [12].

Table 1. DOD renewable energy production FY2010, from [7].

Sum of Total Output (Electric + Non-Electric) BBTU								
Renewable Energy Type	Air Force	Army	DLA	Marine Corps	Navy	NSA	TMA	DoD Total
Biogas (captured methane)	-	175	-	-	-	-	-	175
Daylighting	7	2	-	1	-	-	-	10
Geothermal	1	-	-	-	4,292	-	-	4,293
Ground Source Heat Pumps	332	5	-	4	18	-	-	358
Hydropower	-	60	-	-	-	-	-	60
Landfill Gas	52	-	-	-	-	-	-	52
Solar Photovoltaic	20	14	0.01	22	25	0.05	-	80
Solar Thermal (including water and space conditioning)	6	11	-	1	34	-	-	52
Wind	57	6	-	16	50	-	-	129
Wood and wood residuals	-	11	-	-	-	-	-	11
Municipal Solid Waste	-	-	-	-	538	-	47	586
Total	474	284	0.01	44	4,957	0.05	47	5,806

Solar power has become a common investment. The U.S. Navy has more than four megawatts of electricity from installed photovoltaic (PV) arrays. MCAGCC Twenty-nine Palms produces 1.1 MW from a ground-mounted system. Naval Base Coronado has a total of 857.1 kW from carports and building integrated PV. Naval Facilities Pearl Harbor uses a 309 kW array on the roof of an old WWII aircraft hangar. Marine Corps Recruiting District San Diego has a 225 kW rooftop array. Finally, Naval Base Ventura County gets 87 kW from a thin-film rooftop PV system. This may not seem like a lot, but there are over 20 megawatts of additional PV being installed, a 500% increase over the current amount of PV [12]. More important than the PV being installed, are the public/private ventures being created, otherwise known as Power Purchase Agreements (PPAs). These agreements allow the DOD to lease land to private companies that will build, operate, and maintain solar power plants with the security of selling energy to the Navy for the next 10 to 30 years [12]. More investment in solar should be expected as investment costs continue to decrease, as shown in Figure 5. After 2010, PV pricing decreased enough that the cost was comparable to traditional fossil fuel, and with increased affordability came a large increase in the amount of U.S. energy coming from solar power (see Figure 6). More DOD solar projects are outlined in [5].

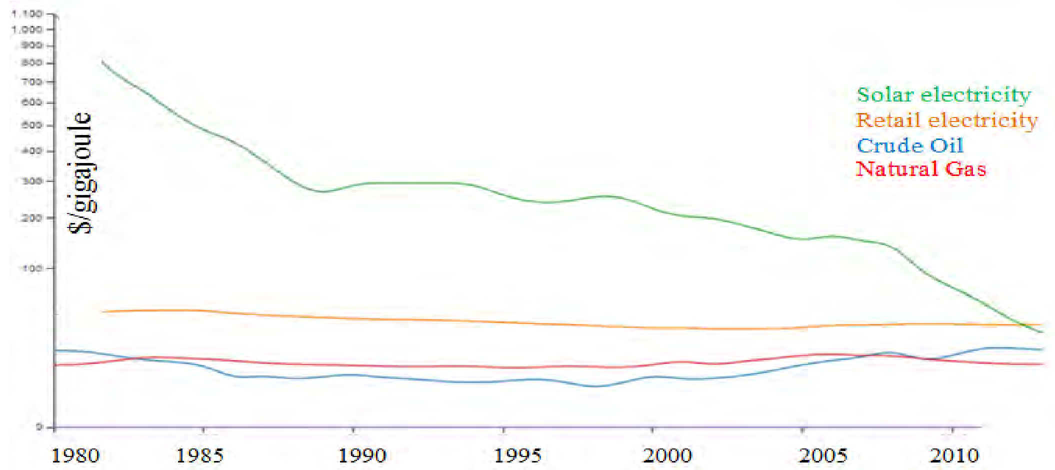


Figure 5. Production costs of various forms of energy, from [13].

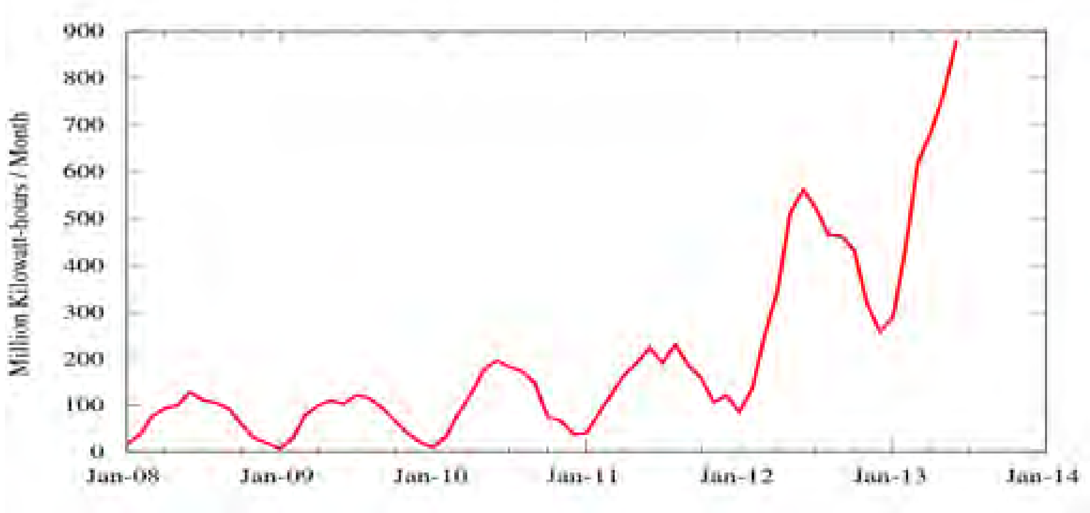


Figure 6. U. S. Monthly Solar-Generated Electricity, from [14].

One of the most promising renewable sources making news recently is the use of landfill methane. Marine Corps Air Station (MCAS) Miramar serves as a successful implementation of such a system using a PPA. Figure 7 shows how a landfill provides energy. Energy began flowing from the Miramar landfill on 14 June 2012. The capture of the methane gases means approximately a 75% reduction in emissions from the landfill [15]. Combine that with the benefits of the cleaner energy being used in place of fossil fuels and the estimated reduction in carbon dioxide (CO_2) emissions per year is 19,354 tons [15]. This is roughly equivalent to over 2 million gallons of gasoline being burned. More importantly, the landfill generates more power than is consumed by MCAS Miramar. This has two significant implications. One is that the base can operate independently of the commercial power grid. The other is that the remaining power can be sold to the community and be a great benefit during grid power outages [15].

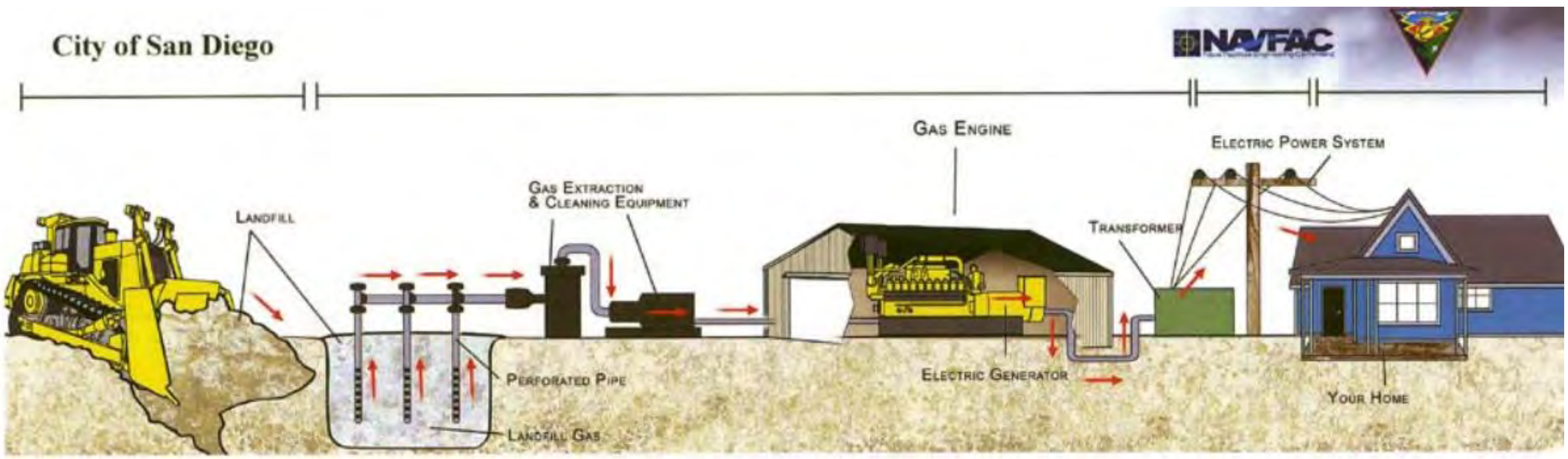


Figure 7. Energy from landfill methane illustration, from [15].

Wind energy is also a very promising form of renewable energy. The Navy has invested in wind power at the Marine Corps Logistics Base Barstow, Guantanamo Bay, San Clemente Island, and another project under development in Newport, Rhode Island [12]. As depicted in Figure 4, wind power is expected to see the largest growth by 2040. Figure 8 shows how the capacity of wind turbines has evolved. Figure 9 shows the exponential growth in the collective global capacity of wind energy production. More DOD wind projects are outlined in [5].

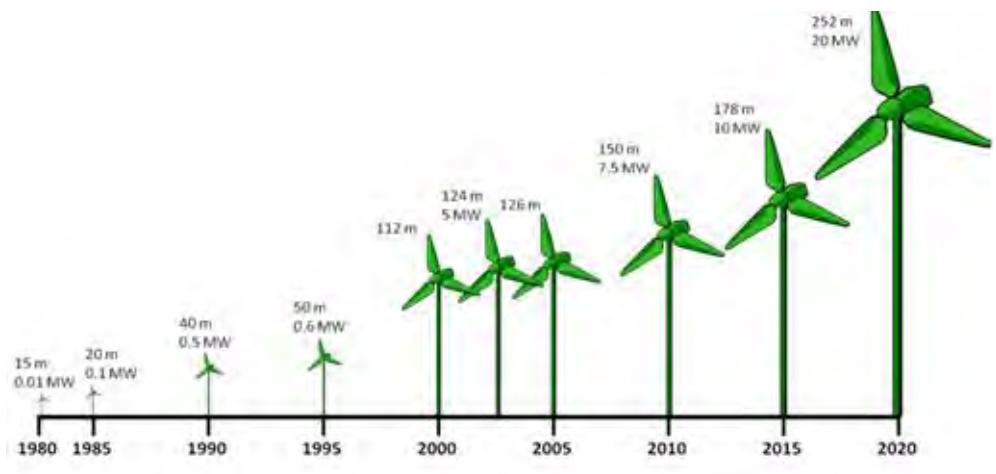


Figure 8. Evolution of wind turbine dimensions and production capacities, from [16].

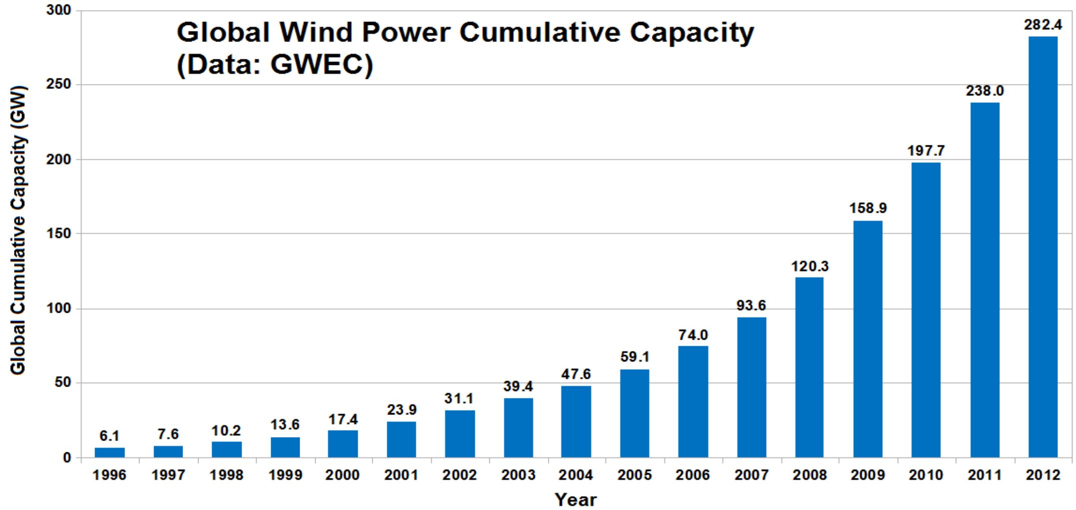


Figure 9. Global cumulative installed wind capacity 1996-2012, from [17].

B. CHALLENGES TO INTEGRATION OF RENEWABLES

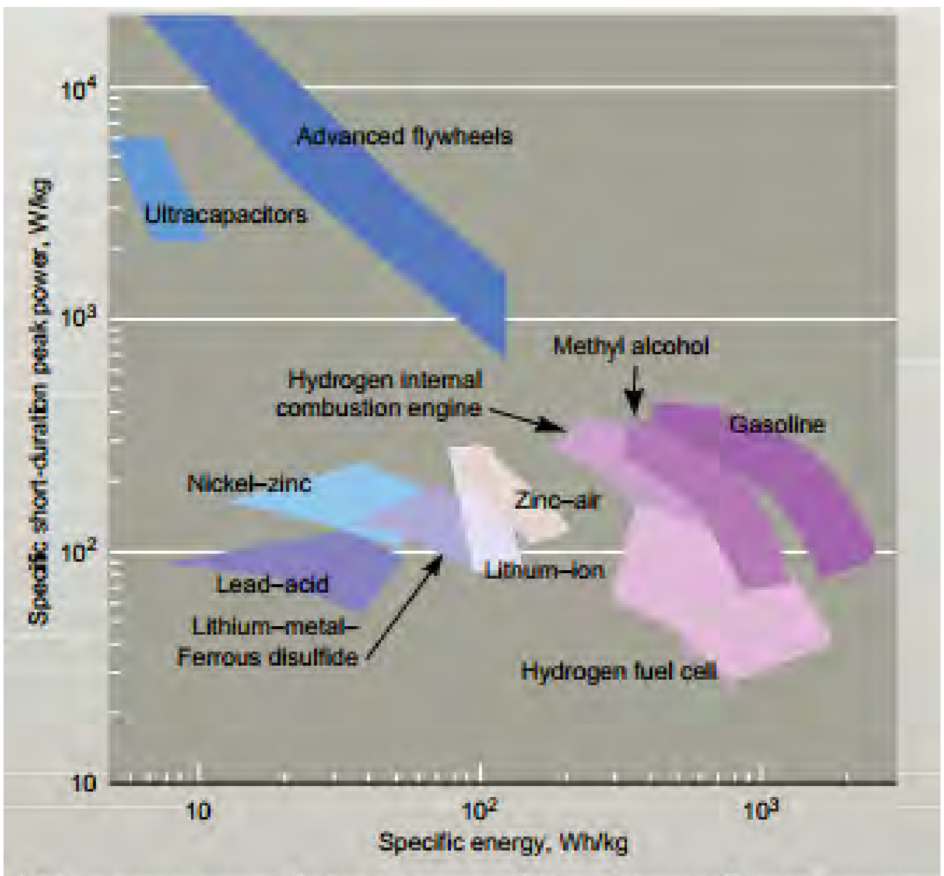
1. Intermittent Availability

In his 2013 thesis, Bouaicha addresses, in detail, the challenges to integrating renewable energy such as wind and solar due to their intermittent availability [5]. His research shows how wind forecasts can be used to conduct day-ahead scheduling. This technique is applicable because the two most common sources of renewable energy that DOD installations employ are wind turbines and solar arrays. Both of these sources are intermittent and difficult to predict. Using a rolling horizon technique, his study uses weather forecasts to perform day-ahead scheduling. By intelligently scheduling generator operations to complement renewable production, we can gain greater benefit from the renewables.

2. Inadequate Storage

Batteries are the most common form of storage when smoothing the intermittent renewable energy sources such as solar and wind. They store chemical energy that can, in turn, run electronic devices. As in hybrid automobiles, batteries can be added to electric grids to reduce fossil fuel consumption.

Some of the latest developments in flywheels by Lawrence Livermore National Laboratory have given hope back to this old but relevant technology [18]. Figure 10 shows on a Ragone plot how flywheels are competitive with battery storage and can provide great energy density [18]. Through software use, the discharge rate can be regulated so that it can smooth out the intermittent issues of solar and wind sources. Figure 11 demonstrates the nature of solar when it interrupts the process at peak demand. Conventional or fossil fueled generators are more reliable when the demand being met is relatively constant. Providing a quickly accessible stored energy allows the demand to be met. Excess production can either be discarded or, potentially, sold back to the commercial electric grid.



Various energy storage devices are compared for peak power and specific energy.

Figure 10. Ragone Plot of various Energy Storage Options, from [18].

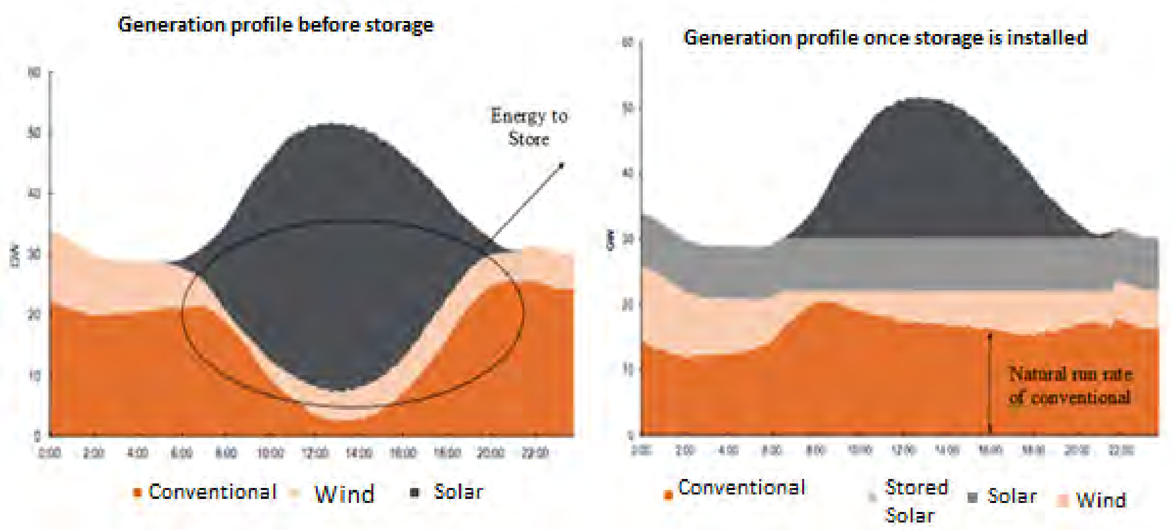


Figure 11. Effect of solar on conventional power generation with and without storage, from [19].

3. Industry Challenges

The sale of electricity back to the commercial grid represents a whole new problem. The physics of energy storage and the demand can dictate how much energy can be sold back to the grid. Figure 12 shows a nationwide net metering picture of kW limits per customer. Physics may play less of a role than economics. The typical U.S. home owner that has installed rooftop solar panels may think it a great idea to install batteries, also, so that in the event of a commercial blackout the home can keep the lights on. However, consumers in California are discovering that there is resistance from the electric companies [20]. The claim is that batteries can be used to "sell electrical power derived from non-renewable sources into the grid in a program designed to promote renewables" [20]. Working groups have been assigned to address this concern, but in the meantime, consumers are incentivized away from installing energy storage, with the side-effect of stalling the development of that technology [20]. It seems this problem will be resolved in the near future. However, Goossens and Chediak bring up an interesting point in their *Bloomberg* article when quoting a solar systems analyst: "People with rooftop panels are already buying less electricity, and adding batteries takes them closer to the day they won't need to buy from the local grid at all" [21]. Is this the real reason for the limits presented in Figure 12? What this means to government investment in renewable energy and energy storage is that some amount of attention needs to be paid to the contractual relationships with private and public power companies to ensure investments are chosen wisely.

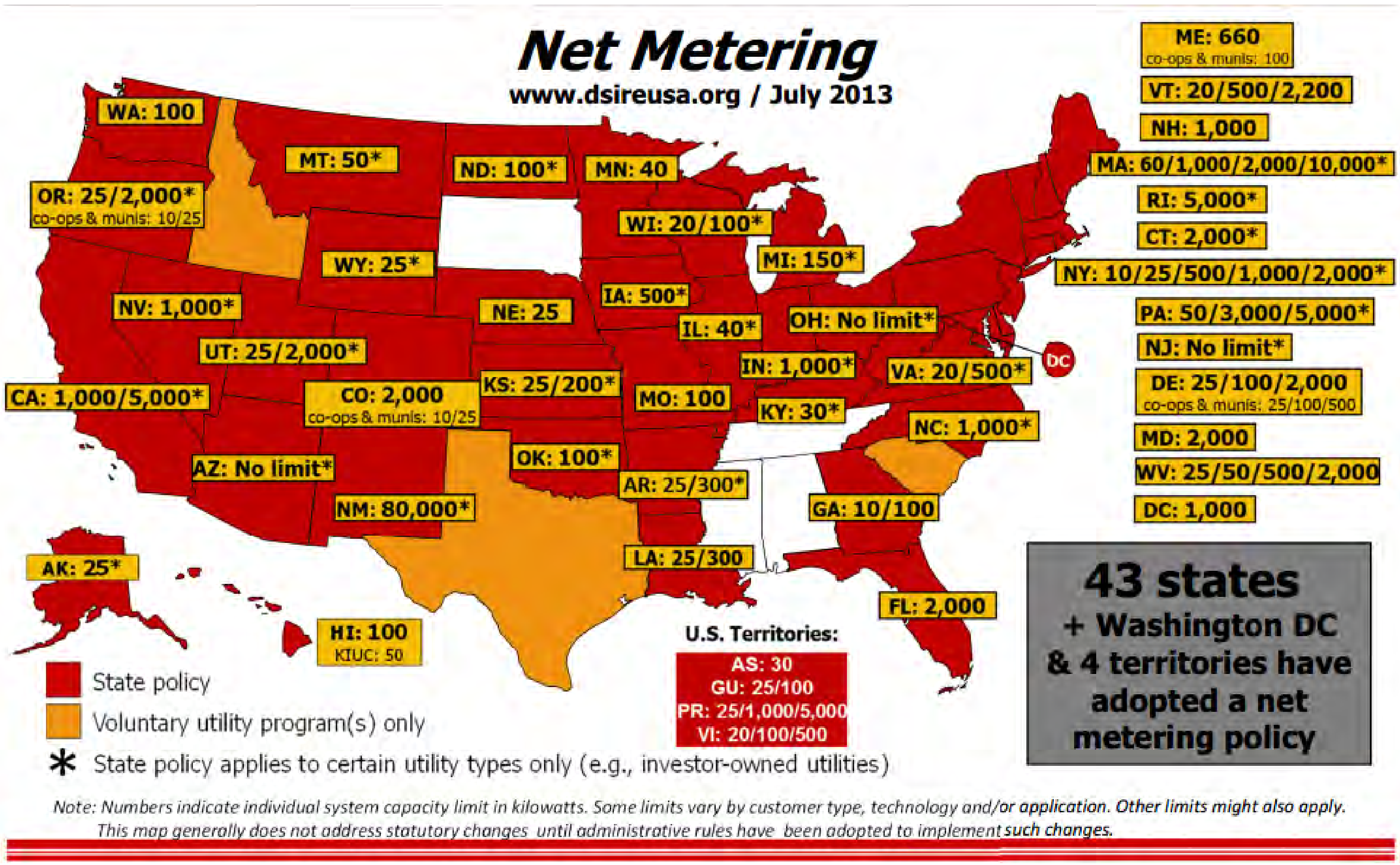


Figure 12. Net metering limits in kW, from [22].

4. The Microgrid Solution

Bouaicha discusses in detail the evolution of the energy management systems and how it is vital to optimal distribution of power in a hybrid renewable energy system (HRES) [5]. A microgrid is simply the amalgamation of the energy management center (EMC) and HRES in the context of the larger power grid. Figure 13 is an illustration from Sandia National Laboratories of a micro-grid, capable of being both grid-connected and islanded.

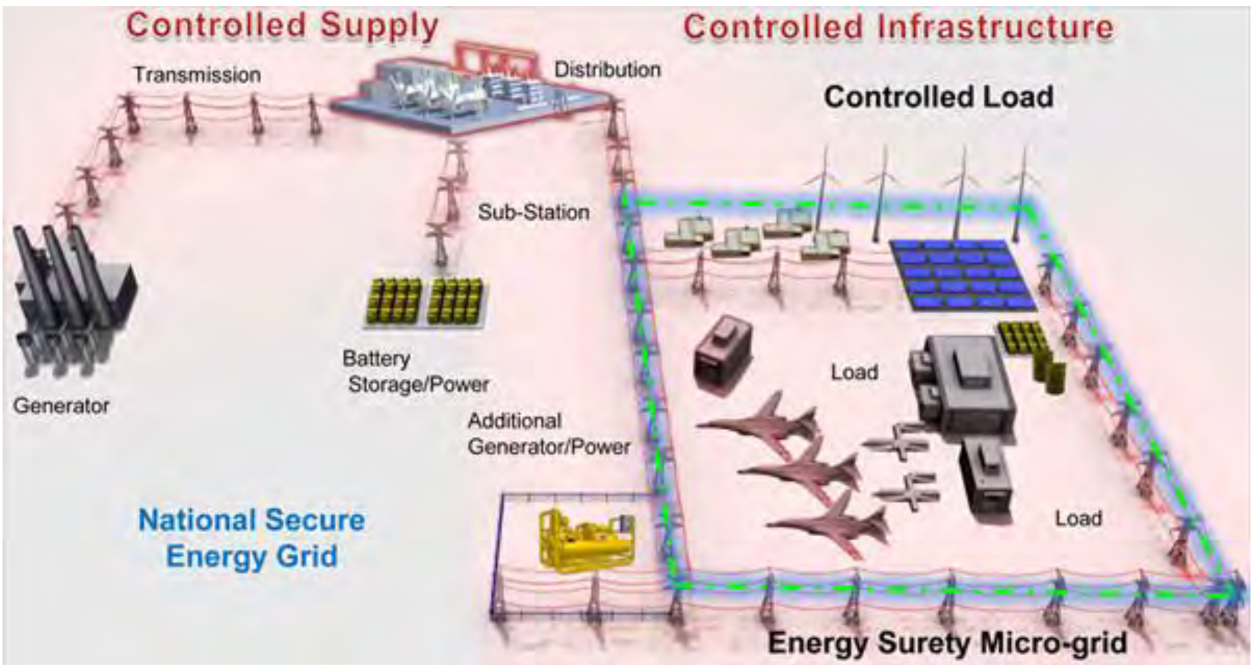


Figure 13. Energy surety microgrid, from [23].

C. OBJECTIVES

Our primary objective is to provide an optimization-based first-cut decision support tool that provides a provably optimal (or near-optimal) hybrid microgrid design. The current commercial products such as MGO and HOMER offer a simulation first approach to the problem. Sandia National Laboratory (SNL) provides a methodology that involves a large commitment of time and resources while using a meta-heuristic to find a solution. We hope to provide a simple mixed integer linear program (MILP) that can be easily modified to conform to meet the needs of DOD installation energy managers and flexible enough to adapt to new technologies as they emerge.

1. SCOPE, LIMITATIONS, AND ASSUMPTIONS

a. Historic Renewable Data

We utilize actual solar energy production numbers from the U.S. Army Garrison Presidio of Monterey. We also obtained wind forecasts for the same historic period of time from the National Oceanic and Atmospheric Administration's (NOAA) Global Ensemble Forecast System Reforecast (GEFS/R). Ultimately, both wind and solar are intermittent and historic data is only useful so far as it relates to future conditions.

b. Continuous Variables

Fuel-based generators are given the range of 10% to 100% of their operating capacity in which to operate. They cannot switch their operating status as much as they want, but they do have a continuous spectrum of capacity choices. In reality, generators will have set modes. For simplicity we have chosen not to define those in this model.

c. Constant and Historic Demand

Initially demand is held at a constant rate in the model to study the effect of the other inputs. Later we introduce historic demand. The model still optimizes over the whole spectrum of historic demand, but just as in real-life operations, there is no certainty regarding the demand. A rolling horizon method is used to help capture some of that uncertainty for modeling purposes and the results analyzed.

d. Additional Set Up and Operational Costs

There are certain costs that are attributable to any possible recommendation for capital planning. These include at a minimum the following items:

- Power lost on transmission lines.
- Cost of establishing transmission lines, controllers, etc.
- Maintenance costs.

- Lifecycle costs and replacement.

2. THESIS CONTRIBUTIONS AND OUTLINE

This formulation builds on Bouaicha's 2013 work on using weather forecasts to do day-ahead scheduling of generators. This thesis uses that foundation to create a flexible capital planning model to support decision makers. In Chapter III, we discuss the methodology and provide our optimization model. Chapter IV provides analysis of sample results and notional case study results for the Presidio of Monterey. Chapter V provides conclusions and recommendations for future work.

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II. LITERATURE REVIEW

The field for optimizing microgrids primarily includes industry and government. The commercial products available are primarily focused on minimizing costs. The government is pursuing many options but we have found no optimization model that does not use some form of heuristic. We use an academic approach to look for an optimal solution that maximizes islanding time.

A commercial product originally developed at the National Renewable Energy Laboratory (NREL), the Hybrid Optimization Model for Electric Renewables (HOMER), is software that helps planners determine the best mix of power sources to meet their energy demands. Upon visiting the softwares's website, homerenergy.com, one can read the statement that HOMER is the global standard for microgrid optimization. However, at the heart of the software is a simulation rather than an optimization. Figure 14 is taken from Chapter 15 in the book *Integration of Alternative Sources of Energy* titled "Micropower System Modeling with HOMER." The authors specifically state that the optimization relies on the simulation capability [24]. HOMER uses a preset list of decision variables. It uses the inputs from the user to enumerate all the possible combinations and uses the simulation to calculate the cost of each. It finds an optimal solution by requiring that the demand is met and finding the lowest cost option from among those options enumerated. Sensitivity analysis can further explore changes to preset variables by recalculating and re-sorting the optimal list. Brandon Newell evaluated HOMER and found that it would benefit the U.S. Marine Corps' Experimental Forward Operating Base (ExFOB) as a pre-deployment tool, but had some concerns over how it handled wind turbines [25]. The needs of the ExFOB are, however, quite a bit different than a traditional DOD installation. Also of note is the fact that HOMER's goal is to minimize cost rather than to maximize islanding time.

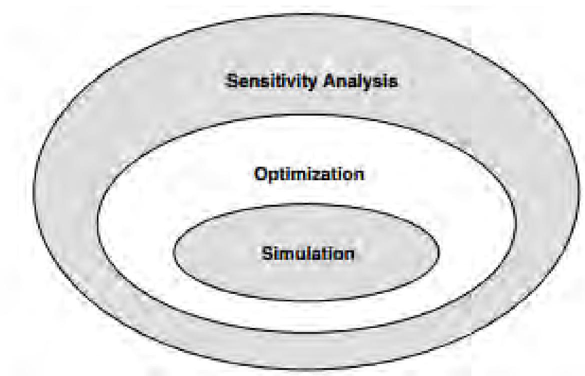

Figure 14. Conceptual relationship within HOMER software, from [24].

The company DNV GL, a 2013 merger of DNV (Stiftelsen Det Norske Veritas) and GL (Germanischer Lloyd), is a leader in advising on energy throughout the world. Some DOD examples of their work include energy-saving projects at the U.S. Air Force Academy, NAVFAC Camp Pendleton, and the Marine Corps Logistics Base in Barstow. DNV GL uses what it calls a MicroGrid Optimizer (MGO). Like HOMER, MGO is primarily a simulation. However, it includes an optimization component in the form of a MILP that minimizes cost or greenhouse gas (GHG) emissions, as selected by the user. MGO includes reliability simulation for catastrophic events [26]. Although MGO is a great tool for assessing energy reliability, it is designed to consider only short-duration outages. A long-term commercial outage, defined as multiple days or longer, is such a small possibility that most commercial entities do not invest much time or money into planning for it. The DOD does not have this luxury.

The DOD has begun implementing a solution to provide energy assurance. SNL's approach, the Energy Surety Microgrid (ESM) methodology, is the current choice. Figure 13 illustrates the ESM concept. Allowing an installation to have local power control provides smart grid functionality, integration of small energy sources, and net metering [27]. To demonstrate this methodology, a Joint Command Technology Development (JCTD) project was funded that includes the Department of Energy, Department of Defense, and Department of Homeland Security. This project is called the Smart Power Infrastructure Demonstration for Energy Reliability and Security (SPIDERS). SPIDERS has completed its projects at Hickam Air Force Base and Fort

Carson. The final portion is at Camp Smith; this portion includes the highest level of renewable power integration among the three projects. The aspect of the ESM methodology most relevant to this thesis involves the choice of microgrid architecture. As we understand the process, the optimization portion of SPIDERS uses a metaheuristic known as a genetic algorithm rather than a MILP. This approach does not guarantee an optimal or provably near-optimal solution. The SNL methodology represents a large multi-step process that constitutes a large investment of time and money.

In his 2013 master's thesis, Bouaicha explores the possibility of minimizing the operating cost of a hybrid electric microgrid (HEG) over a 24-hour time horizon [5]. He accomplishes this with a MILP that dispatches fuel-based generators with consideration to an ensemble of forecasted inputs from renewable power sources, subject to physical constraints on the system. In his recommendation for future work, Bouaicha recommends using his model with a rolling horizon to capture multiple days of generator scheduling [5]. However, this process assumes that certain renewable sources are already installed. Most DOD installations are still in the capital planning phase and need a tool that will help then decided what to install to achieve optimal results. This thesis builds upon Bouaicha's model to accomplish this goal.

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III. MODEL

The model is a mixed-integer linear program that maximizes the islanding time of a microgrid subject to budget and physical constraints. This is achieved through requiring that demand be met but using a relaxation variable to allow failure. The model then minimizes the number of failures and uses a constraint to shift all failures to the end of the planning horizon. The model is tested both on notional data and a case study of the U.S. Army Garrison Presidio of Monterey.

A. COMPOSITION AND CHARACTERISTICS

1. Fuel-Based Generators

The diesel generator is the most common type of back-up generator and already is in place on most DOD installations. Gasoline, propane, and natural gas are other potential fuel sources. These generators can vary widely in output capacity and efficiency. In this thesis, we consider a single efficiency figure and fuel capacity per available generator.

Fuel consumption is limited to the assigned generator. No fuel exchange between generators is allowed. Generators may operate anywhere between 10% and 100% of their stated capacity. Fuel consumption is directly related to the output being provided. For simplicity this is kept as a linear relationship. Generators cannot change their operating level more than a set number of times during the planning horizon. We call this number $NMax$. For the purposes of increasing islanding time, a generator that has the ability to change speeds more frequently may be unnecessary. This information helps define the type of generator that best suits the needs of an installation.

When a generator is initially powered up, it must undergo a warm-up period. If a generator is subsequently turned off, then it must again go through a warm-up period before contributing power again. During warm-up a generator is not coupled to the microgrid and thus cannot provide power. For the purposes of this thesis, we assume that all generators are capable of providing power in the first period of the analysis. Both this assumption and the length of the warm-up period are parameters that can be adjusted.

2. Solar

The U.S. Army Garrison Presidio of Monterey has a 380 kW solar capacity that was installed in 2012. According to conversations with their energy manager, Jay Tulley, this came at a cost of approximately $1.7 million. For this thesis, we utilize actual 2013 data for solar power production, obtained from Sun Edison's Client Connect system. Figure 15 displays a portion of this data and illustrates the day-to-day intermittency issues inherent in solar power production. Figure 16 shows solar production for a 14-day period at 3-hour intervals; note the cyclical pattern in the power being provided.

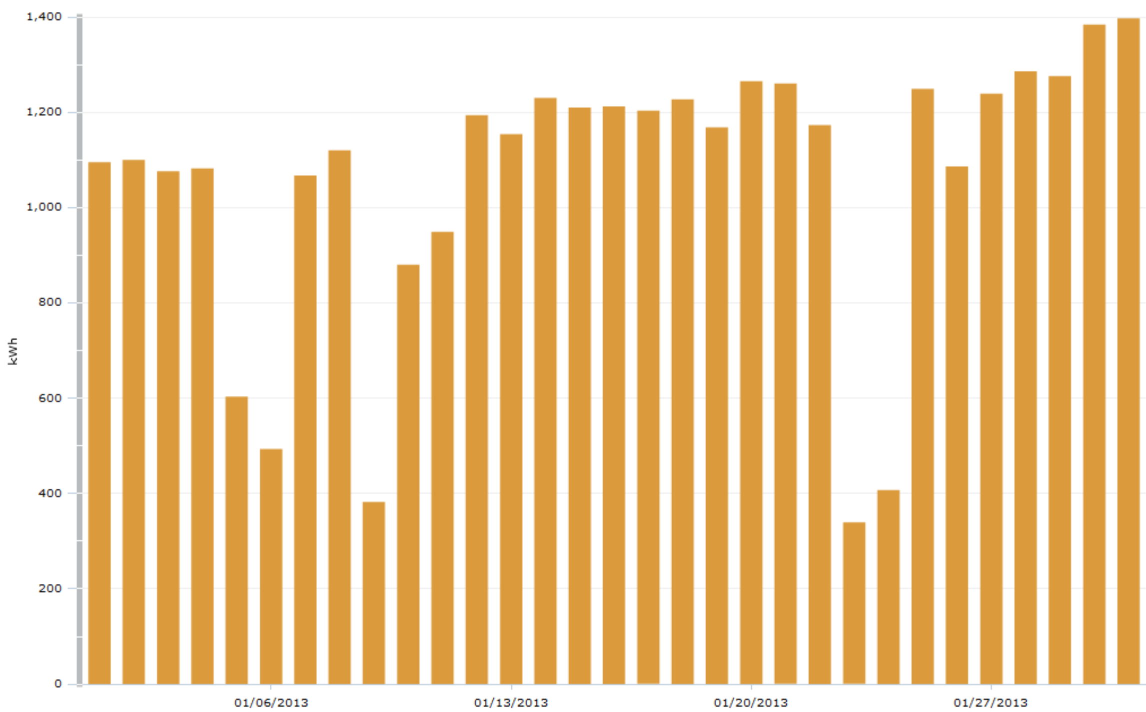

Figure 15. kWh produced per day January 2013 by 380kW array (created using Sun Edison Client Connect)

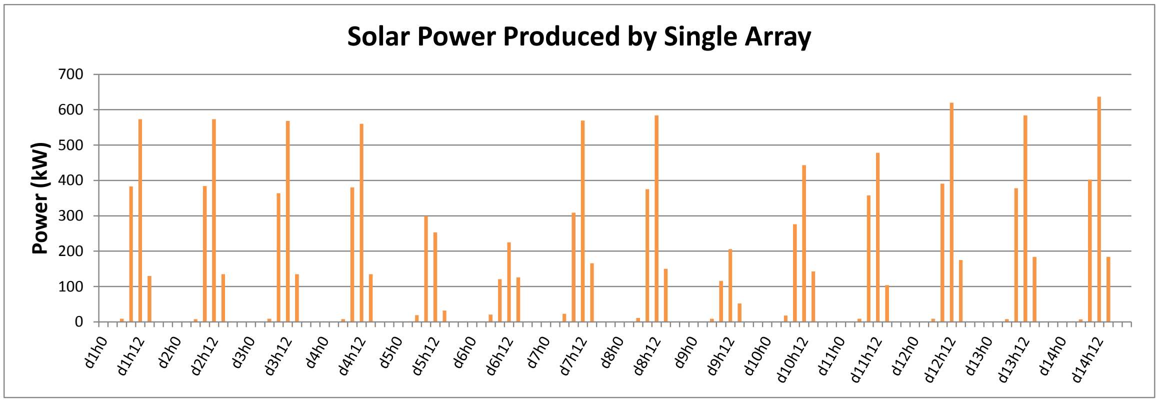

Figure 16. Cyclical solar production for a 14-day period at 3-hour intervals.

3. Cost of Solar

Bouaicha provides an overview of how solar panels work and how different materials result in different efficiencies. He references the figures in Table 2. For the purposes of this analysis, we have actual solar production data and the approximate cost of installing a system capable of producing such output: our 380 kW array purchased in 2012 at a cost of $1.7 million equates to $4.47/watt capacity. The numbers in Table 2 indicate that the most expensive option in 2013 was $3/watt, which would imply a $1.14 million investment for a 380 kW array. For simplicity, most of the analysis in this thesis will assume the provided production corresponds to a $1 million investment. This helps account for the decreasing cost of solar. If one tried to reproduce this study without having actual solar data, a comparison of the relative solar irradiation data for the subject geographic region would be useful.

Table 2. Comparison of Common Commercial PV cells, from [28].

Type	Efficiency (%)	Cost ($/watt capacity)	Market share (%)
Monocrystalline Si	17-20	3.0	30
Polycrystalline Si	15-18	2.0	40
Amorphous Si	5-10	1.0	5
CIGS	11-13	1.5	5
CdTe-CdS	9-13	1.5	10

4. Wind Turbines

We obtained historical wind forecasts from NOAA's Global Ensemble Forecast System Reforecast (GEFS/R) tool. The data provides ensemble forecasts of wind speed at 80 meters, which we convert to wind power output using a Python script according to Equation 1.1. Note that this equation represents the maximum achievable power output from a wind turbine. Most likely, a turbine of the size used in this analysis can expect 75% to 80% of maximum efficiency, according to Betz Law, which is approximately 59% for wind turbines in general [29]. Let C_P denote the Betz Limit, ρ the air density, R the blade radius, and V the wind velocity. Following [28] we calculate wind power as follows:

$$\text{Power (Watts)} = \frac{1}{2}C_P\rho(\pi)\left(R^2\right)V^3 = \frac{1}{2}(0.59)\left(1.29\frac{kg}{m^3}\right)(\pi)\left(R^2\right)\left(V^3\right) \tag{1.1}$$

Our analysis assumes a blade radius of 50 meters and an air density of 1.29 kg/m^3.

Turbines operate between minimum cut-in speeds and maximum cut-out speeds. Bouaicha elaborates on this concept and provides Figure 17 as an illustration. In order to model this, our Python script produces a value of zero power produced when the wind speed is outside these bounds. Our data contained no wind speeds above the 28-34 m/sec range at which most turbines cut out. There were, however, periods of low wind speed. We assumed a cut-in speed of 3 m/sec; most turbines cut in between 3 and 5 meters per second.

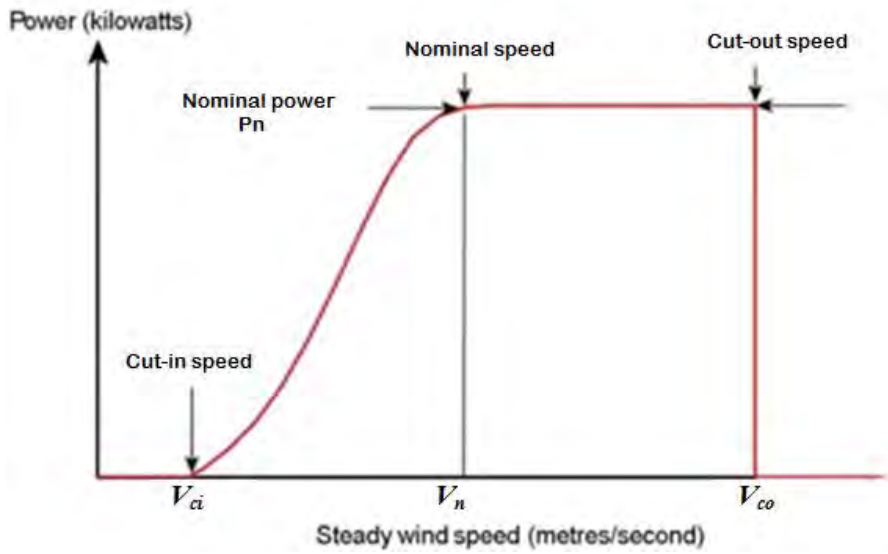

Figure 17. Typical wind turbine power curve with steady wind speed, from [5].

Like solar, wind can also be intermittent. On the Monterey Peninsula, there can also be a wide range of wind speeds. Figure 18 clearly illustrates that wind can provide much more gross power than solar, but this power may not occur in a predictable pattern.

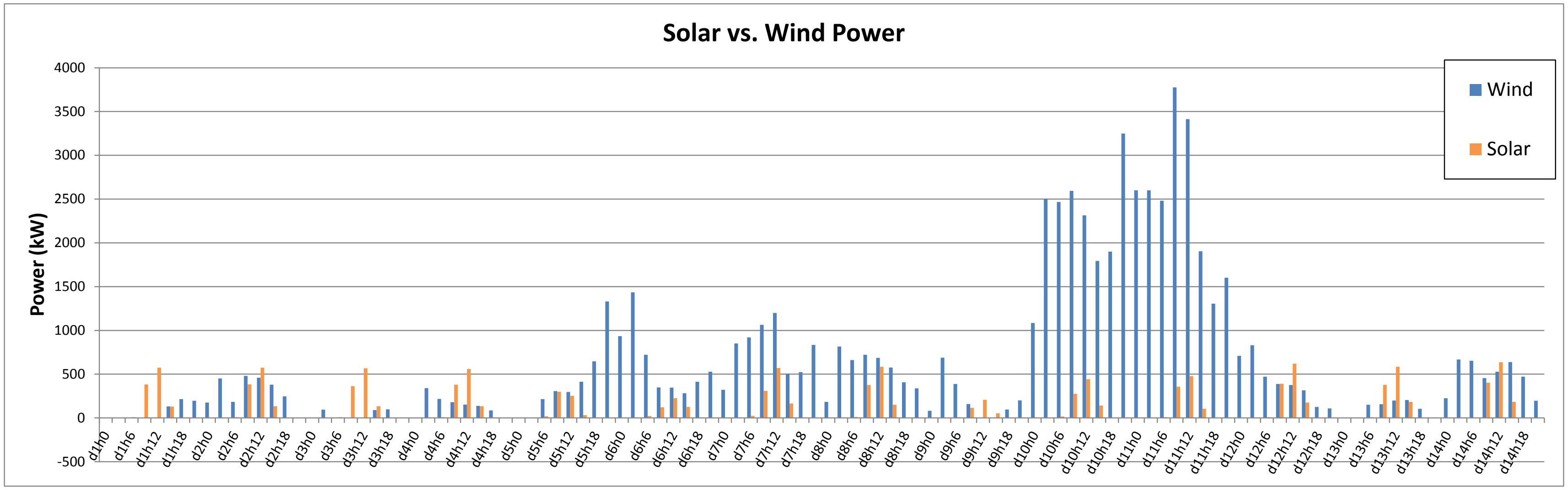

Figure 18. Three-hour intervals of solar and wind power used in the analysis portion of this thesis.

5. Cost of Wind

The average cost of a wind turbine project in the U.S. is \$1.94/W [30]. Figure 19 compares this average cost to the cost of projects in various geographic regions; note the large variation in cost. Assuming a cost of \$1.94/W, a 1.62MW, 50 meter blade radius wind turbine would cost approximately \$3,241,800. Another study quoted a value of \$1.85/W [31]; this would result in a cost of \$2,997,000 for the same turbine. For simplicity, in this analysis we assume the wind turbine in question costs \$3 million.

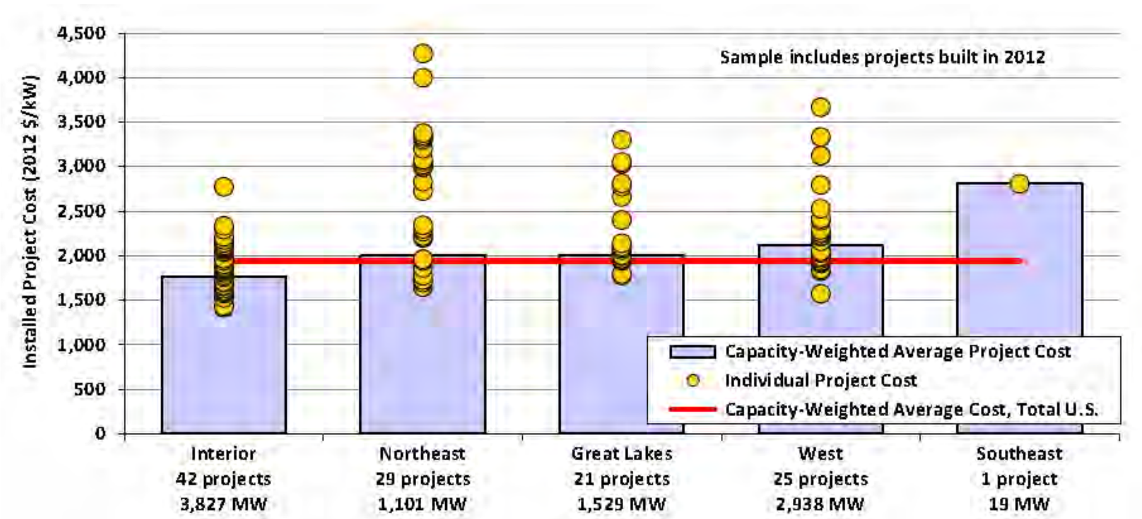

Figure 19. Installed wind power project costs by region: 2012 projects, from [30].

6. Weather Forecasts

Weather forecasts are often presented as a single prediction; however, they are produced as a collection of forecasts known as an ensemble. Each ensemble member contains information valuable to a planner conducting day-ahead scheduling of a microgrid. Our model is capable of optimizing over multiple forecasts. However, for simplicity, our analysis considers only a single forecast.

7. Rolling Horizon

For capital planning purposes we utilize an omniscient approach where the weather for the entire planning horizon is known and the model is able to provide the optimal solution. The solution obtained will be very difficult to achieve in practice.

There is an inherent stochastic element in any model using weather, as the weather is unknown in advance. Because forecast uncertainty increases with lead time, it is prudent to plan based on near-term forecasts, which are the most accurate, and re-run a scheduling model each day [32]. Figure 20 illustrates this concept.

We also find it useful to use a rolling horizon approach to reduce the run-time of the problem. As such, we create a single-day version of the optimization problem and solve each problem as if the view is limited. The planning horizon is the available weather forecasts. The single day is the execution horizon. We start the first run with a known feasible solution. We record the end values of each run and initialize them for the following run. We then utilize the final solution to warm start the capital planning model that utilizes the full planning horizon.

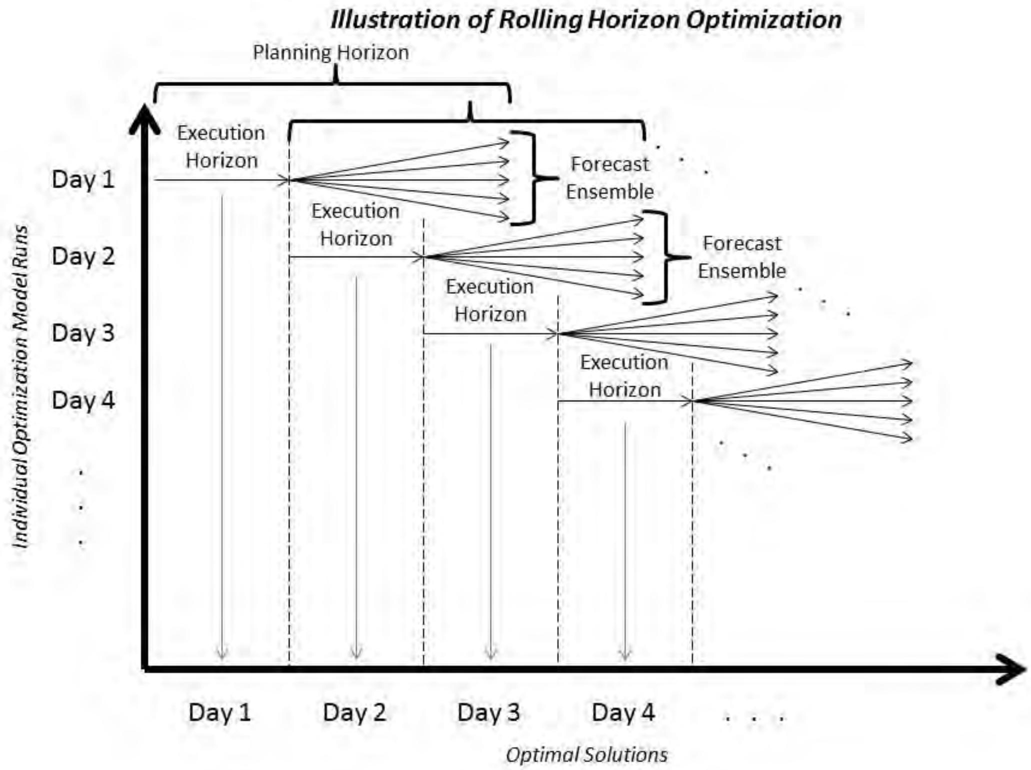

Figure 20. Illustration of how rolling horizon optimization can be used with weather forecasts.

8. Batteries

Storage allows capture and future use of excess power production often seen when using renewable sources of energy. As in Bouaicha, we model the round trip efficiency of charging and discharging a generic storage device henceforth referred to as a "battery." This efficiency is represented by α, the fraction of power lost. Other relevant parameters include the maximum and minimum charging rates, maximum discharge rate, storage capacity, and initial storage.

9. Cost of Batteries

Energy storage is a less mature technology than solar and wind power production technologies, and it is evolving rapidly. Thus, accurate pricing information is difficult to obtain. For this thesis, we consider a 200 kW battery that costs $40,000 and has an α of

0.1, as well as two 100 kW batteries that cost $20,000 each and have α values of 0.5 and 0.8. Through sensitivity analysis we further explore the effects of improvements to energy storage technology.

B. FORMULATION

We now describe a mathematical model that maximizes microgrid islanding time subject to a capital planning budget and other constraints.

1. Sets

$g \in G$	Fuel-based generators
$s \in S$	Solar arrays
$w \in W$	Wind turbines
$b \in B$	Batteries (energy storage devices)
$c \in C$	Customers (sources of demand)
$k \in K$	Time steps
$f \in F$	Forecast scenarios

2. Parameters [units]

$deltaT$	Duration of a time step [hours]
$Nmax$	Maximum number of changes in generator speed during planning horizon [changes]
$setupC_g$	Cost of installing generator *g* [$]
$setupC_s$	Cost of installing solar array *s* [$]
$setupC_w$	Cost of installing wind turbine *w* [$]
$setupC_b$	Cost of installing battery *b* [$]
$timeStepCost_g$	Fuel used by generator *g* [gal/kW/time step]

$InitialContrib_g$	Binary contribution status of generator *g* at initial time step [unitless]
$warmup_g$	Number of time steps generator *g* must run before it can contribute power [time steps]
$GenP_g$	Energy production capacity of generator *g* [kW]
$SolarP_{k,s,f}$	Power produced by solar array s at time step *k* in forecast *f* [kW]
$WindP_{k,w,f}$	Power produced by wind turbine w at time step *k* in forecast *f* [kW]
$MaxCharge_b$	Maximum rate of charging battery *b* [kW]
$MinCharge_b$	Minimum rate of charging battery *b* [kW]
$MaxDischarge_b$	Maximum rate of discharging battery *b* [kW]
$MaxCapacity_b$	Maximum storage capacity of battery *b* [kWh]
α_b	Fraction of power lost while charging battery *b* [unitless]
$InitialStorage_b$	Initial energy stored in battery *b* [kWh]
$dem_{c,k}$	Energy demand from customer *c* at time step *k* [kWh]
$fuel_g$	Fuel allocated to generator *g* [gallons]
fuelpen	1 / (1+ worst fuel efficiency x total critical demand) [unitless]
setupBudget	Total capital planning budget [$]

3. Decision Variables

$FAIL_{k,f}$	Binary	Equals 1 if demand in not met in time step *k* for forecast *f*, and 0 otherwise
$ON_{g,k}$	Binary	Equals 1 in generator *g* in on in time step *k*, and 0 otherwise.
$INSTALL_g$	Binary	Equals 1 if generator *g* is installed, and 0 otherwise.

$INSTALL_s$	Binary	Equals 1 if solar array *s* is installed, and 0 otherwise.
$INSTALL_w$	Binary	Equals 1 if wind turbine *w* is installed, and 0 otherwise.
$INSTALL_b$	Binary	Equals 1 if battery *b* is installed, and 0 otherwise.
$GPERCENT_{g,k}$	Continuous (≥ 0)	Percent of generator *g*'s capacity used in time step *k*.
$CONTRIB_{g,k}$	Binary	Equals 1 if generator *g* is contributing power in time step *k*, and 0 otherwise.
$PCONTRIB_{g,c,k}$	Continuous (≥ 0)	Power contributed by generator *g* to customer *c* in time step *k* [kW].
$PSCONTRIB_{w,c,k,f}$	Continuous (≥ 0)	Power contributed by solar array *s* to customer *c* in time step *k* in forecast *f* [kW].
$PWCONTRIB_{w,c,k,f}$	Continuous (≥ 0)	Power contributed by wind turbine *w* to customer *c* in time step *k* in forecast *f* [kW].
$PCHARGE_{b,k,f}$	Continuous (≥ 0)	Rate of charging battery *b* at time step *k* [kW].
$PDCHARGE_{b,c,k,f}$	Continuous (≥ 0)	Rate of discharging battery *b* at time step *k* to customer *c* [kW].
$CHARGE_{b,k,f}$	Binary	Equals 1 if battery *b* is charged at time step *k* in forecast *f*, and 0 otherwise.
$DCHARGE_{b,k,f}$	Binary	Equals 1 if battery *b* is discharged at time step *k* in forecast *f*, and 0 otherwise.
$CHANGE_{g,k}$	Binary	Equals 1 if there is a change in generator *g*'s speed at step *k*, and 0 otherwise.

4. Objective Function

The primary goal of this model is to maximize the islanding time of a microgrid by selecting and scheduling power sources which are constrained by a capital planning budget. This is achieved by minimizing the number of time periods the microgrid fails to meet demand as reflected by the *FAIL* decision variables. A secondary term in the objective function reflects a "fuel penalty" that encourages the use of renewable power sources over fuel-based generators.

$$\min Z = \sum_{k,f}\left(k-(k+1)(FAIL_{k,f})\right) + fuelpen \times \sum_{g,k}(timeStepCost_g)(GenP_g)(GPERCENT_{g,k}) \tag{1.2}$$

5. Constraints

The constraints are used to ensure the model adheres to certain laws of physics and general operating principles of a microgrid.

$$FAIL_{k,f} \leq FAIL_{k+1,f} \qquad \forall k \qquad (3.1)$$

$$\sum_{g}(INSTALL_{g} setupC_{g}) + \sum_{s}(INSTALL_{s} setupC_{s}) + \sum_{w}(INSTALL_{w} setupC_{w})$$

$$+\sum_{b}(INSTALL_{b} setupC_{b}) \leq setupBudget \qquad (3.2)$$

$$\sum_{k}\left(timeStepCost_{g}\right)\left(GenP_{g}\right)\left(GPERCENT_{g,k}\right) \leq fuel_{g} \qquad \forall g \qquad (3.3)$$

$$GPERCENT_{g,k} \leq ON_{g,k} \qquad \forall g,k \qquad (3.4)$$

$$\sum_{g,c} PCONTRIB_{g,c,k} + \sum_{s,c} PSCONTRIB_{s,c,k,f} + \sum_{w,c} PWCONTRIB_{w,c,k,f} + \sum_{b,c} PDCHARGE_{b,c,k,f}$$

$$-\sum_{c}\left(dem_{c,k} critcal_{c}\right) \text{ x } (1-FAIL_{k,f}) \geq \sum_{b} \frac{PCHARGE_{b,k,f}}{1-\alpha_{b}} \qquad \forall k,f \qquad (3.5)$$

$$\sum_{g} PCONTRIB_{g,c,k} + \sum_{w} PWCONTRIB_{w,c,k,f} + \sum_{s} PSCONTRIB_{s,c,k,f} + \sum_{b} PDCHARGE_{b,c,k,f}$$

$$\geq \left(dem_{c,k} critcal_{c}\right) \text{ x } (1-FAIL_{k,f}) \qquad \forall c,k,f \qquad (3.6)$$

$$\sum_{c} PCONTRIB_{g,c,k} \leq (GenP_{g})(CONTRIB_{g,k}) \qquad \forall g,k \qquad (3.7)$$

$$\sum_{c} PCONTRIB_{g,c,k} \geq (GenP_{g})(GPERCENT_{g,k}) - (1-CONTRIB_{g,k})(GenP_{g}) \qquad \forall g,k \qquad (3.8)$$

$$\sum_{c} PCONTRIB_{g,c,k} \leq (GenP_{g})(GPERCENT_{g,k}) \qquad \forall g,k \qquad (3.9)$$

$$GPERCENT_{g,k} \geq 0.1(ON_{g,k}) \qquad \forall g,k \qquad (3.10)$$

$$ON_{g,k} \leq INSTALLG_{g} \qquad \forall g,k \qquad (3.11)$$

$$\sum_{c} PSCONTRIB_{s,c,k,f} \leq Install_{s} SolarP_{k,s,f} \qquad \forall s,k,f \qquad (3.12)$$

$$\sum_{c} PWCONTRIB_{w,c,k,f} \leq Install_{w} WindP_{k,w,f} \qquad \forall w,k,f \qquad (3.13)$$

$$PDCHARGE_{b,c,k,f} \leq MaxDischarge_{b} INSTALL_{b} \qquad \forall b,c,k,f \qquad (3.14)$$

$$CONTRIB_{g,k} \leq ON_{g,k'} \qquad \forall g,k,k': k\text{-}warmup_{g} \leq k' \leq k \qquad (3.15)$$

$$CONTRIB_{g,k} \le InitialContrib_g \quad \forall g,k : k \le warmup_g \tag{3.16}$$

$$InitialStorage_b + \sum_{k' \le k} ((PCHARGE_{b,k',f} - \sum_c PDCHARGE_{b,c,k',f}) \text{ x } deltaT) \le MaxCapacity_b \quad \forall b,k,f \tag{3.17}$$

$$InitialStorage_b + \sum_{k' \le k} ((PCHARGE_{b,k',f} - \sum_c PDCHARGE_{b,c,k',f}) \text{ x } deltaT) \ge 0 \quad \forall b,k,f \tag{3.18}$$

$$PCHARGE_{b,k,f} \le MaxCharge_b \text{ x } CHARGE_{b,k,f} \quad \forall b,k,f \tag{3.19}$$

$$PCHARGE_{b,k,f} \ge MinCharge_b \text{ x } CHARGE_{b,k,f} \quad \forall b,k,f \tag{3.20}$$

$$\sum_c PDCHARGE_{b,c,k,f} \le MaxDischarge_b \text{ x } DCHARGE_{b,k,f} \quad \forall b,k,f \tag{3.21}$$

$$CHARGE_{b,k,f} + DCHARGE_{b,k,f} \le 1 \quad \forall b,k,f \tag{3.22}$$

$$CHANGE_{g,k} \ge GPERCENT_{g,k+1} - GPERCENT_{g,k} \quad \forall g,k \tag{3.23}$$

$$CHANGE_{g,k} \ge GPERCENT_{g,K} - GPERCENT_{g,k+1} \quad \forall g,k \tag{3.24}$$

$$\sum_k CHANGE_{g,k} \le Nmax \quad \forall g \tag{3.25}$$

$$FAIL_{k,f} \in \{0,1\} \quad \forall k,f \tag{3.26}$$

$$ON_{g,k} \in \{0,1\} \quad \forall g,k \tag{3.27}$$

$$Install_g \in \{0,1\} \quad \forall g \tag{3.28}$$

$$Install_s \in \{0,1\} \quad \forall s \tag{3.29}$$

$$Install_w \in \{0,1\} \quad \forall w \tag{3.30}$$

$$Install_b \in \{0,1\} \quad \forall b \tag{3.31}$$

$$CONTRIB_{g,k} \in \{0,1\} \quad \forall g,k \tag{3.32}$$

$$CHARGE_{b,k,f} \in \{0,1\} \quad \forall b,k,f \tag{3.33}$$

$$DCHARGE_{b,k,f} \in \{0,1\} \quad \forall b,k,f \tag{3.34}$$

$$CHANGE_{g,k} \in \{0,1\} \quad \forall g,k \tag{3.35}$$

$$GPERCENT_{g,k} \ge 0 \quad \forall g,k \tag{3.36}$$

$$PCONTRIB_{g,c,k} \ge 0 \quad \forall g,c,k \tag{3.37}$$

$$PSCONTRIB_{s,c,k,f} \ge 0 \quad \forall s,c,k,f \tag{3.38}$$

$$PWCONTRIB_{w,c,k,f} \geq 0 \qquad \forall w,c,k,f \quad (3.39)$$

$$PCHARGE_{b,k,f} \geq 0 \qquad \forall b,k,f \quad (3.40)$$

$$PDCHARGE_{b,c,k,f} \geq 0 \qquad \forall b,c,k,f \quad (3.41)$$

We now explain the constraint equations. Equation 3.1 pushes any failed time periods to the end of the planning horizon. Equation 3.2 ensures that the total cost of installing infrastructure does not exceed the capital planning budget. Equation 3.3 ensures that the total fuel used over the planning horizon for each fuel-based generator does not exceed the total fuel allotted to that generator. Equation 3.4 ensures that a generator must be on in order to contribute power. Equation 3.5 calculates the net power available in each period and ensures it is enough to meet demand, while relaxing this requirement as necessary using the *FAIL* variable. Equation 3.6 ensures that each customer demand is met. Equation 3.6 is not required in the current model; however it provides the possibility to further the functionality by defining which customers can be supplied by which power sources. Further expansion of customer priorities would also necessitate this addition. Equation 3.7 through 3.9 mange the power contributed by the fuel-based generators. Specifically, Equation 3.7 ensures a generator is contributing before it can provide power. Equation 3.8 forces all of the power generated to be consumed. Equation 3.9, in turn, ensures that the power contributed cannot exceed the production. Equation 3.10 sets a lower limit on the operating mode of fuel-based generators. This represents the physical reality that generators have a minimum speed at which they can generate power. This also ensures that fuel will be consumed even during generator warm-up periods. Equation 3.11 requires that fuel-based generators be installed before they can be turned on and used. Equations 3.12 and 3.13 limit the maximum contributable power of solar arrays and wind turbines to a user-defined parameter. Equation 3.14 requires that a battery be installed before it is used. Equations 3.15 and 3.16 force fuel-based generators to warm up before they can provide power to the grid. Equation 3.16 allows for a generator to be available in the first time period of the planning horizon, provided the $InitialContrib_g$ binary parameter is set to one. Equations 3.17 through 3.22 manage how the batteries operate. Equation 3.17 ensures that the maximum capacity of each battery is not exceeded. Equation 3.18 prevents batteries from dropping below zero stored energy. Equations 3.19 and 3.20 set the maximum and minimum charging limits for the batteries. Equation 3.21 limits the rate of discharge possible from each battery. Equation 3.22 ensures we are not charging and discharging a battery in the same time period. Equations 3.23 through 3.25 manage the speed changes allowed for the fuel-based generators. Equations 3.23 and 3.24 identify generator speed changes based on changes in generator output. Equation 3.25 sets the maximum number of such changes to a user-defined parameter. Equations 3.26 through 3.41 declare variable types.

IV. ANALYSIS

To explore the impact of capital planning budget on islanding time and study its sensitivity to various input parameters, we implement our model using the General Algebraic Modeling System (GAMS) version 24.0.2 and solve using CPLEX. This chapter is divided into two sections corresponding to the type of demand data utilized for analysis. Section A assumes a constant demand of 1271 kW. Section B uses actual demand for six critical buildings on the Presidio of Monterey.

A. CONSTANT DEMAND

1. Value of a Microgrid

We first consider a simple constant-demand scenario in order to validate the model and provide insights into the most important factors for capital planning of a microgrid. This scenario includes ten buildings, or customers, with different but constant demands. Customers represent buildings whose demand must be satisfied when commercial power is interrupted. Nine of the ten customers have back-up generators dedicated to meeting their needs, and we first consider the impact of allowing customers to share their generator power with other customers. Figure 21 shows a comparison of islanding times for each customer in two scenarios. The first scenario, shown in blue, represents a situation in which no microgrid is installed, meaning that each generator serves only a single customer. The second scenario, shown in red, includes a microgrid and allows customers to share generator power. Note that while two of the ten customers show a loss in their islanding time in the second scenario, the other eight have improved islanding time. The two customers who lost islanding time lose a combined total of 78 hours, while the other eight gain 462 hours. Overall, the installation-wide islanding times for the two scenarios are 876 hours and 1,260 hours, respectively. Table 3 summarizes the results of these scenarios.

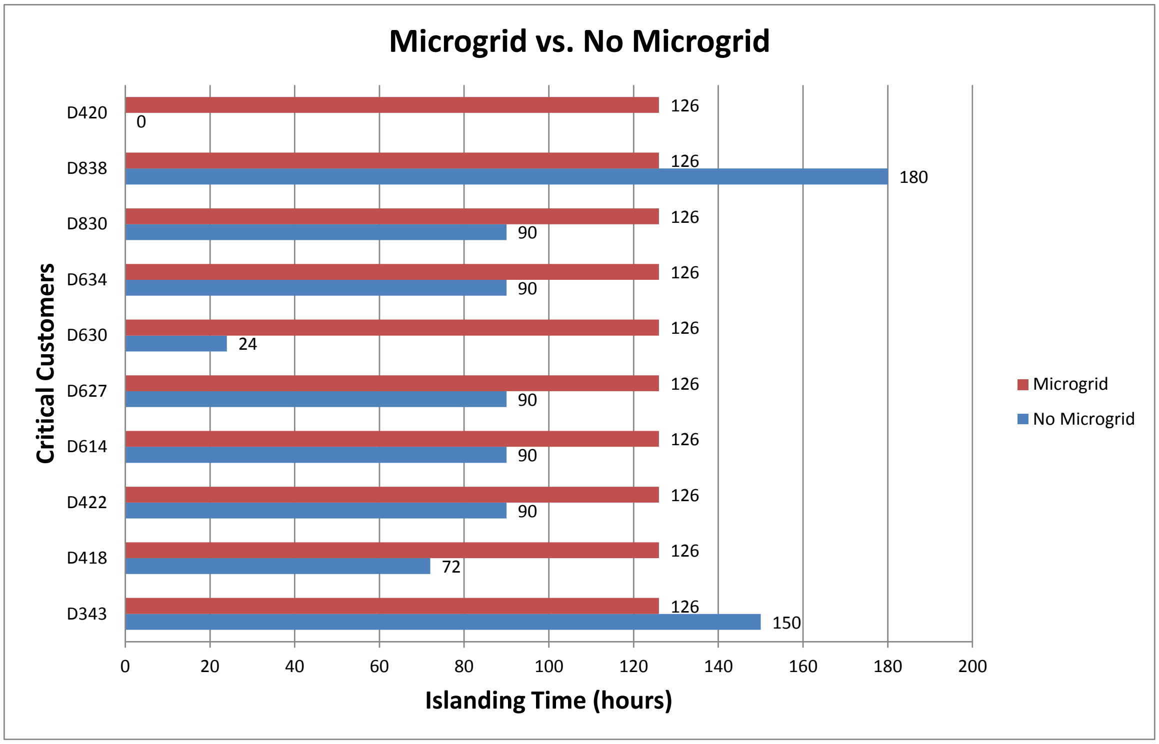

Figure 21. Generator-only run of the optimization model showing the difference in islanding time with the addition of a microgrid.

Table 3. Complete results of the generator-only run of the optimization model.

		Islanding Hours		
Customers	**Microgrid**	**No Microgrid**	**Difference**	**% change**
D420	126	0	126	N/A
D838	126	180	-54	-30%
D830	126	90	36	40%
D634	126	90	36	40%
D630	126	24	102	425%
D627	126	90	36	40%
D614	126	90	36	40%
D422	126	90	36	40%
D418	126	72	54	75%
D343	126	150	-24	-16%
Total	**1260**	**876**		
		No Microgrid	Difference	% change
	2 Customers	330	-78	-24%
	8 Customers	546	462	85%

2. The *NMax* Parameter

We explore the *NMax* parameter both with and without renewable energy. The follow sections provide results of applicable sensitivity analyses.

a. Generator-Only Scenario

In order to model the physical constraints of generator operation, we use a value known as *NMax* to determine the number of times in a given planning horizon that a generator may switch modes (i.e., change its output level). As a practical matter it is undesirable for a generator to undergo frequent changes in operating mode, however forcing a constant output does not allow a generator to adjust to fluctuations in renewable power production. Therefore, we perform a sensitivity analysis to determine the frequency in which generators respond to achieve good performance. In order to decrease the run time of the model we used a continuous decision variable to represent the level of power output rather than an integer mode indicator. We find that increasing *NMax* in the constant-demand, generator-only scenario does not significantly lengthen the islanding time. Figure 22 illustrates the base scenario where each generator chooses only one output level. Islanding time in this scenario provides 5 days of islanding time, or 120 hours. Figure 23 and Figure 24 show *NMax* equal to 8 and 14, respectively. There is clearly more change in the operating status of generators, but the overall gain is only six hours over the case where *NMax* is equal to one. Even with constant demand, one might expect some improvement in islanding time with increasing *NMax* due to the existence of a minimum operating speed for each generator and the resulting potential for wasted power production if no changes are allowed. However, for the scenarios considered, we find that the differences in islanding time are easily within the margin of error in the model. The relative optimality gap option, *optcr*, is set to 10%. Figure 25 shows the results of changing *NMax*.

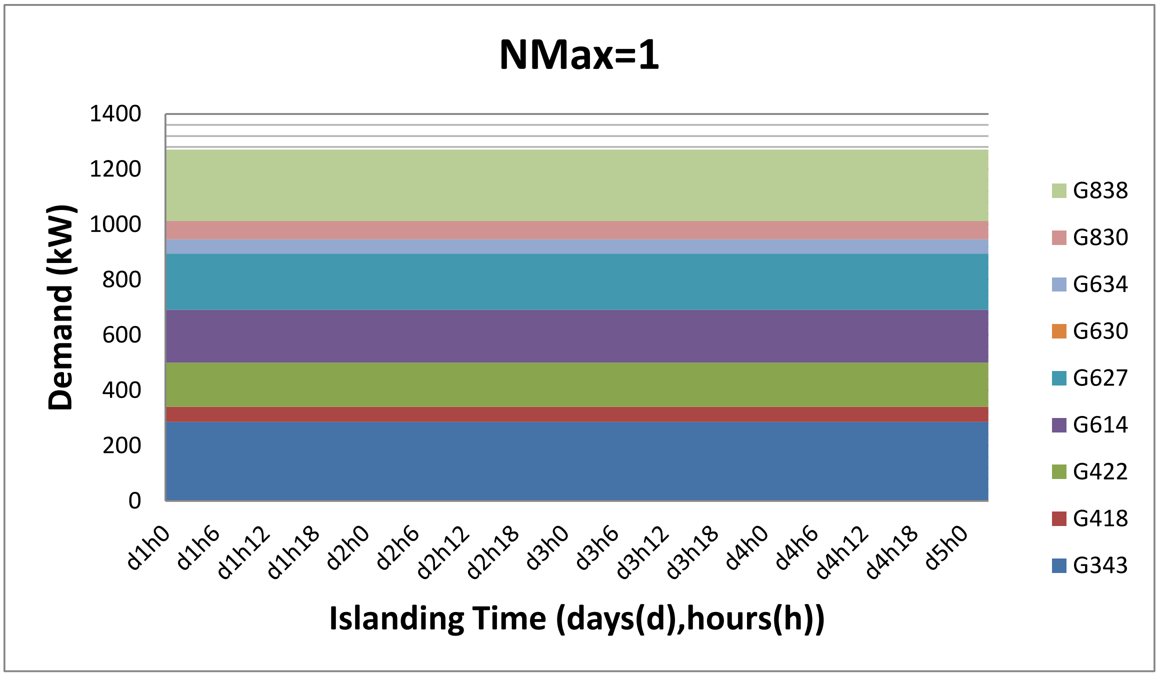

Figure 22. Power contributed by each generator when *NMax*=1.

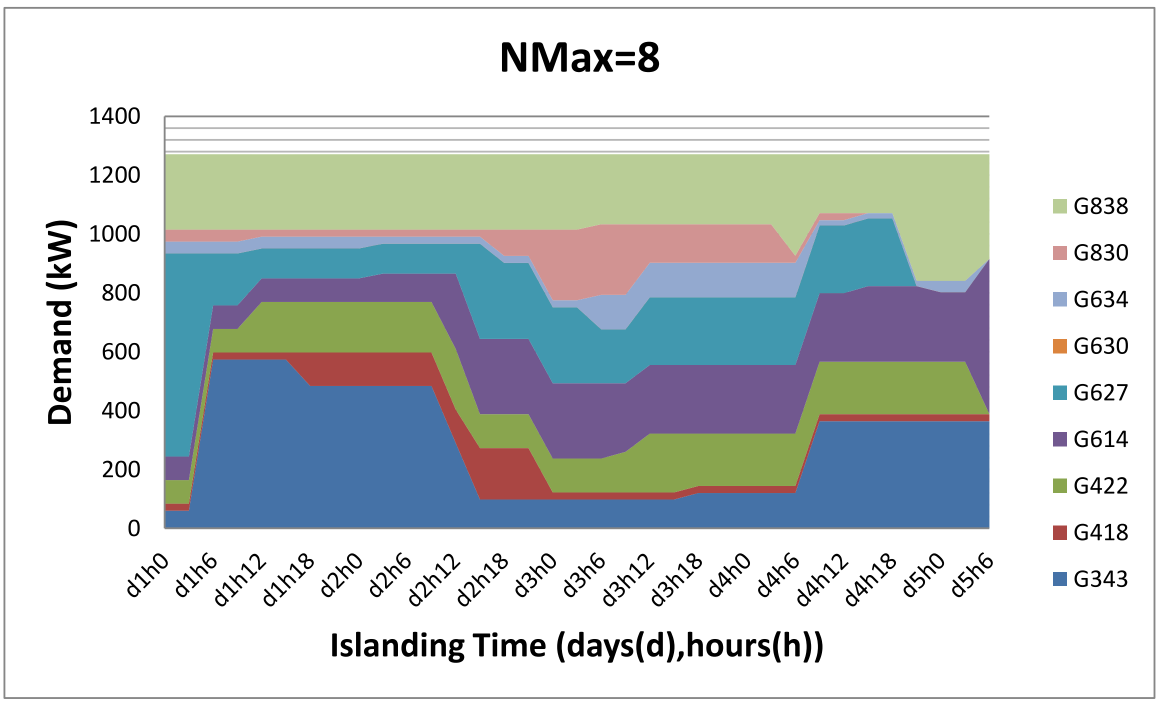

Figure 23. Power contributed by each generator when *NMax*=8.

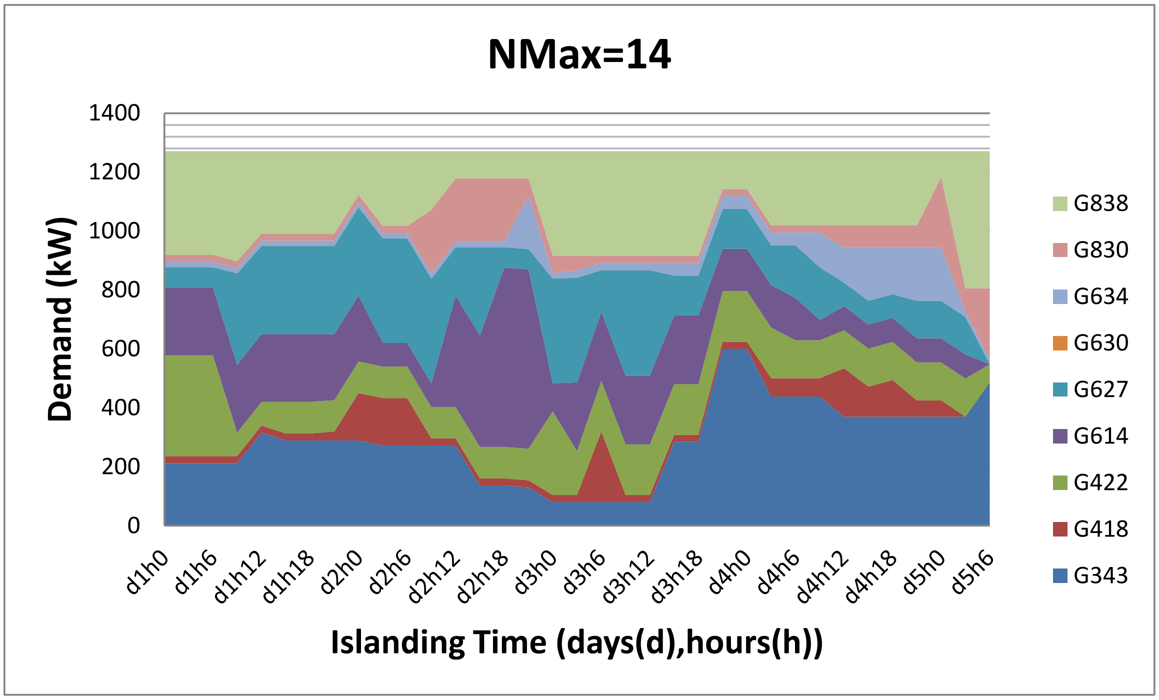

Figure 24. Power contributed by each generator when *NMax*=14.

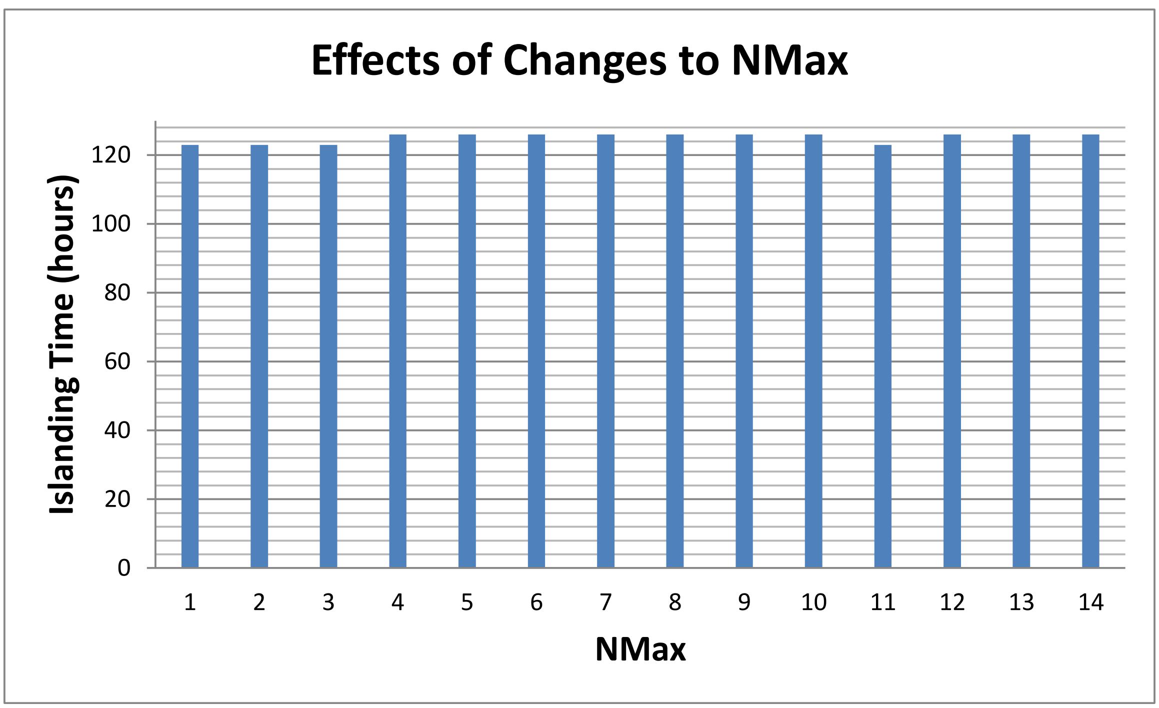

Figure 25. Total islanding hours achieved when *NMax* ranges from 1 to 14.

b. *Scenario Including Renewables*

NMax plays a much greater role when renewable energy sources such as solar and wind are available. Solar and wind power are intermittent in nature, and thus we must be able to adjust generator contributions to accommodate gaps in the renewable power being provided. We find that even with a low number for *NMax* (e.g., two), we begin to see improvements in the performance of a microgrid. Figure 26 shows how this small gain provides an extra six hours above even the generator-only run with *NMax*=14. This is not only a benefit to the overall objective, but it could also extend the lifespan of the generators. To determine whether this trend continues, we increase *NMax* further. Figure 27 shows a case where *NMax*=10. When comparing Figures 26 and 27, we see that much less energy is wasted when the larger value for *NMax*. The dashed line in each plot represents the constant demand. In Figure 26 it is clear that some of the renewable power is going unused. In a business case analysis, it may be possible to sell this power back to the commercial grid. However, recall that we are focused on an islanding scenario; thus, selling unused energy is not possible.

Our findings indicate that the use of batteries is much less important with a higher value of *NMax*. This makes intuitive sense, as a higher value for *NMax* results in less excess energy to be stored. To demonstrate this phenomenon, we again run scenarios across multiple values of *NMax*. We use a budget and costs that allow up to two solar arrays and numerous small wind turbines to be installed. We also allow for batteries to be installed. Interestingly, as shown in Figure 28, we find that for $NMax \geq 4$, there is little difference in performance. This value should not be taken as an absolute, since changes in the scenario could alter this number. However, our experiments indicate that each scenario is likely to have such a number, and it is important that planners identify it. In summary, generator changes and storage devices represent two separate means of compensating for fluctuating renewable energy production. Note, however, that if the renewable energy production exceeds demand in some time periods, generator changes alone cannot prevent wasted energy, even if all generators are shut down completely. In such a situation, storage represents the only viable option for preventing waste.

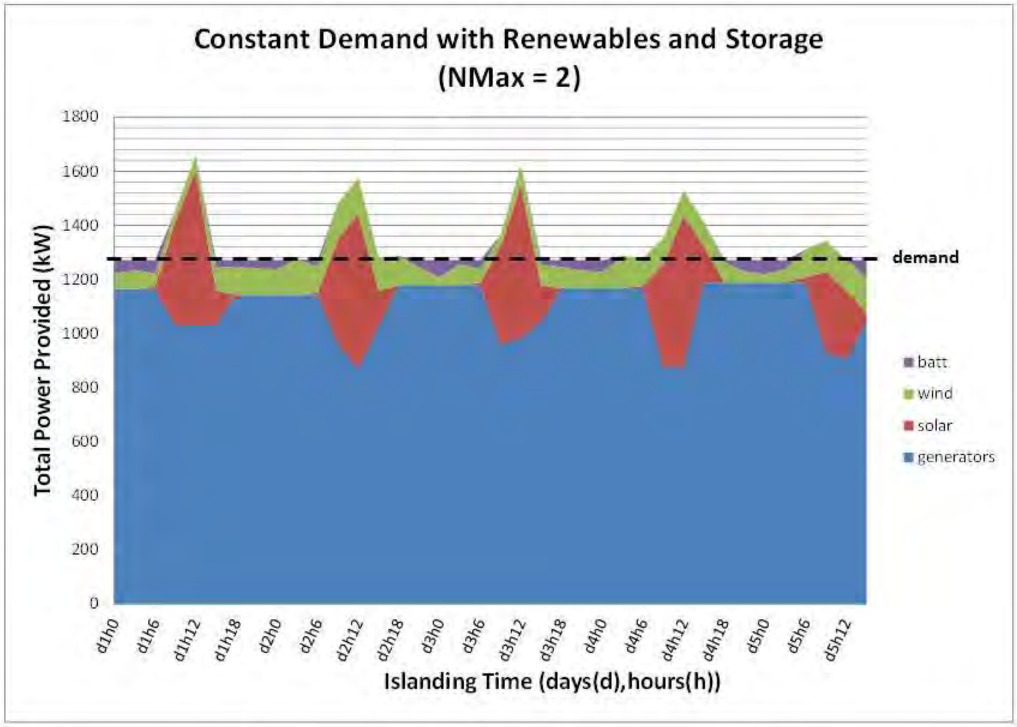

Figure 26. Effect of a low value of NMax on a run of the optimization model which includes renewable energy options. Note the amount of renewable energy above the dashed line, which represents loss or waste.

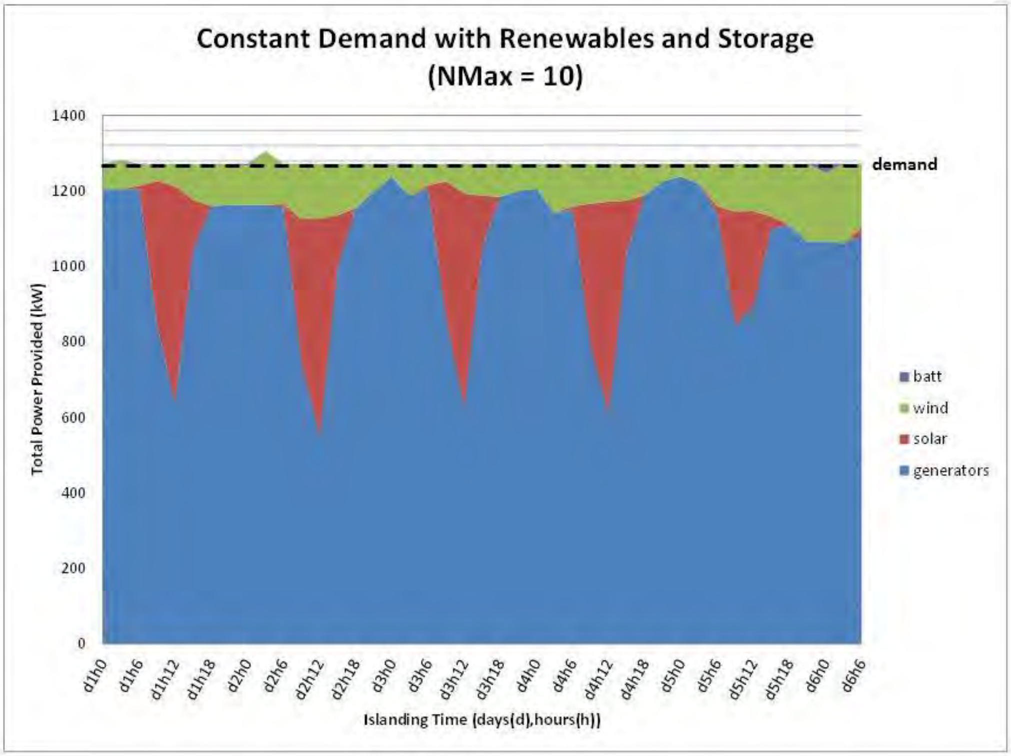

Figure 27. Effect of a large *NMax* on a run of the optimization model which includes renewable energy options. Note that very little energy goes unused (indicated by values above the dashed line).

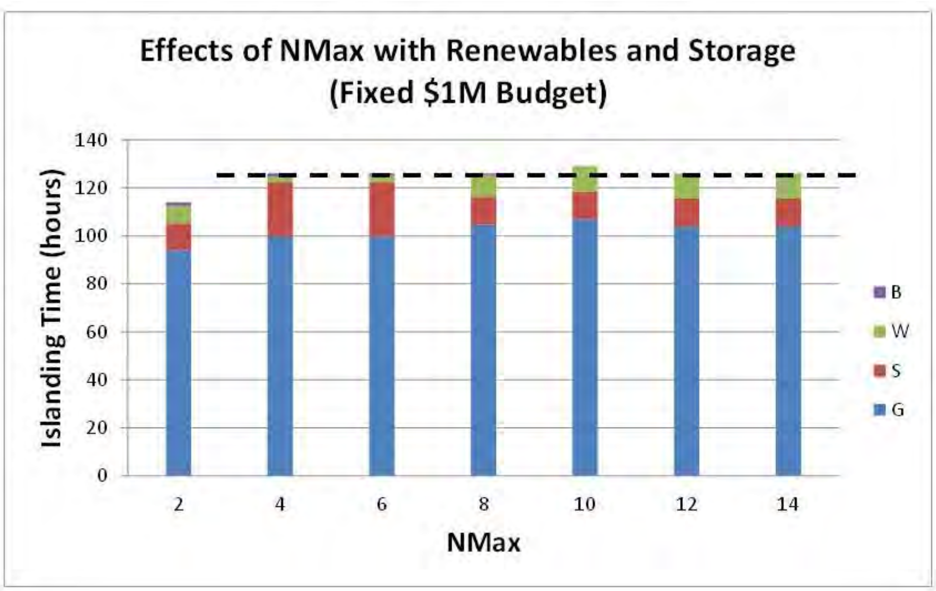

Figure 28. Run of optimization model including a choice of renewables and varying values of *NMax*. Note how there is very little performance change as *NMax* varies from 4 to 14.

3. The Effect of Capital Planning Budget

In order to determine the effect of changes in the capital planning budget, we repeat our experiments performed thus far with varying values for the budget parameter *setupBudget*. Basic intuition says that more money equals more islanding time, and this intuition is accurate, up to a point. At some point, which we do not illustrate in these results, the expected power being obtained from renewable sources could exceed demand for almost all realizations of the weather data. That ideal world is not yet likely. Thus, we consider a more realistic scenario in which it is possible to purchase up to two $1 million solar arrays capable up producing up to 380 kW, one $3 million wind turbine capable up producing up to an unrealistic 65 MW, one $40,000 battery capable of storing 200 kW, and two $20,000 batteries capable of storing 100 kW. Any subset or combination of these purchases is allowable during each run of the model, if sufficient budget is available. Figure 29 shows the results of runs with capital planning budgets ranging from $500,000 to $5,500,000 in increments of $500,000. As expected, we see jumps in performance corresponding to the ability to install a previously unavailable option. Going from $1.5 million to $2 million, for instance, we see an increase in solar power because a second solar array is installed. Something slightly unexpected happens at a budget of $3 million. $3 million is the cost of a wind turbine, and thus we expect to see a possible jump in performance at this budget level. Instead, the model chooses the lower-cost option of installing solar with batteries. To compare this option with that of installing the wind turbine, Figure 30 includes a run of the model in which batteries are not available. The result is that the wind turbine is installed, and we see a slight increase in islanding time (within the optimality gap of our experiments). These results are based upon notional data, but they indicate that points in which a new option becomes financially viable are indeed where analysis needs to be done. In this scenario, we see how simply adding batteries to solar arrays as a low-cost option could result in performance similar to that of choosing a wind turbine.

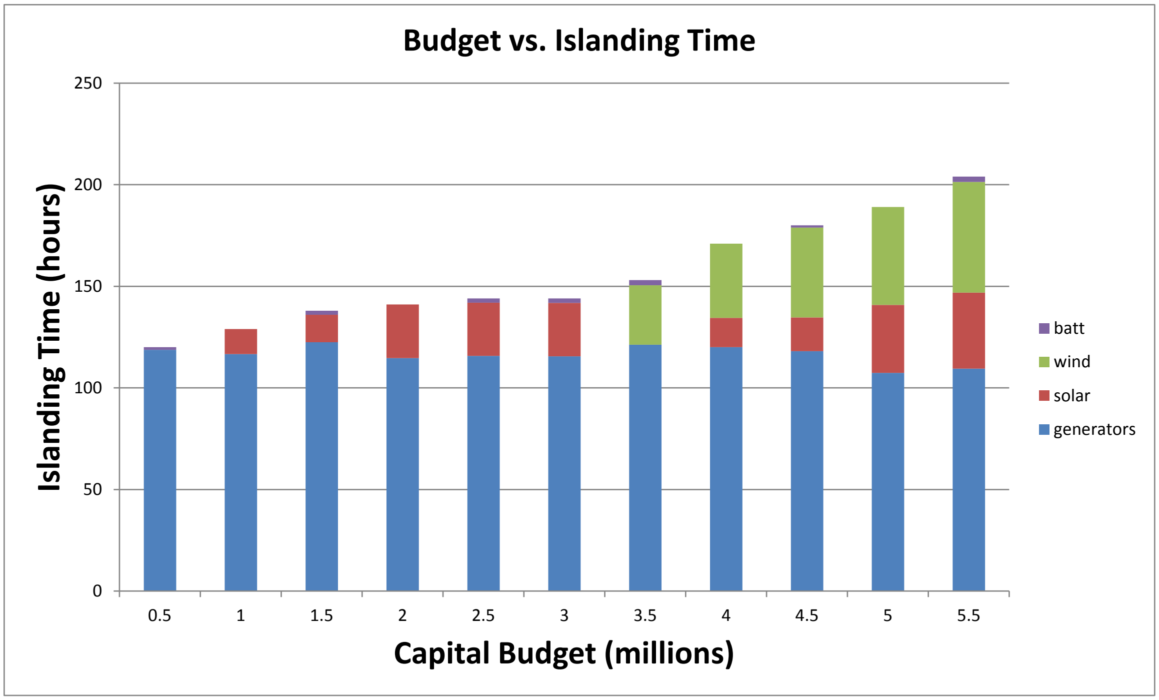

Figure 29. Islanding time resulting from varying capital planning budgets. As expected, more money invested provides more islanding time.

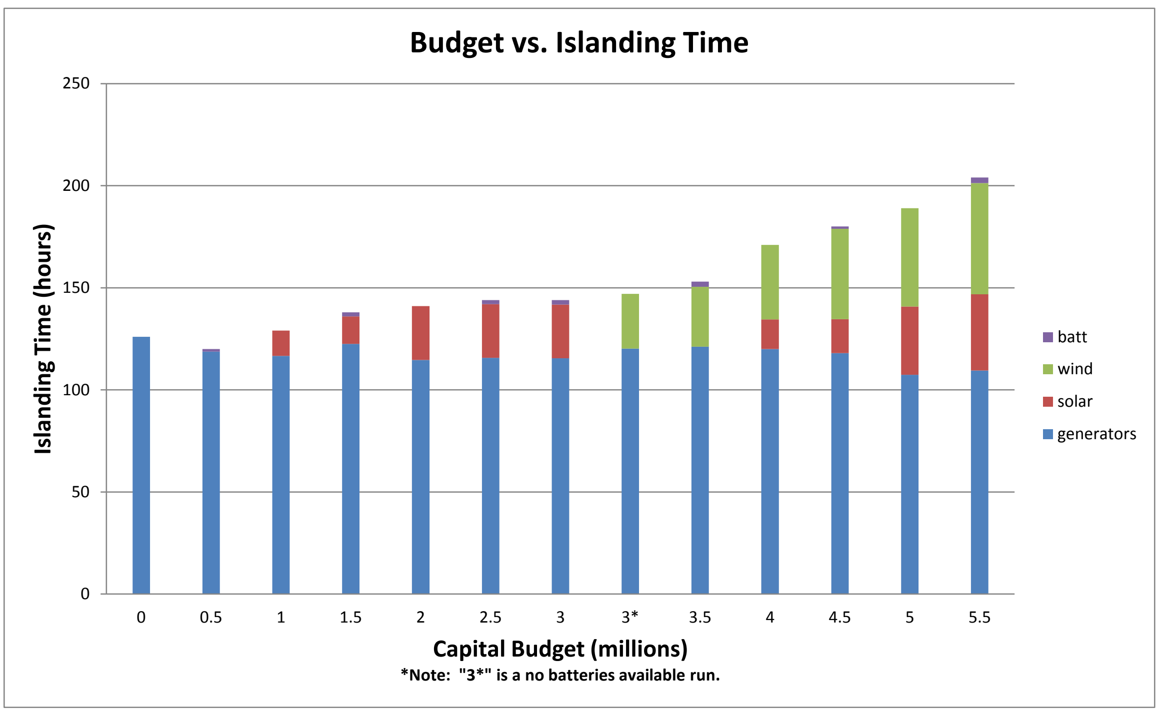

Figure 30. Variation of Figure 9 that includes an additional run at $3 million. The notable difference here is how batteries can provide a lower cost option to achieve the same performance as a wind turbine.

A further benefit of renewables is found in reducing our sensitivity to fluctuations in the price of fuel. Although fuel reserves represent a sunk cost in our model and are not included in the capital planning budget, they must presumably be replenished after a period of islanding, and the cost to replenish them represents money that cannot be spent elsewhere. Using the same model data, we determine at each budget level the amount of money spent on fuel and compare it with the corresponding islanding time. We then vary the price of fuel from $4/gallon to $8/gallon. Figure 31 shows how an increased capital planning budget, and thus an increase in number of islanding hours provided by renewable energy, leads to a decline in the cost of fuel per hour of islanding time. It also shows how the lines begin to converge as the budget increases. This represents a reduced sensitivity to fluctuations in the price of fuel. Just as the driver of a hybrid vehicle which gets 40 miles per gallon (MPG) and is less sensitive to changes in the gas prices than a truck driver who gets less than 10 MPG, an energy manager who utilizes renewable sources does not need to be as concerned with the price of fuel as one who relies heavily on generators. Ultimately the lines in Figure 31 should converge when all power comes from non-fuel based sources.

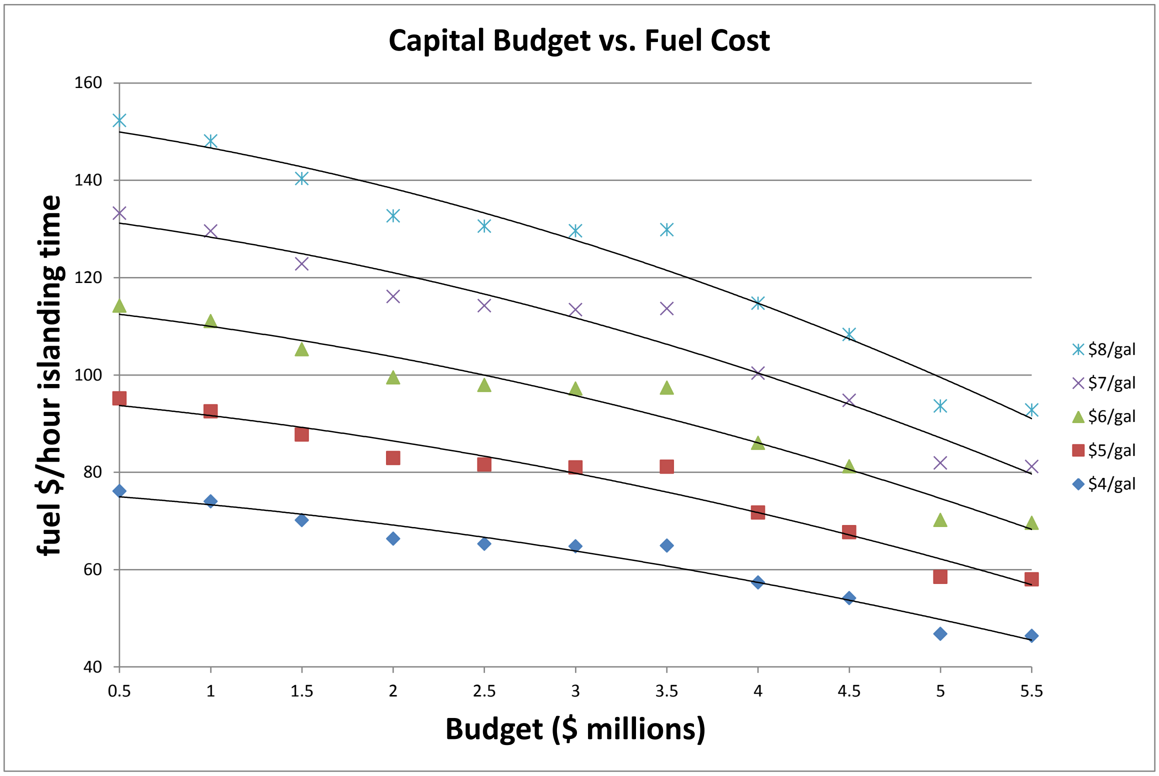

Figure 31. By calculating the fuel cost per hour of islanding time it is possible to show how more renewable energy sources, as provided by a larger capital planning budget, result in reduced sensitivity to fluctuations in the price of fuel.

4. The Battery Effect

Although current energy storage options are very limited, our model can be used to determine how much increases in battery capacity affect the objective. We find that even a 700% increase in battery capacity had very little impact on performance. These results are based on one particular scenario that includes fuel-based generators, *NMax*=10, and total power production that exceeds demand. Scenarios with greater percentages of intermittent renewable power are more likely to be much more sensitive to the amount of capacity of the batteries (energy storage). Figure 32 shows the slow increase in islanding time across an increasing storage capacity.

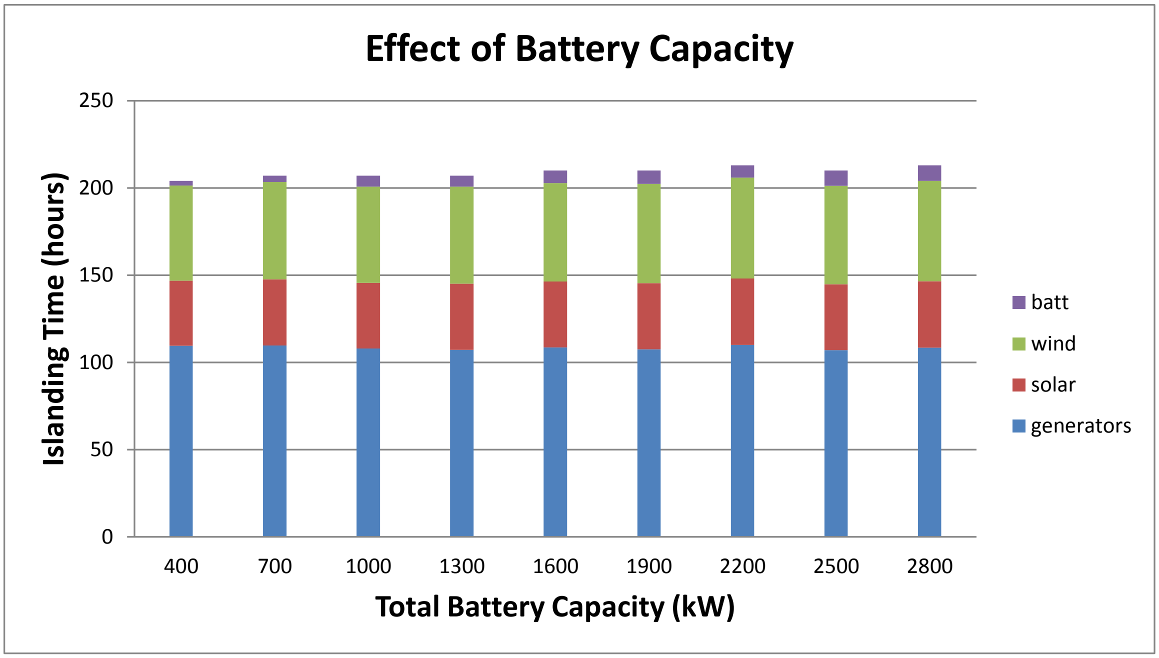

Figure 32. A very slow increase in islanding time as battery capacity increases. A scenario with a heavier reliance on renewables is likely to show a much larger increase in islanding time.

B. PRESIDIO CASE STUDY

1. Demand Data

We now consider scenarios utilizing actual historic data for six customers (buildings) on the Presidio of Monterey rather than the constant demand data from the previous section. Figure 33 shows the first two weeks of this data; note the cyclic nature of the demand. Previous runs of the optimization model used a constant demand of 1271 kW, which was an estimate that included more buildings. The actual demand profile is capable of islanding for a much longer period of time under a given capital planning budget, and thus the planning horizon must be extended to accommodate.

Due to lower demand, solar and wind data are extended to a 30-day planning horizon rather than as in the previous runs, which used only 14 days. This causes a significant impact on the run time of the model. A 14-day planning horizon results in 4,151 binary and 10,752 continuous variables. A 14-day planning horizon runs anywhere from minutes to almost a full day, dependent on the size of the capital planning budget.

Running a 30-day model with the same parameters requires 8,895 binary and 23,040 continuous variables. The time required to solve this 30-day model ranges from hours to potentially over a week.

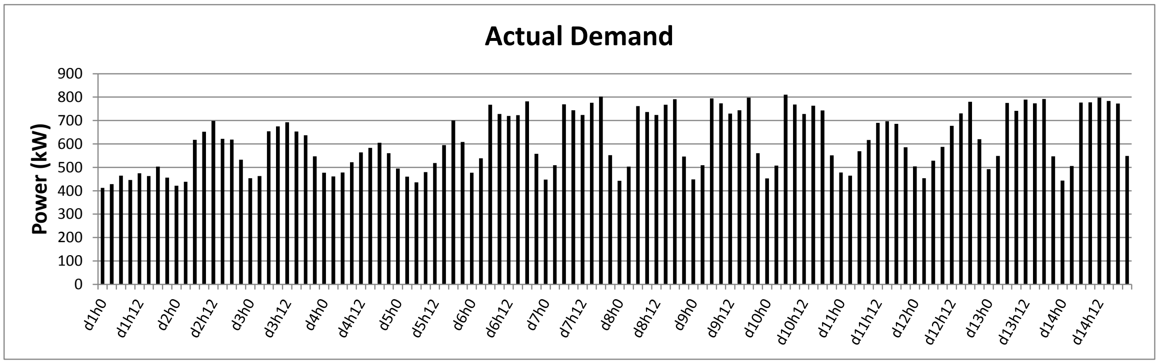

Figure 33. Presidio of Monterey historical demand for the first two weeks of January 2014, representing six critical buildings.

The Presidio currently has one solar array installed; the orange bars in Figure 34 reflect the power it provides. The blue bars represent power from one 50m wind turbine. Note that solar power coincides more consistently with peak demand, while wind can provide more raw power. Such tradeoffs are at the heart of the problem we consider.

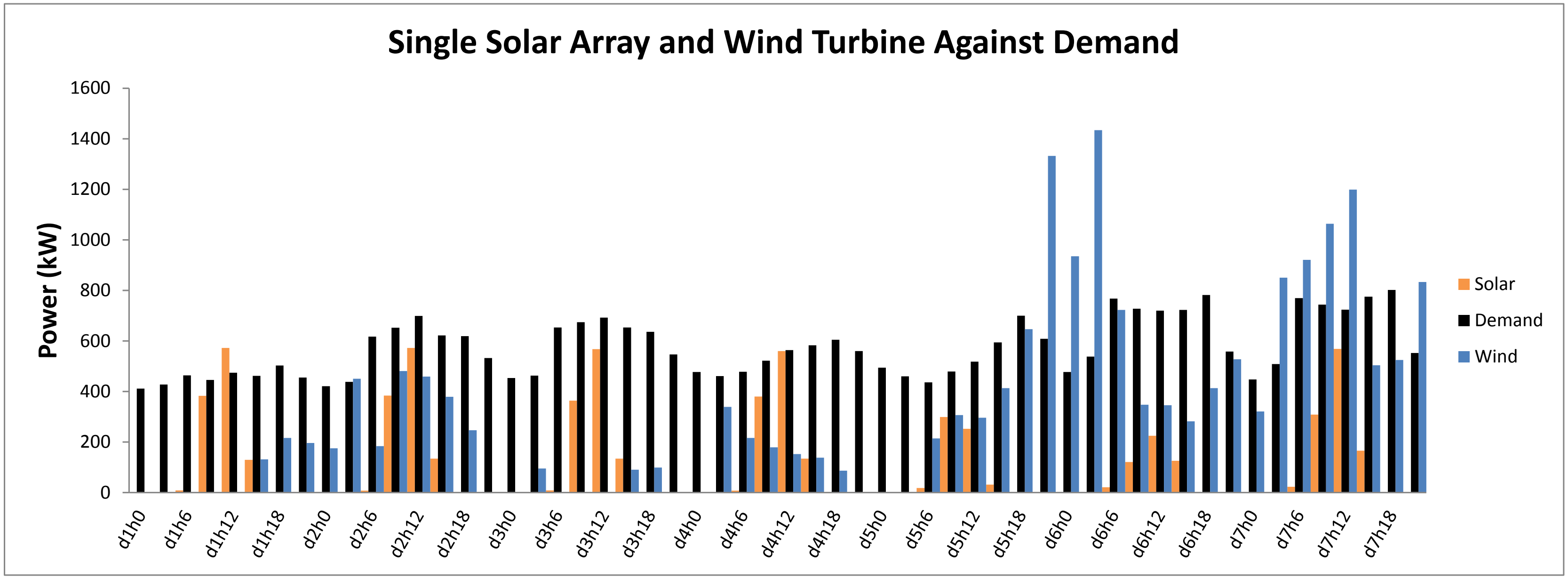

Figure 34. Seven days of demand at Presidio of Monterey, with power from one solar array and one wind turbine overlaid.

2. Value of a Microgrid Revisited

As in the constant demand scenario, we first consider utilizing only the nine generators currently available with this new demand data. We see the value of a microgrid in the overall gain in islanding time. Figure 35 shows the difference to three customers that a microgrid represents. In this particular run of the optimization model we have three customers that have generators and three that do not. Figure 35 only shows those customers that had an ability to island before the microgrid was used, i.e., the three customers with generators. However, the other three customers would also be able to island for 264 hours with a microgrid.

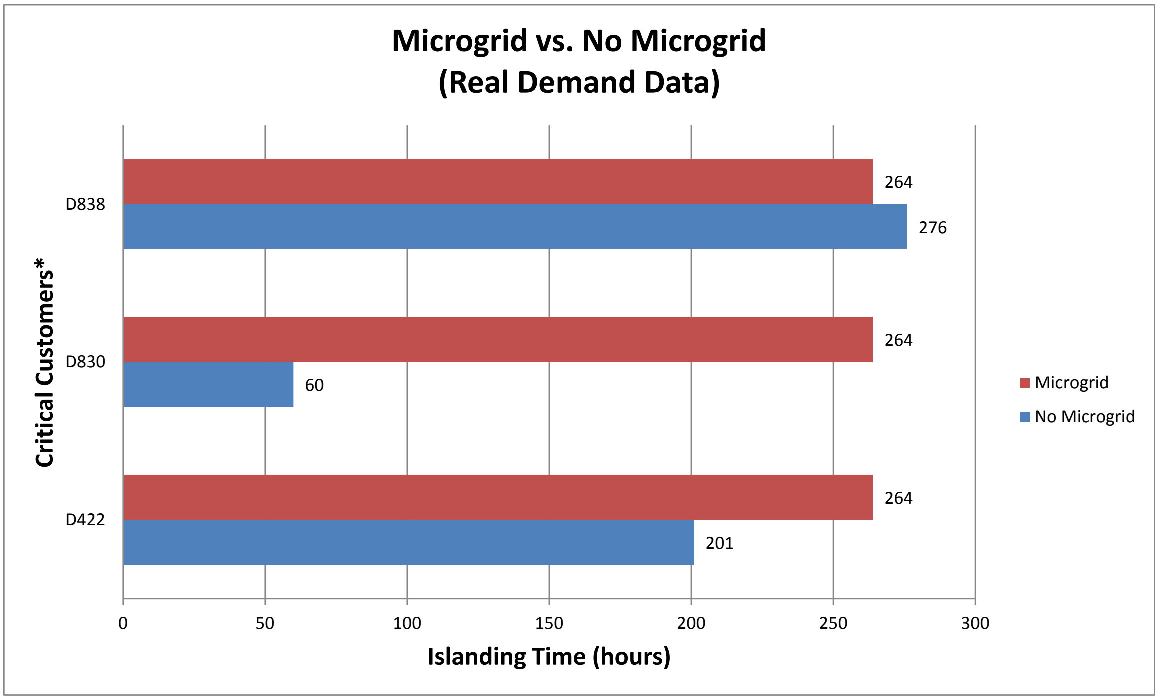

Figure 35. Three Presidio of Monterey customers and their before and after microgrid islanding times.

3. The *NMax* Parameter Revisited

Recall that we are interested in determining the point at which *NMax* is so large that further increases do not improve islanding time. Figure 36 shows that with variable demand, the largest improvement in islanding time is seen at *NMax*=6, vice *NMax*=4 in the constant demand model. Thus, we conclude that in this scenario, *NMax* makes little difference in objective value above six. This is important because we also realize that as the planning horizon and the capital budget increase, there is a need to increase *NMax* proportionally. We increase/decrease *NMax* in further runs of the optimization model with the Presidio demand data to provide faster solve times with some assurance that it has little impact on the objective value obtained.

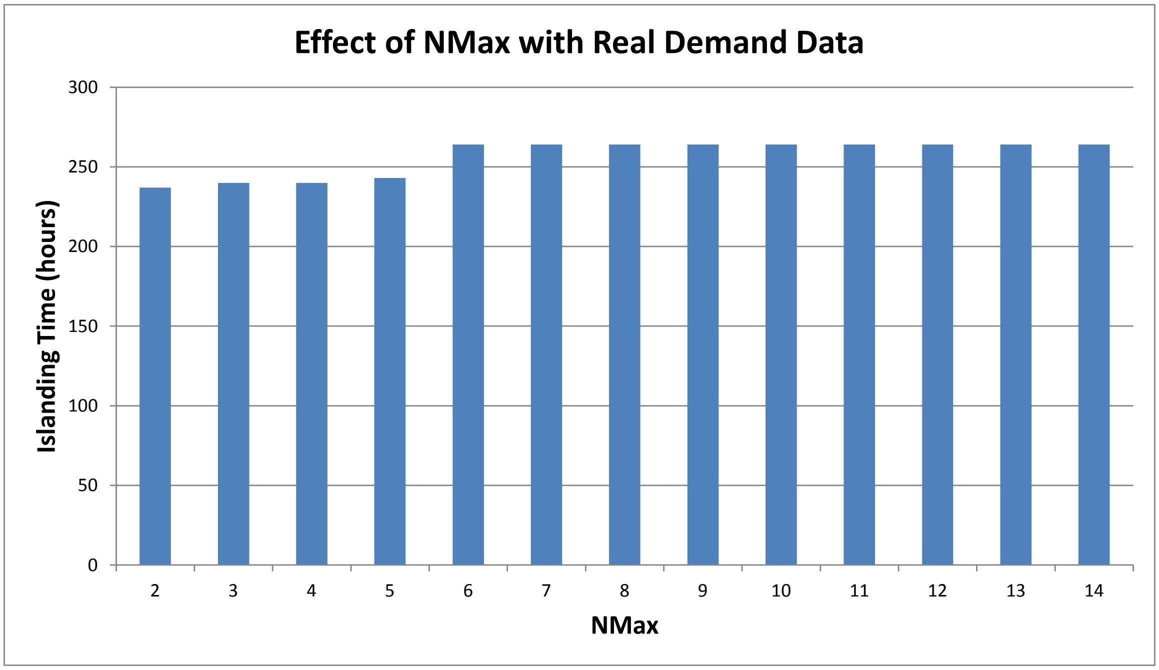

Figure 36. Using real demand data from the Presidio of Monterey we see that *NMax* value of interest is now at six, rather than four when using constant demand data. A higher proportion of renewable energy may also benefit from higher *NMax* values.

4. Where to Spend the Money

We now contrast the current setup at the Presidio of Monterey with potential capital planning choices. Recall Figure 35, where a microgrid with generators alone can provide as much as 11 days of islanding time. Adding the currently-installed solar array to the optimization model, we find that we achieve an additional 15 hours of islanding time. Our next goal is to determine the optimal way in which to spend additional capital planning money.

As before, we perform a sensitivity analysis of the capital planning budget. Figure 37 depicts islanding times resulting from capital investments varying from $0 to $3,500,000 in increments of $500,000. Adding a second solar array, shown as the $1 million budget, results in over a two-day increase in islanding time. The next important jump is at a $3 million, which represents installing a wind turbine (but not the second solar array) and the jump goes to 13 additional days over the existing infrastructure, or 11 days more than installing a second solar array. Note that these results are specific to the demand data used and should be explored across other sets of demand data to ensure consistent results.

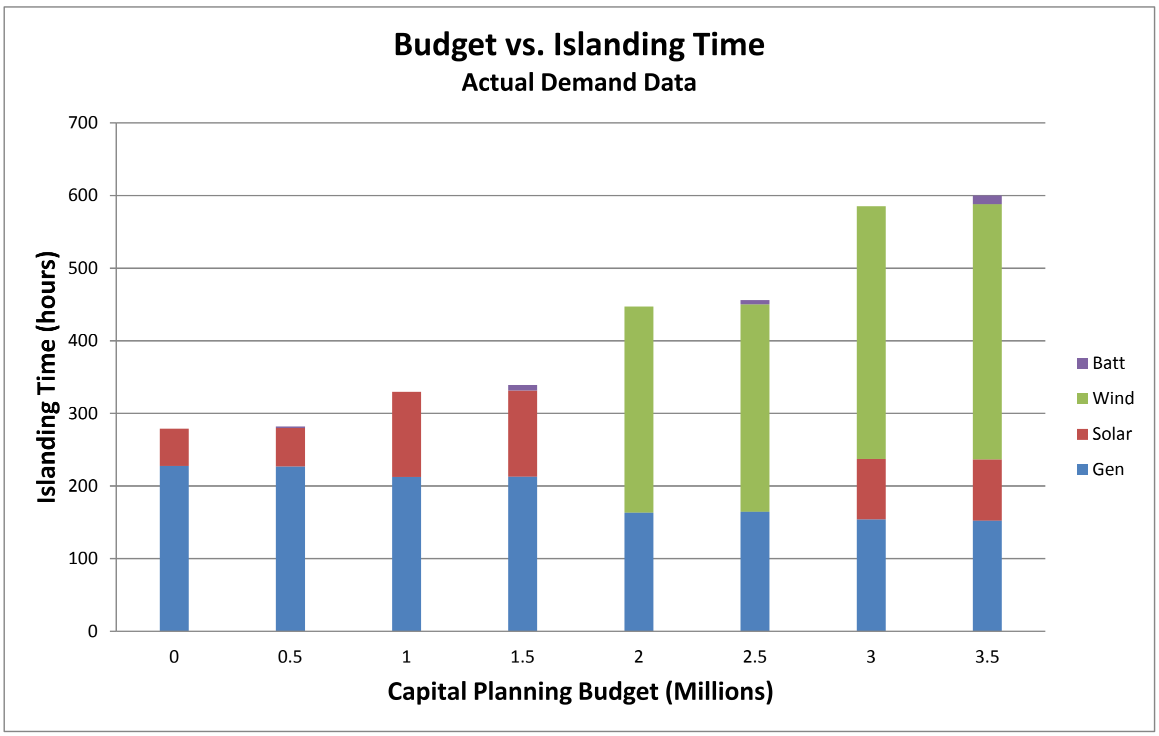

Figure 37. Sensitivity analysis of capital planning budget in order to show effect on islanding time.

5. Excess Energy Production

Caution should also be used when assuming that more infrastructure and more islanding time create a linear relationship with islanding time. In reality, the amount of wasted energy must also factor into the decision. We define wasted energy as the energy produced but not utilized to meet demand or charge a storage device. As the amount of infrastructure in renewable energy increases, so does the potential for unused energy. Better storage options may someday provide a good option to offset this effect, but currently they are inadequate. The desired length of islanding time is also a factor that increases the amount of wasted energy. Figure 38 illustrates how the amount of excess energy increases. However, recall that in the case of a connected grid, this energy could be sold back to the commercial market.

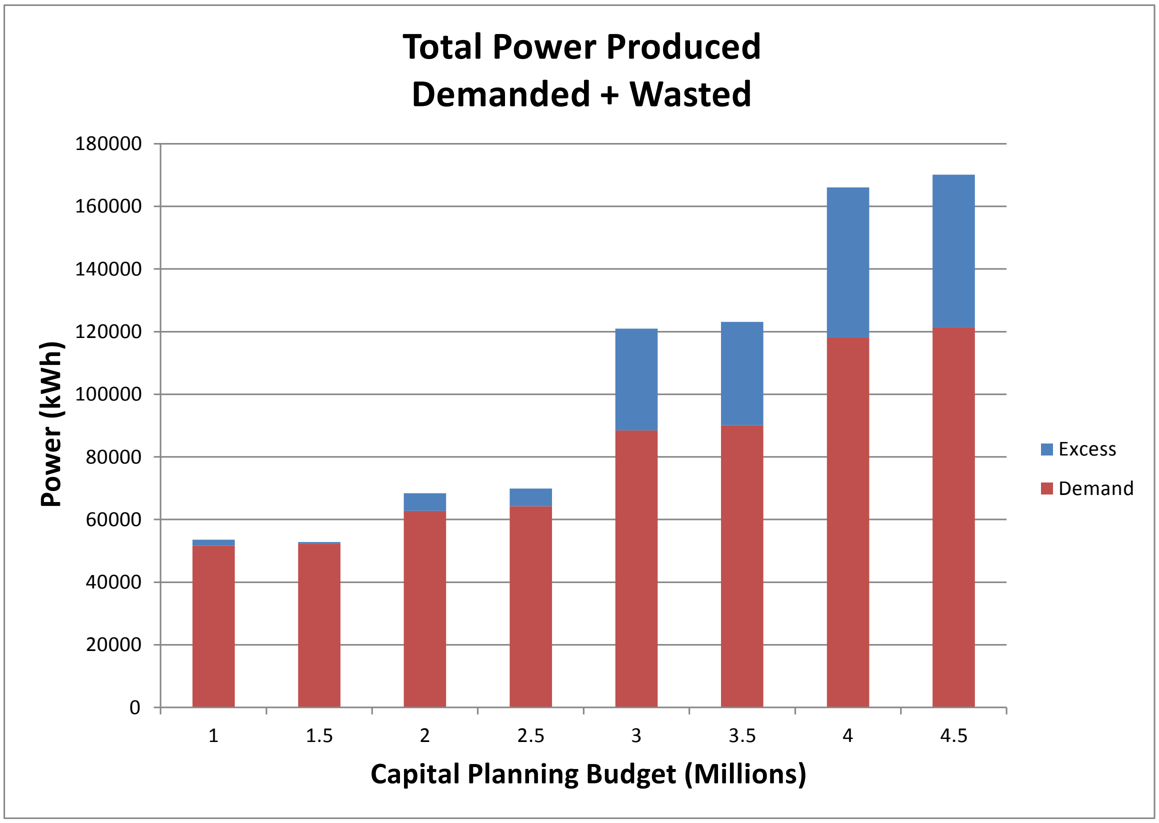

Figure 38. Illustration of excess energy produced, shown in blue, above total demand.

6. Seasonal Effects

Supply and demand of energy are anything but consistent, but some insight can be gained by considering seasonal trends. Figure 39 shows the daily power production for the existing solar array at the Presidio of Monterey in 2013. One cautionary tale relates to the values of zero shown in late August and early September. The data is not missing;

rather, there was no production during that time period due to a malfunction in the array. Thus, some amount of redundancy is perhaps desirable. Looking past the obvious gap, it is clear that the solar power is subject to seasonal trends.

Similarly, Figure 40 shows the notional contributions from a single wind turbine with a 50 meter blade radius based on historical weather forecast data for the same time period. Note that seasonal trends are less identifiable in this plot, and the peaks in power production are sometimes more than twice the peaks seen in solar power. Wind power clearly needs large energy storage options to benefit from the peaks in power production.

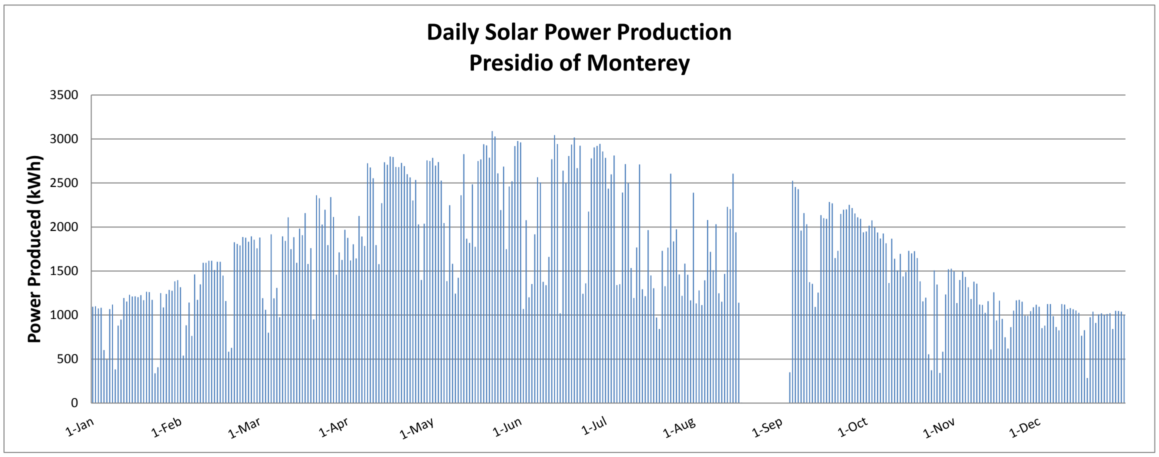

Figure 39. Total solar power produced at the Presidio of Monterey in 2013.

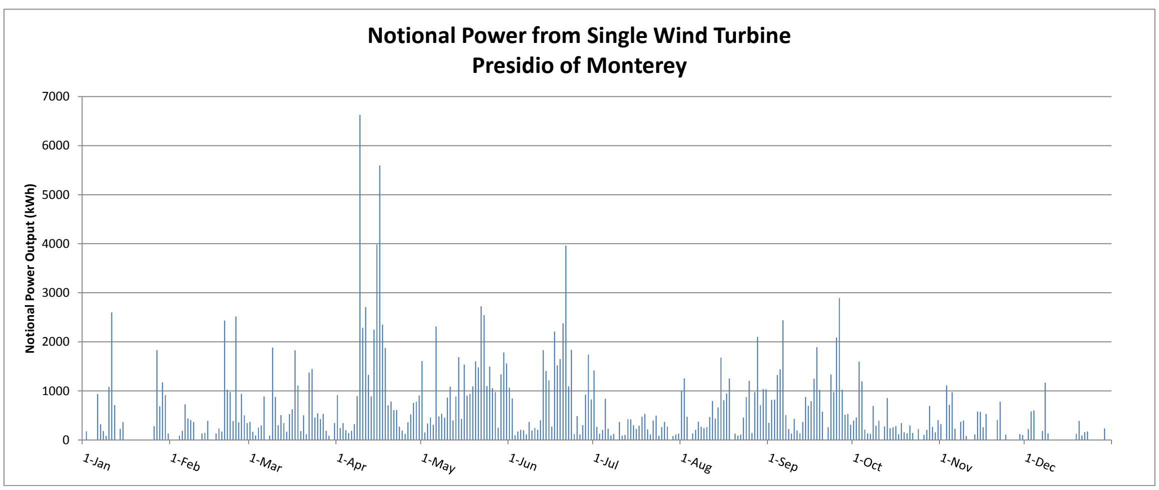

Figure 40. Notional wind power production from a single 50-meter wind turbine based on 2013 forecast data.

7. Demand Effects

The Presidio of Monterey provided demand data for the six critical buildings from both December 2013 and January 2014. Using this data, we run the optimization model using known solar production for the existing array and a microgrid. Starting from the first day of each month, the islanding times achieved in December and January are identical. Given that the solar irradiation during December and January is similar, these results are not surprising. Further analysis, however, does show that a certain amount of energy is wasted in January. Figures 41 and 42 show the contributions from generators and the solar array during December and January, with excess production annotated for January.

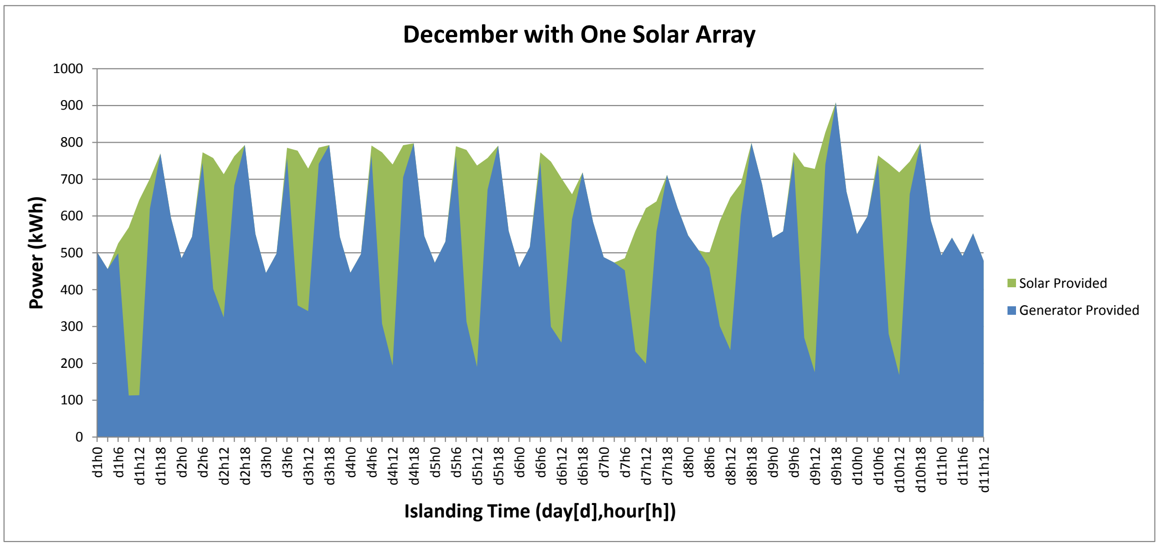

Figure 41. December 2013 islanding time using generators and solar array, over variable demand.

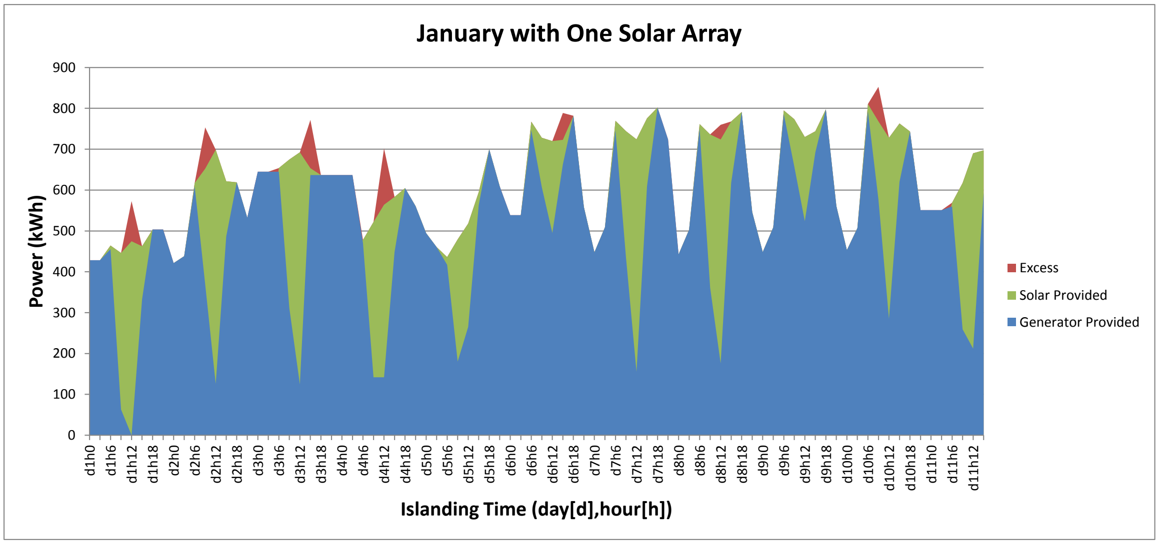

Figure 42. January 2014 islanding time using generators and solar array, over variable demand. Excess power production annotated.

This excess demand is a function of the demand signal. Figure 43 shows demand during December and January. There is a very obvious dip at the end of December and beginning of January, likely due to the installation being on stand down for the holiday season. The optimization model is run from the first day of each month. Figure 44 shows demand for only the first two weeks of both December and January. Demands in the first few days of January were clearly lower. Total demand does not exceed 60 kWh for almost the entire first week of January, where as it exceeds 60 kWh every day the first week of December. While islanding time is equivalent, there is excess power production in January due to lower demand. Further research should be done to determine if this effect persist for varying values of *NMax* and storage capacity.

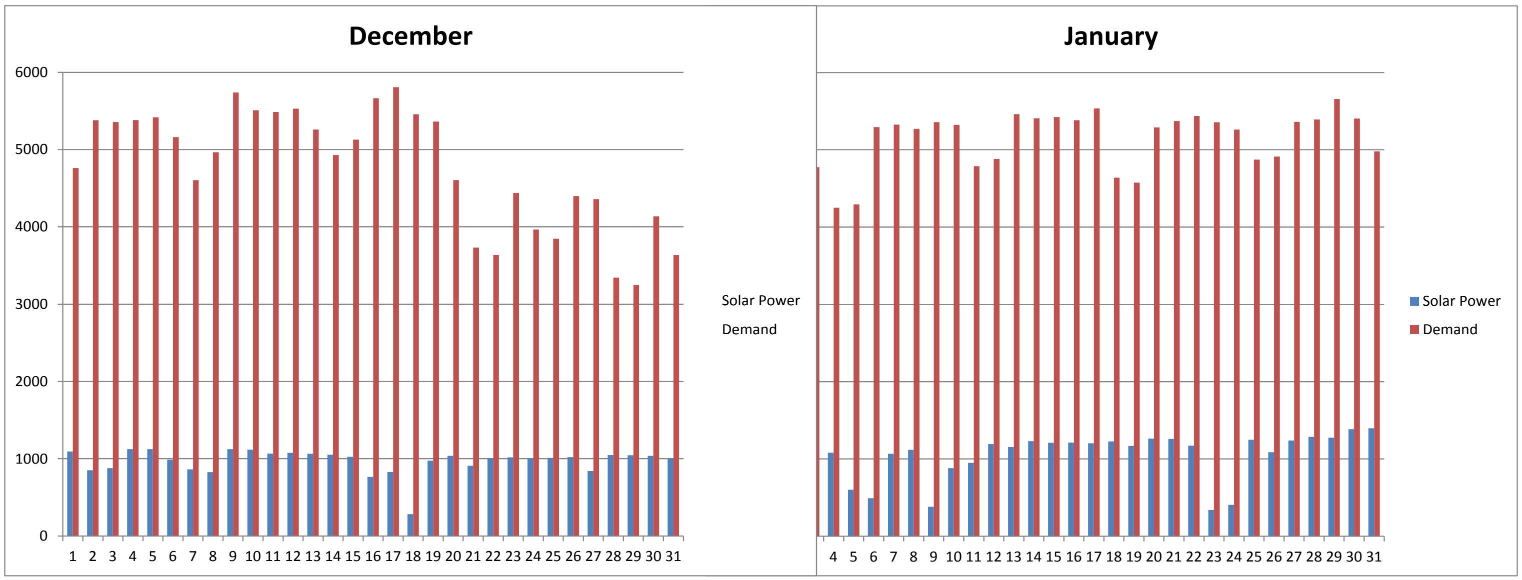

Figure 43. Demand and solar power data for December 2013 through January 2014.

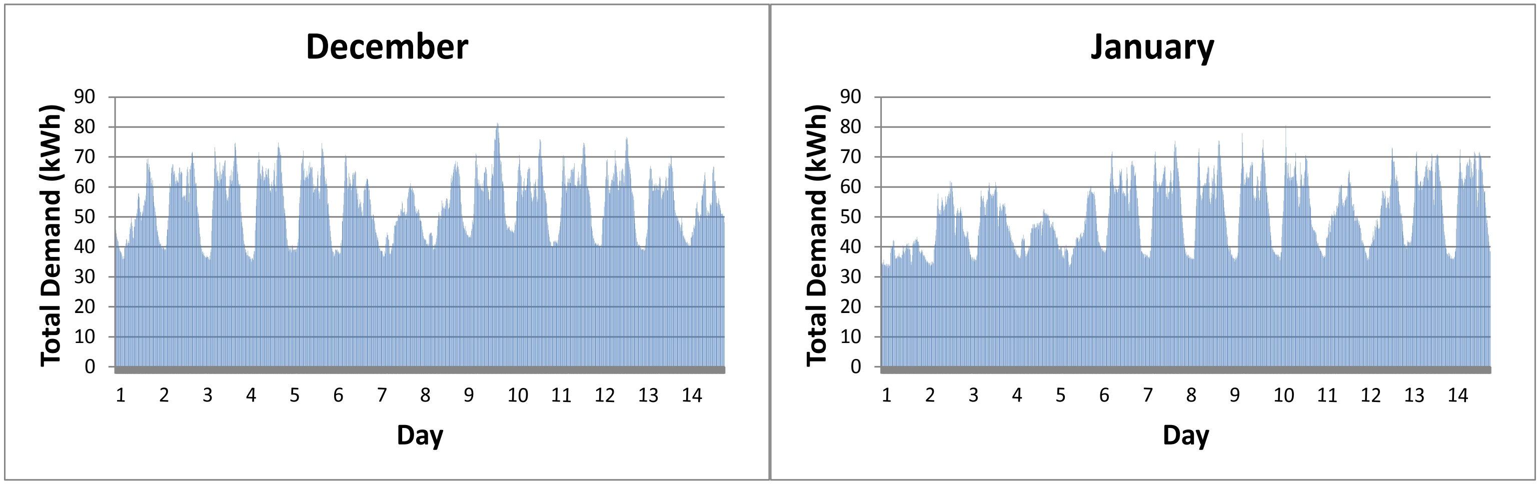

Figure 44. Demand data for first two weeks of December 2013 and January 2014.

V. CONCLUSIONS AND FUTURE WORK

A. CONCLUSIONS

The intermittency of renewable power continues to present a challenging problem. The goal of the thesis is to provide a first-cut decision support tool to energy managers who are weighing the capital planning options for their installations. The strength of this model is its flexibility to adapt to a wide range of options. The model can incorporate new energy technology. It can be modified to accommodate any existing architecture already installed. There is even a component to allow optimization over multiple forecasts.

We have considered both a constant demand scenario and a case study of the Presidio of Monterey. The constant demand model provided insights into various components in the model. Running an instance with only generators, we easily saw the communal benefit of having a microgrid. Specifically, we observed that while two customers lost 78 hours of combined islanding time, the other eight customers gained a combined 462 hours.

We found that the number of times a generator is allowed to change operating speed, denoted as *NMax*, can have a large impact on islanding time when renewable power is a factor. We saw in one scenario that going from *NMax* of 2 to *NMax* of 10 yielded approximately 18 more hours of islanding time. However, by conducting sensitivity analysis we were able to show that *NMax* of 4 or greater would yield the same gain in islanding time for that instance. This is an important distinction as new, and more expensive, generators increasingly are equipped to change speed based on demand signals while older models are often not.

Sensitivity analysis of one scenario showed us that a 700% increase in battery capacity had very little effect on islanding time. This, however, needs to be prefaced with the fact that battery capacity is only useful if there are recurring periods of excess energy production, which is more likely when there are a larger proportion of renewable sources with intermittent behavior. Thus, other instances may yield different results concerning the benefits of battery capacity.

In our case study of the Presidio of Monterey we saw similar results. We show that running the model with existing generators and solar array for both December 2013 and January 2014 data that islanding time was the same, but with the January data there was wasted energy. This was found to be a direct result of the demand profile. Demand in one scenario started much lower than in the other, and thus excess energy was produced. In this study the wasted energy did not affect islanding time; however, it is very plausible that other scenarios would be different. This leads to the conclusion that infrastructure size is dictated as much by demand as by the investments options available.

Overall there are some key insights that our model can help decision makers quantify. First, it allows a user to estimate the islanding time if a microgrid is implemented on current infrastructure. It also allows users to add infrastructure and measure the effects. In general, more infrastructure equates to longer islanding times. Investment in energy storage results in increasing islanding time only so long as there is excess power production that exceeds the storage capacity. The model can also help identify the value of *NMax* where returns in islanding time no longer improve. The best islanding time achievable in any scenario requires a mix of infrastructure that meets demand by matching renewable power with appropriately sized energy storage, and using generators of sufficient quality to fill the gaps in renewable power production.

B. FUTURE WORK

We suggest that more forecasts, solar data, and demand data be considered in order to provide more robust optimal solutions. The runs conducted in this thesis only covered a small time period, and varying the time of year could have a large impact on the optimal solution. The start time, which represents the time the grid begins islanding operations, should also be varied in order to reflect the uncertainty inherent in emergency operations.

We also recommend that further detail be added regarding the physical location of power sources and the potential for power lost over transmission lines. Additional power source types, such as geothermal, natural gas, biogas, etc., can also be incorporated due to the flexibility of the model.

Our model utilizes a binary parameter to distinguish between critical and non-critical customers, and our analysis considered only critical customers. Conceivably, this parameter could be modified to reflect multiple levels of customer importance. Future work may incorporate customer importance into the objective function by means of a series of penalties for unmet demand. This would provide for the use of excess power to service customers who may not be essential, but who could benefit from otherwise wasted energy.

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LIST OF REFERENCES

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