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Resilience and Cost Trade Space for Microgrids on Islands

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***Abstract*—This article examines the trade space between the resilience and cost of an island microgrid. The article presents two models for the resilience and the cost of the microgrid. The resilience model considers the invulnerability and recoverability of the microgrid and represents the power balance of the microgrid, energy storage, and maintenance policies. The cost model adapts the levelized cost of energy measure to the context of island microgrids. We conduct experiments to investigate two microgrid architecture decisions of how much excess generation capacity and redundancy to provide. The experiments show that redundancy of generative sources provides greater resilience for similar cost, and resilience improves quickly as excess power capacity is added while the cost grows more slowly. Case studies for island microgrids show how a redesign of the microgrid can improve resilience without increasing costs. The article contributes to the literature a model for decisions makers to evaluate the tradeoffs between resilience and cost for island microgrids that must depend on their own distributed energy resources.**

***Index Terms*—Cost of energy, island, microgrid, recoverability, resilience, trade space.**

I. Introduction

THE US Department of Defense (DoD) is the largest energy consumer in the USA with energy consumption classified as either installation for the bases and facilities or operational for powering military vehicles, planes, and ships. In response to various laws and regulations, the US DoD has been increasing the efficiency of energy usage and reducing overall energy costs [1]. However, the US military's energy policy goes beyond energy efficiency. The US military wants to increase energy security defined as the secure and reliable provision of energy to meet mission needs [2]. Energy security is composed of resilience and reliability in addition to the aforementioned efficiency. Reliability describes the ability to deliver needed energy, and resilience describes the ability to anticipate, adapt, and react quickly to changing conditions and disruptions to normal operations.

The US military operates bases on islands and elsewhere, where the base is not connected to the utility power grid. These bases generate power locally, currently mainly by diesel gensets connected directly to the loads they serve. The logistics and costs of delivering diesel to remote island locations create a vulnerability to energy security of these facilities. For this reason, among others, the US military wants to diversify their energy sources away from an over-reliance on diesel gensets. While our motivation stems from the US military case, energy security is a wider concern shared by many diverse entities including island nations, regions, as well as businesses. Returning to our focus on islands, providing energy is difficult and expensive. Most islands have relied on diesel, and given the fuel logistics, storage, and other issues, many islands pay high rates for electricity [3].

Many islands have already, and many others are looking into switching from primarily diesel generators (DGs) to microgrids with significant amounts of renewable energy sources such as wind and solar. In fact, the US Navy has set a goal for 25% renewable energy sources [4]. Microgrids are system solutions to the energy generation and distribution problem because it involves the design of sufficient energy generation, storage, and controls to deal with the intermittent generation of renewable sources as well as balancing load and supply across the network [5]. The diversification away from diesel should also make the energy infrastructure more resilient to natural as well as man-made disasters. Resilience is the ability of a system to withstand external disruptions and, if damaged, to recover quickly from the damage. Resilience is especially important to the military because of the need for energy to sustain operations. Additionally, military installations are not only concerned with disruptions due to natural events but to attacks on the infrastructure from adversaries.

The military uses the resilience concept to describe a system that is trusted and effective in a wide range of mission contexts, is easily adapted to operational and environmental changes through reconfiguration and/or replacement, and has predictable and graceful degradation of function [6]. In this article, we define the energy resilience of a military installation as the ability of the base to avoid disruption to its energy supply and, if disrupted, to minimize the impact and duration of the disruption. We explore the establishment of a microgrid on the base as the means to provide energy resilience. We consider both microgrid design factors as well as operational capabilities and policies contributing to energy resilience.

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The Navy designs microgrid systems using a top-down, multiphase process of architecture design followed by detailed design [5]. The microgrid architecture describes the structure of the microgrid in terms of its components, how they are configured and related to each other as well as the environment, and how the microgrid balances the competing stakeholder requirements. The microgrid architectural decisions include the type and quantity of distributed energy resources and energy storage systems in the microgrid to meet the loads' power demands. The subsequent detailed design phase addresses the power and electrical engineering issues of microgrid control, frequency regulation, voltage regulation, and so forth.

This article focuses on the microgrid architectural design phase and the architectural decisions of the type, number, and power rating of distributed energy resources to include in a microgrid architecture. The architect must balance the military's requirements for resilience and efficiency (cost) of power delivery. This article contributes to the literature on microgrid resilience two models to analyze the tradeoff between resilience and cost during the architectural design phase. We use the model to explore two design strategies commonly used on these islanded Naval bases. The first design strategy is simply to have excess energy generation and storage capacity. The second design strategy is to decentralize and distribute energy sources or to have redundancy in the energy generation. Both excess capacity and redundancy are well-known architecture heuristics [7].

The article is organized as follows. Section II defines resilience in the context of microgrids. Section III reviews the literature and finds gaps in understanding resilience of island microgrids and in exploring the trade space between resilience and cost. Section IV presents the model of resilience and the levelized cost of energy (LCOE) demanded. Section V presents the method to assess resilience and cost. Section VI presents experiments of excess capacity, redundancy, and maintenance policies. Section VII applies the model and method to case studies of island bases operated by the Navy. Section VIII summarizes the article and draws conclusions.

II. Resilience

Resilience describes a system that can resist and recover quickly from disruptions. Resilience is multidimensional, contextual, and dependent on the time frame considered [8]. We limit our context to microgrids. The literature defines resilience with respect to system performance [9]. In the energy domain, most research measures performance as delivered power [10].

The dimensions of resilience can be traced to the states shown in Fig. 1. A microgrid can anticipate, prepare, and take precautions against disruptions during the predisturbance phase. The time frame for such preparation is typically long and, for our study, out of scope. We focus on the resilience dimensions once a disruption occurs. Once a disruption affects the microgrid, the important resilience dimension is the microgrid's invulnerability or ability to resist a degradation in performance. The microgrid operation prefers either none or as small as possible drop in performance resulting from a disruption. Following a disruption, the microgrid must stabilize itself and recover from the disruption. The second measure of interest is the microgrid's recoverability or ability to quickly return to required performance. Clearly, the faster the recovery, the more resilient the system.

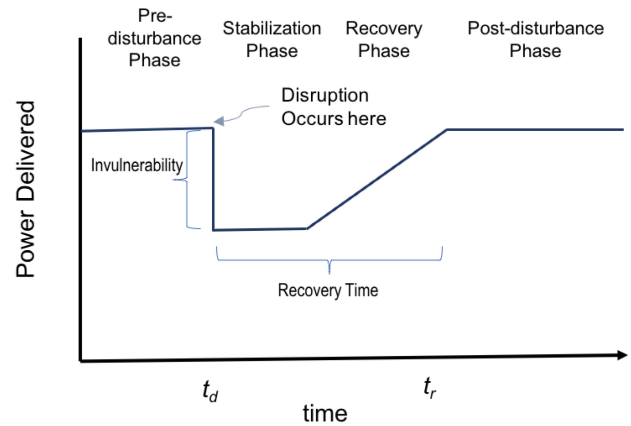

Fig. 1. Resilience curve showing power performance behavior before, during, and recovering from a disruption.

Resilience is also threat dependent [10], [11], and we model it as such. Resilience to hurricanes, tsunamis, and other extreme weather events is different than resilience to intentional attacks on the system such as cyber attacks on the microgrids control system or even destruction of parts of the microgrid infrastructure such as transformers or DGs. For example, transmission lines over poles are more vulnerable to hurricanes (the disruptive event) than transmission lines buried underground. While burying transmission lines will improve resilience with respect to hurricanes, it does nothing against other disruptions such as cyber attacks.

The provision of a system's resilience depends on both design and operational policies. We can design systems in such a way that they are less vulnerable and able to quickly recover. From an architectural perspective, engineers have long used functional redundancy because different distributed energy resources will likely have different vulnerabilities and ability to recover to different disruptions [8]. Similarly, excess capacity or overdesigning the microgrid increases the overall resilience [8]. Likewise, from an operational perspective, policies for maintenance, training, and logistics affect system resilience. Maintaining equipment, having trained personnel, and readily available spares all enhance the microgrid's resilience.

III. Literature Review

Measuring resilience is a first step to assessing and improving the resilience of a system. Multiple survey papers review quantitative measures of resilience from different perspectives such as long-term and short-term aspects of large power grids [12], a design perspective [13], or with respect to certain threats [14]. The measures reviewed mostly are based on the resilience curve (shown in Fig. 1) with many attempting to capture resilience in a single measure. Gholami *et al.* [15] describe the two main resilience measures as the ratio of the area defined by normal operational performance and the actual operational performance, which is the trapezoidal area of Fig. 1. Alternatively, researchers have defined components of resilience. Francis and Bekera [16] as well as Vugrin *et al.* [17] include absorption capacity, which we label invulnerability, as the initial drop in performance. How quickly the system can recover is an important aspect. Renschler *et al.* [18] describe measures for this aspect of resilience. The US Aid program measures recoverability as the difference between nominal and actual system performance. They also measure how much manpower effort goes into recovering the microgrid [19].

Quantitative measures are important to support resilience analysis. However, the resilience measures must be incorporated into a larger model and/or method to support an overall assessment of resilience. Several tools in use by government agencies to assess resilience take the approach of a broad-based assessment using questionnaires without quantitative measures of the resilience. The US DoD uses the Energy Security Assessment Tool (ESAT), a spreadsheet application, in which the user enters data on power loads and infrastructure as well as answering questions about the base's mission and facilities. The Energy Resilience Assessment Methodology helps clients identify risks and vulnerabilities, analyze those risks, and develop a strategy to mitigate and/or avoid the risks [20]. The resilience analysis process for the DOE uses measures of outage magnitude in terms of customer days, recovery costs, and community impact that could be used to generate Pareto frontiers of resiliency improvement costs vs. power outages [17]. Their outage magnitude measure is very similar to System Average Interruption Duration Index and is more a measure of reliability than resilience.

Increasing the resilience of an installation will likely incur a cost above what is needed to provide energy, absent any disruptive events. The decision of whether to make the investment usually depends on a cost–benefit analysis. Lambert *et al.* [21] describe an optimization model to design microgrids to meet power load requirements using net present value to cost the microgrid design. Measuring benefits is the more difficult part of the analysis. Anderson *et al.* [20] use the value of lost load (VoLL) metric defined as the price consumers are willing to pay for uninterrupted power. VoLL varies by customer, time of day, and both the extent and duration of power loss. Shroeder *et al.* [22] compiled data from 21 VoLL studies conducting mainly in Europe and the USA and found VoLL ranged widely from a few dollars per MWh to over $100 per MWh. VoLL is relevant for businesses but less so for military installations because they are not profit-making ventures and instead are concerned with mission accomplishment. For this reason, Peterson proposes a mission index to measure the ability of a base to continue its mission [23].

Closely related studies of resilience of islands and military microgrids include the work of Anderson *et al.* [24] who formulate a mixed integer linear programming to minimize life-cycle costs with meeting the loads one of the constraints. They find that the addition of photovoltaic (PV) to a grid-connected microgrid that only had diesel gensets for backup power can double the duration the loads could be supported when disconnected from the main power grid. They further note that the renewables provide energy throughout their life and, therefore, have economic benefit besides increasing resilience. Other studies have shown the cost of enhancing microgrids with renewable energy sources and storage can often only be justified if resilience is valued [25]. Judson *et al.* [26] evaluate that the resilience of a military base is in the context of a disruption causing loss of the connection to the power grid. The authors visited military bases and observed that most have diesel gensets as backup power to individual buildings and/or loads. Among their recommendations is centralization of DGs to serve multiple loads. Rocky Mountain Institute [27] presents ten case studies of actual island microgrids including their capacity, generation profile, and cost per kWh. They report several findings such as adding renewables improves resilience, islands need energy storage, and efficiency is important. Peterson [23] studies the resilience of microgrid for a military base by analyzing what happens when each component of the microgrid fails.

The literature on microgrid resilience and architecture design highlights several areas worthy of further research, which this article addresses. First, most research on microgrid resilience considers the scenario of a microgrid connected to the larger electrical grid and the disruptions are usually limited to disconnection from the grid. Or, as in Peterson [23], the researchers ask what if a particular microgrid component fails? We have not found any research where the models consider the probability of damage given a disruption, which, as we will show later, helps us analyze and compare microgrid architectures with excess capacity and/or redundancy. Second, the literature has not explicitly considered the tradeoffs involved, nor has the literature examined how to quantify the trades in a format amenable for decisions makers. We view the microgrid resilience through the lens of an architectural design problem, in which a decision maker must trade off resilience with the cost of power provision. This reflects how many military microgrids are designed first in an architecture design phase and then in a detailed design phase. The architectural context allows us to analyze two common resilience design principles of excess capacity and redundancy, which has not received much attention in the literature.

IV. Microgrid Resilience and Cost Model

We want to support the microgrid system's architecture design phase with a model to trade off the cost of energy with the resilience of the microgrid. We model resilience as how well a given microgrid architecture can avoid being affected by disruptions, but if the disruption causes damage, then how quickly can the microgrid recover from the disruptive event. Second, we want to know the cost of the microgrid architecture over the planning horizon. We present the information to the decision maker as a trade space between resilience and cost, which are two of the components of energy security for military bases (the third one being reliability) [2]. To generate the trade space, we use two separate models: 1) a cost model to estimate the cost of a microgrid architecture and 2) a resilience model to estimate the invulnerability and recoverability of the microgrid architecture. The models are stochastic because they include distributions for

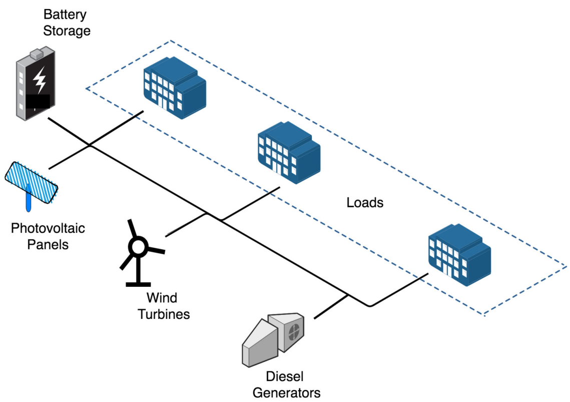

Fig. 2. Notional microgrid architecture.

probability of damage to a resource, given a disturbance and the time to repair a resource. The models deal with the initial microgrid architecture decisions and the microgrid's resilience with respect to delivering power. The model time step is 1 h, and, consequently, the model ignores issues that happen more quickly than 1 h such as frequency and voltage issues important to the control of microgrids (see [28] for a description of these issues). The following sections describe the formulation of the resilience and cost models and how we use them to generate the trade space.

A generic microgrid architecture for an island is shown in Fig. 2. The microgrid consists of three types of power sources: DGs, wind turbines (WTs), and PV panels. A particular island microgrid may have zero, one, or more of each of the power source types. The microgrid has a battery for energy storage. All the power sources and loads are connected to a power distribution bus. An important component of a microgrid is a controller; however, we do not model or analyze any control issues because it is out of scope for the architecture decisions we analyze. Also not shown are all the inverters from dc to ac power and other power network elements necessary for a microgrid. We assume that the microgrid has these components as well as suitable controllers. For the microgrid architecture shown, the architectural decisions we focus on are: How many of each generation source to have? and How much power generation capacity for each source?

A. Resilience Model

We measure two aspects of resilience: 1) invulnerability (I) describing the ability of the microgrid system to resist power loss immediately following a disturbance and 2) recoverability (R) describing the ability of the microgrid system to repair generation resources and meet the full demand.

We measure invulnerability in a manner similar to [16] and [17] as the drop in power generated immediately after the disruption, which is given by the ratio of power generated to load demand

$$I = \frac{P_t}{D_t}. \tag{1}$$

The term P_t denotes the power delivered at time t, and not the total rated power available. This is an important distinction for the island microgrids we are investigating because they all have excess power generation capacity. For example, we analyzed one island naval installation with five times more generation capacity than needed. The installation could lose two of its five generators and still be able to meet the demand. Rather than using the total rated power available and allowing $I > 1$, we use the actual power delivered. Consequently, $P_t <= D_t$ and $I \in [0, 1]$.

We define recoverability, referring to Fig. 1, as the ratio of the area bounded by the demand and the postdisturbance power generated between the time of the disturbance and full recovery [19]. The area represents what proportion of demand goes unmet and for how long

$$R = 1 - \frac{\sum_{t=t_d}^{t_r} D_t - P_t}{\sum_{t=t_d}^{t_r} D_t}. \tag{2}$$

We only determine recovery when P_t decreases less than D_t. The recoverability measure $R \in [0, 1]$ with 0 representing a microgrid that never recovers and 1 representing a microgrid in which power generation never decreases less than the demand.

The two dimensions of invulnerability and recoverability for resilience can be combined to obtain an overall metric with $\omega \in [0, 1]$ to weigh one dimension more than the other

$$\xi = \omega I + (1 - \omega)R. \tag{3}$$

In the face of a disturbance scenario S_k, such as a hurricane or cyber attack, power is lost when one or more resources are damaged. Let the conditional probability $P(d_i|S_k)$ denote the probability of damage to a resource i due to disruptive event S_k. The conditional probability of damage allows us to capture differences in the vulnerability of various power generation resources to each disturbance type because, for instance, WTs will exhibit differences in damaged experienced from PV panels. Hence, we model resilience to specific types of threats because, as previously said, resilience is threat dependent [11].

Each resource has an associated control authority, which is a binary variable with values defined as

$$\mu_{it}^{\alpha} = \begin{cases} 1, & \text{iff power source } i \text{ of type } \alpha \text{ in time } t \text{ is on} \\ 0, & \text{otherwise} \end{cases}$$

where the type α can be DG, PV cells, WT, or battery (BAT).

The model assumes that a resource is either damaged or not damaged. To model partial damage, at the expense of extra computations, we can take a single resource such as PV and partition it into multiple resources, each with their own conditional probabilities and control authority variables.

1) Power Balance: The power balance constraint, given by (4), ensures for each time period t the power generated equals the loads and any necessary load shedding. The summation adds up all the power sources (diesel, solar, and wind) multiplied by their control authority μ_{it}^{α} to determine if they are operational during the time period. The power generated by solar and wind is intermittent and dependent on the solar irradiance and wind speed, which is governed by the model data inputs. The diesel gensets have the additional variable of the loading denoted by L_{it}. The battery is either discharging or charging; consequently, only one of P_t^C or P_t^D is nonzero. The variable LS_t denotes any necessary load shedding, and P_t^{load} denotes the total loads

$$\sum_{i=1}^{N}(\mu_{it}^{\text{DG}} L_{it} P_i^{\text{DG}} + \mu_{it}^{\text{PV}} P_{it}^{\text{PV}} + \mu_{it}^{\text{WT}} P_{it}^{\text{WT}}) - \eta_c P_t^C + P_t^D/\eta_d + LS_t = P_t^{\text{load}}\ \forall t = 1,\ldots,T. \quad (4)$$

The DGs provide dispatchable power and must operate within their minimum and maximum loading limits, typically between 0.3 and 0.9. The minimum loading for the DG prevents premature aging and failure due to wet stacking [29]

$$L_i^{\min} \le L_{it} \le L_i^{\max}. \quad (5)$$

The fuel consumed by the DGs must be less than the fuel available. Diesel fuel consumption is a function of the loading factor and the maximum fuel consumption rate f_i measured as gallons per hour

$$\sum_{t=1}^{T}\sum_{i=1}^{N}(\mu_{it}^{\text{DG}} L_{it} f_i) \le F. \quad (6)$$

2) Energy Storage: A microgrid with renewable energy sources typically incorporates energy storage, usually a battery, for multiple reasons such as frequency and voltage regulation. However, here, we are only concerned with the storage capacity to sustain loads for a desired time duration when the renewable energy sources are unavailable. In determining the appropriate size of backup storage for a particular application, one generally selects the energy rating on the basis of the period of time one expects to have to support the load in the event of a failure of the primary supply [30]. A straightforward physics-based approach to sizing the battery is found in [31].

The battery has three states of charging, discharging, or neither. We assume that the battery is fully charged at the start of a disruption. The energy in the battery at time *t* is the energy in the previous time period plus any energy charged or discharged into the battery during the time interval Δ_t (taken as 1 h) and is given by

$$E_t^{\text{BAT}} = E_{t-1}^{\text{BAT}} + \Delta_t \eta_c P_t^C - \Delta_t P_t^D/\eta_d \quad (7)$$

where η_c and η_d denote the charging and discharging efficiencies, respectively, and P_t^C and P_t^D denote the charging and discharging power, respectively.

The battery is constrained by its rated energy capacity and maximum charge and discharge rates

$$E_{\min}^{\text{BAT}} \le E_t^{\text{BAT}} \le E_{\max}^{\text{BAT}} \quad (8)$$

$$P_t^C \le P^{C\max} \quad (9)$$

$$P_t^D \le P^{D\max}. \quad (10)$$

3) Maintenance: The model mostly considers how microgrid design decisions affect resilience. However, resilience is achieved not only through design but also by operational policies concerning the microgrid. Studies have shown that preventive and routine maintenance can mitigate against damage as well as contribute to quicker repair of realized damages. Moreover, the availability of spares can greatly increase the ability to quickly repair and restore power. Consequently, more and better maintenance, training, logistics, and inventory policies improves both invulnerability and recoverability.

The time to repair resource i is given by a lognormal distribution with mean t_i^{repair} and standard deviation σ_i [32]. The model considers three operational policies for maintenance of none, medium, and full level of preventative maintenance. The full level is when the base follows the manufacturer's suggested maintenance schedule, has trained maintenance staff, and available spares. The mean time to repair (MTTR) for no and medium maintenance levels is 1.5 and 2.5 times greater than the MTTR when the installation follows the full maintenance policy.

When a resource is damaged, the model calculates the time to repair and sets the corresponding control authority for that resource (i.e., μ_i^α) to 0 for the duration of the time to repair. Upon reaching the time to repair, the resource is repaired and the control authority is set to 1, making its power generation available to the microgrid.

B. Cost Model

The LCOE is a common means to determine the price of energy in order to recover all the costs of installing and operating the energy system [33].[1] The LCOE calculates the net present value of all the costs and divides it by the energy generated to provide the unit cost per kWh. The LCOE assumes that all the energy generated can be used and/or sold back to the power grid. Islands do not have a larger power grid to sell power to, and any excess energy beyond their storage capacity goes unused. Consequently, the LCOE would underestimate the actual cost of energy used.

To address this issue, we revise the LCOE to account only for actual energy usage called the levelized cost of energy demanded (LCOED).

The net present value of the costs of energy production are given by

$$\text{NPV}_{\text{costs}} = \frac{\sum_{t=1}^{T}\sum_{i=1}^{N}(I_t + M_t + F_t - H_i^T)}{(1+r)^t}.$$

The numerator captures all the costs of investment (I_t), maintenance (M_t), and fuel (F_t) minus the residual remaining value (H_i^T) of any equipment i with useful life past the planning horizon T, in which the planning horizon is set equal to the expected life of the Distributed Energy Resource (DER) component with the shortest expected economic life. The total costs are discounted by the discount rate r. The fuel cost for the DGs in time t is

$$F_t = \sum_{i \in I}(c_g f_i L_{it} \mu_{it}^{\text{DG}})\ \forall t \in T \quad (11)$$

where c_g denotes the price of diesel in \$/gal.

The maintenance cost depends on the level of maintenance the base commander determines for the equipment. Maintenance

[1]The LCOE is usually applied to a single energy source for the purposes of comparing it against other alternatives.

cost is a function of the power rating of the equipment. Consequently, the model assumes that the maintenance cost is the same for two 500-kW rated diesel gensets as for one 1000-kW genset.

The net present value of the energy actually used by the microgrid is

$$\text{NPV}_{\text{energy}} = \frac{\sum_{t=1}^{T} D_t}{(1+r)^t}.$$

The LCOED is calculated as the costs per unit energy

$$\text{LCOED} = \frac{\text{NPV}_{\text{costs}}}{\text{NPV}_{\text{energy}}}. \quad (12)$$

The denominator calculates the total energy consumed over the planning horizon. Both the costs and energy used are discounted by the marginal rate of return r. The LCOED provides cost per unit energy ($/kWh), which we use to compare microgrid architectures in much the same way that LCOE is used to compare individual energy generation sources.

V. Resilience Assessment Method

We solve the models using a scenario-based approach in which each scenario is a disruptive event with the potential to cause damage to the microgrid. Many of the threats a military installation wants to protect against are rare and, in some cases, have not ever occurred but can be imagined. Such events are called high-impact, low-probability (HILP) events. The likelihoods and impacts of HILP events remain difficult to predict [34]. Our approach is to say, "what if low-probability event k occurs?" Our reason is that we are not so much concerned with trying to estimate the occurrence of the event but rather understanding the resilience of the microgrid in case the event occurs.

We apply the following steps:

1) Collect input data. The model requires input of a power demand profile, solar irradiance, and wind speed—all by hour of the day. The data for the solar and wind is converted into power generation by those DER sources. For some island installations, historical data of solar and wind generation is available and was used directly.
2) Identify and characterize threats. The threats include natural events such as extreme weather as well as disruptions caused by adversaries such as a cyber attack. For each threat scenario k, the probabilities of damage $P(d_i|S_k)$ must be estimated by either historical data or subject matter expert (SME) estimation. Quantification of expert judgment is common in risk analysis, especially in defense contexts [35],[36] and can be performed using the method of [37].
3) Generate microgrid architecture alternatives. A microgrid architecture specifies the number, type, and rating of each generative resources. By varying each factor, we can generate a trade space.
4) Evaluate the resilience and cost of each architecture alternative for each threat scenario.

TABLE I
Scenario Probability of Damage $P(d_i|S_k)$

Scenario	DG	PV	WT	BAT
Hurricane	0.3	0.7	0.5	0.2
Fire	0.2	0.4	0.9	0.5
Earthquake	0.2	0.3	0.5	0.1
Cyberattack	0.3	0.3	0.3	0.3

TABLE II
Cost Data for All Experiments

DER	life (yrs)	Invest $/kW	Maintenance
WT	20	1,650	38 $/kW
PV	25	3,100	18 $/kW
DG	30	620	15.5 $/kW
BAT	10	4,200	1500 $/year

   1) The resilience model determines the invulnerability and recoverability of each design. The time step t is set to 1 h. We use the Monte Carlo method and determined 7500 simulations provided a 90% confidence interval for the results [38]. The mean results are combined across all scenarios.
   2) The cost model determines the LCOED for each architecture alternative.

5) Generate graphs depicting the trade space between cost and resilience for the architectures.

VI. Experiments

This section presents experiments conducted on the model using the assessment method. All experiments use the data in Table I derived from multiple sources [39]–[43].

In all the experiments, the weighing factor ω between invulnerability and recoverability is 0.5. The decision maker can, through adjustment of the weighing factor, evaluate only invulnerability ($\omega = 1$) or only recoverability ($\omega = 0$). The planning horizon is 10 years with a discount rate of 7.5%, and fuel is $2.60 per gallon. Table II shows the cost data for each DER [44], [45]. The residual value is estimated as $I_i(n-T)/n$. Battery storage is priced per kWh at $270/kWh and operational and maintenance costs annually of $1500 and batteries have an economic life of 10 years. More thorough discussion of the data can be found in [46].

A. Sensitivity Analysis

Some of the inputs depend on SME judgement and/or quantities difficult to measure precisely. For this reason, we conducted extensive sensitivity analysis of the output on variations in the input variables. A full sensitivity analysis can be found in Anderson [46]. Here we highlight those inputs to which the model output is highly sensitive.

Fig. 3 shows how changes of +/– 50% to the input variables affects the LCOED. The LCOED is most sensitive to changes in the DG's fuel consumption rate and fuel cost. Fortunately, these are two variables that are well known in the case studies we did.

Figs. 4 and 5 both show how changes of +/– 50% to the input variables affect invulnerability and recoverability. Recovery is

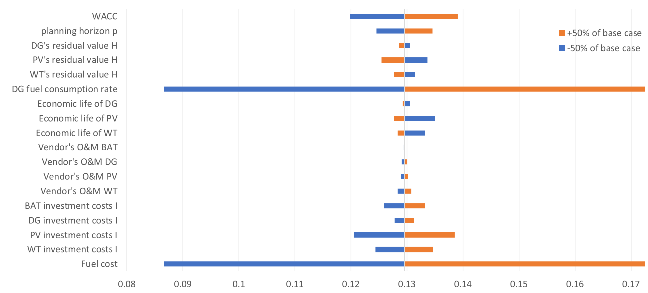

Fig. 3. Sensitivity of LCOED to input variables.

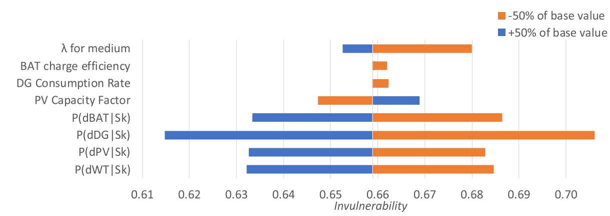

Fig. 4. Sensitivity of invulnerability to input variables.

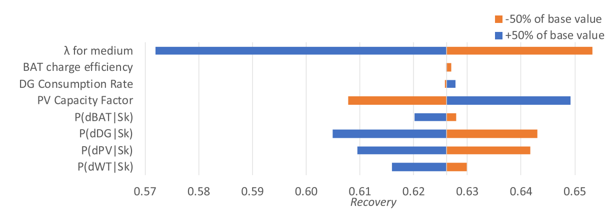

Fig. 5. Sensitivity of recoverability to input variables.

very dependent on the MTTR given by λ. Invulnerability is sensitive to the SME estimates of the probability of damage; however, even being off by 50% on the input, the output measure is not off by more than 10%.

B. Excess Capacity

The first set of experiments we conduct investigate the resilience and cost of having excess capacity. A microgrid with a power generation rating much greater than the power demand it serves, and especially when the microgrid uses a diverse and redundant set of power generative sources, will have greater resilience than a microgrid in which its power rating is more or less equal to demand. The reason is that in the face of a disturbance, extra power is an obvious buffer to partial losses of power generation. Of course, having excess power will lead to higher costs. The decision is to determine the best tradeoff between increased resilience for increased costs.

Fig. 6 shows the resilience and LCOED versus the ratio of the microgrid's total power generation rating to the peak demand experienced during the year. The power ratio varies from a value of 1.25 to a value of 5. Fig. 6 shows how resilience initially improves quickly and then tapers off as excess capacity increases. Meanwhile, cost increases linearly as excess capacity increases.

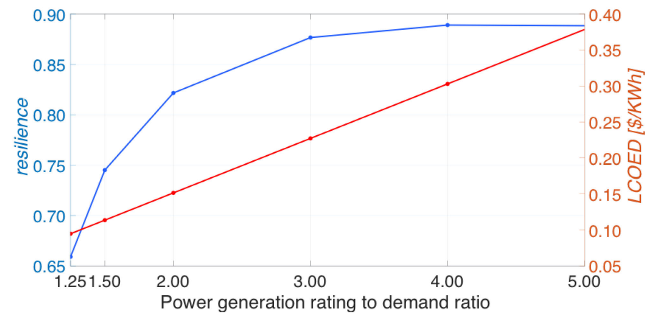

Fig. 6. Effect of excess capacity on resilience and cost.

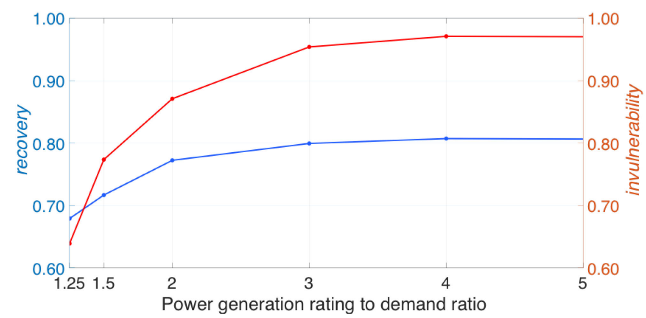

Fig. 7. Effect of excess capacity on invulnerability and recoverability.

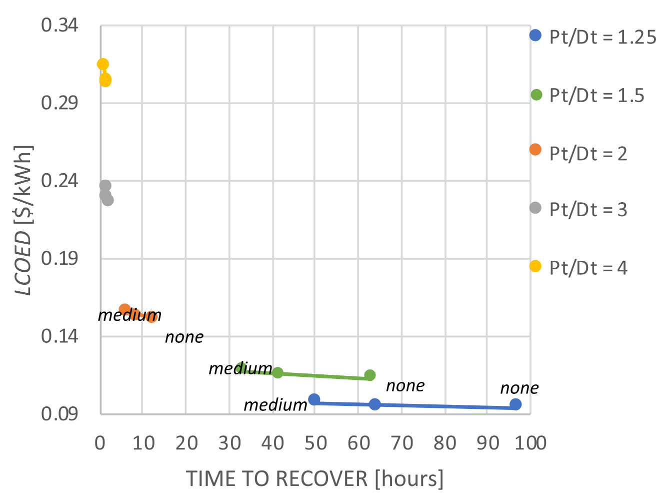

Fig. 8. Maintenance and excess capacity effects on recovery.

We show how each component of resilience responds in Fig. 7. Both invulnerability and recoverability increase with excess capacity, but invulnerability increases more rapidly and to a higher level than recoverability because recoverability also depends on the maintenance level. Fig. 8 shows how better maintenance influences the time to recover when there is little excess capacity, but as the microgrid has more excess capacity, the maintenance level becomes irrelevant.

C. Redundancy

We define redundancy as having multiple smaller power generation sources instead of a single large power generation source.

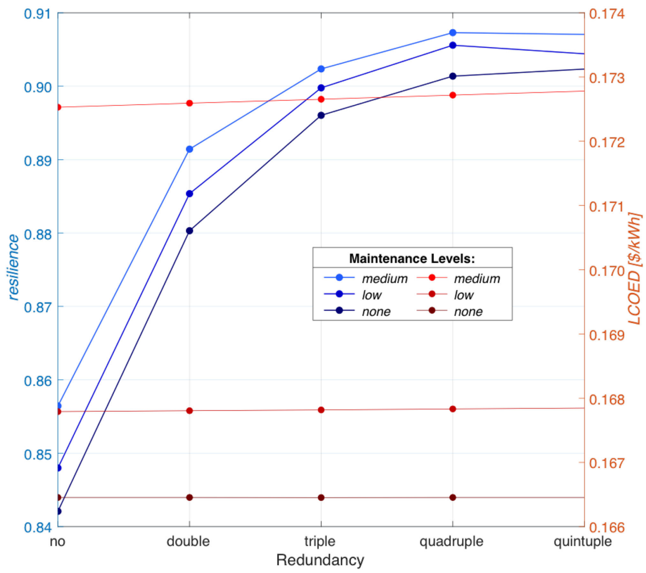

Fig. 9. Effect of redundancy on resilience and cost.

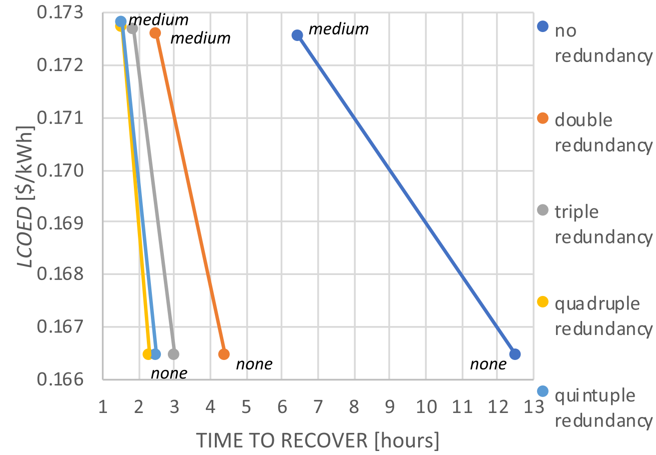

Fig. 10. Redundancy effects on time to recover.

The term "no" means there is no redundancy or only a single source is present, while the terms double, triple, quadruple, and quintuple mean there are 2, 3, 4, and 5 sources, respectively. In the redundancy experiments, if a single diesel genset is rated at 2000 kW, then double redundancy has two diesel gensets rated at 1000 kW each, triple has three rated at 666 kW each, and so forth. Therefore, the microgrid's total power generation capacity remains unchanged in the experiments, with only how the power generation capacity is divided among sources. In the experiment, the total power generation rating was 4 mW and the maximum load was less than 4 mW.

Having redundant power generation sources distributed throughout the microgrid improves the resilience of the microgrid for the same overall cost of delivery. Fig. 9 shows modest but measurable improvements in resilience as redundancy increases from no redundancy to double with decreasing returns on redundancy. At the same time, LCOED remains constant.

Fig. 10 shows the time to recover for different redundancy levels and either full or no maintenance. There is little difference on the LCOED because the maintenance cost is small compared to the investment and operating costs. Maintenance has a larger effect when there is no redundancy as shown by the difference between the no-maintenance and full-maintenance recovery times for a single resource. Once there is some redundancy, the effect of maintenance levels decreases rapidly such that there is no difference in time to recover between quadruple and quintuple redundancy.

VII. Case Study

The purpose of the model is to serve as a decision support for base commanders to explore the trade space of investment decisions concerning microgrids and the impact on resilience and costs. This section presents an examination of a Naval base, which currently has a single, large diesel genset rated at 1.25 mW as backup power to a critical facility with an average load of 200 kW. The diesel genset is extremely oversized for the expected load and, consequently, operates well below its power rating causing extreme inefficiencies due to wet stacking (i.e., inability to burn all the fuel supplied).

TABLE III
Comparison of Three Architectures for the Islanded Naval Installation Case Study

Architecture	Maintenance Level	LCOED ($kWh)	Resilience
Base Case (single diesel genset)	High	1.24	0.70
Redundant Case (five diesel gensets)	None	1.23	0.91
Optimized Case (five diesel, PV and ESS)	None	0.36	0.91

SMEs were employed to estimate the probability of damage, given various scenarios including a tsunami among others. The demand profile varies between 150 and 250 kW. Using Xendee to design the microgrid, we developed a design with five 64-kW diesel gensets (total 320 kW), five PV arrays (total 196 kW), and five batteries with 383-kW power and capable of 760 kWh of storage [47]. The architecture was guided by the desire for greater usage of renewable energy sources as well as efficiency. In the Xendee model, we interpret efficiency as the objective to minimize the costs.

Table III shows the results for the current architecture, which is the base case and two alternatives. The first alternative is simply replacing the single diesel genset with five smaller gensets with equal total power rating, and the second alternative is the Xendee generated architecture described above. The results show that the redundancy as well as excess capacity of the redundant case provides significantly improved resilience for similar cost. The Xendee optimized alternative shows that the diversity of multiple sources of diesel, PV, and battery provides the same expected resilience but at a much lower cost because less excess capacity is required.

1) Other Island Bases: We investigated the power resilience and cost of three other island bases shown in Table IV with their

TABLE IV
THREE ISLAND BASES

Island	Average Demand (kW)	Peak Demand (kW)	Power Sources	LCOED ($kWh)
REG	1.5MW	2MW	3 225kW WT; 500kW, 500kW, 750kW, and 1200kW DG; total of 3.4MW	0.55
DVB	1MW	1.5MW	5 140kW WT; 825kW, 1MW, 1.1MW, 1.1MW, and 1.25MW DG; total of 5.98MW	1.85
CFI	14MW	19MW	4 950kW WT; 5 6.6 MW DG; total of 36.8MW	0.45

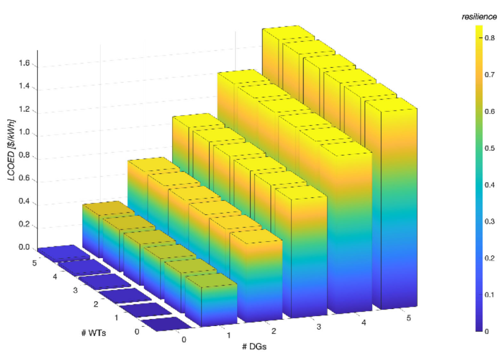

Fig. 11. Trade space between resilience and LCOED for island DVB.

mean demand, peak demand, and power sources and ratings. All three island bases enjoy excess capacity with, for example, DVB having four times as much generation capacity as the peak load.

The LCOED for these islands is very high, especially compared to worldwide average LCOE of $0.05 per kWh for natural gas and $0.1–$0.2 per kWh for wind [48]. Several explanations for the high cost include having far greater capacity than required, meaning on DVB, for example, most of the diesel gensets sit idle, representing large capital expenditures; yet, they mostly go without generating any power. Additionally, islands face higher costs of maintenance, fuel, and installation of the distributed energy resources. Given the high costs, the base commanders can benefit from tools to help them evaluate the costs and benefits of microgrid architectures.

Fig. 11 shows the trade space for DVB for combinations of WTs and diesel gensets. The WTs are all rated at 225 kW each, and the diesel gensets are all rated at 1 mW each. The graph shows that DVB could obtain similar resilience for a much lower overall LCOED by having only two diesel gensets. Additionally, the graph shows that the addition of WTs has minimal improvement on resilience.

Additional information on the case studies is available in [46].

A. Discussion

Resilience is a complex, multidimensional measure of a system's ability to adapt to changing environments and disruptions of which we only consider the two components of vulnerability and recoverability. The experiments provide useful information to a decision maker in determining how much they would want to pay for greater resilience. Provision of excess capacity led to a significant increase in resilience with diminishing returns as more and more excess capacity was added. In the experiment conducted, Fig. 6 showed that at a power-to-demand ratio of 1.25, resilience is 0.68, and at a power-to-demand ratio of 2.0, the resilience is 0.83 with a corresponding increase in LCOED of $0.12–$0.15 per kWh. Such information is very valuable in evaluating microgrid architectures and how much excess capacity to have.

The functional redundancy also improved resilience but to a lesser extent. Having no redundancy gives a resilience of between 0.84 and 0.86 depending on maintenance policies, and having double redundancy improves the resilience to between 0.88 and 0.89. Incorporating some redundancy into a microgrid's architecture does not really cost anything; consequently, such improvements are probably worthwhile in most cases.

The experiments varied the maintenance policies, and, in general, we found that maintenance is most important at low power-to-demand ratios when there is little excess power generation. The affect of no or little maintenance can be significant to the time to recover. The results are reasonable because if a base experiences damage to components and has to wait for spare parts, technical support, etc., then it will take longer to return the microgrid to full operation.

The purpose of the model is to support the early architectural decisions in microgrid design, and the article presents the case studies to illustrate how the model could be used. For the island cases, we show how the model can generate the tradespace and provide information for decisions makers to determine the mix and number of distributed energy resources to have.

The model assumes independence in the probability of damage to resources, but in the face of common cause failure events, this would greatly underestimate the extent of damage. We do not consider common cause failures. Additionally, the model does not address all aspects of resilience. The concept of resilience depends on the time frame under consideration. Our analysis did not investigate the adaptability and/or ability of the microgrid system to evolve to changing conditions over a longer time frame.

VIII. Conclusion

This article describes two models and an associated method for military decision makers to generate the tradespace between resilience and cost for microgrids supporting island naval bases. The first model represents the resilience of the microgrid across two dimensions of invulnerability and recoverability. The model, intended for the early microgrid architecture design, represents the power balance of the microgrid including the distributed energy resources, battery storage, and load. The second model determines the LCOE adapted to island naval bases such that the cost is only spread across the energy actually provided rather than the total capacity available. A resilience assessment method describes how to collect data and apply the two models to generate trade spaces for the decision maker to trade improvements in vulnerability and recoverability with costs.

This article makes several contributions to the literature on microgrid resilience. First, the article adapts resilience and cost metrics to the characteristics particular of island naval bases. Second, the article shows how to use the two models to generate a trade space between resilience and the cost of providing that resilience. Third, the models consider how maintenance policies affect the recoverability of the microgrid. In this way, the models include both design and operational considerations and their effect on resilience and cost. Lastly, the inclusion of the conditional probability of damage, given a disruption, allows us to examine through experimentation two common architecture heuristics of installing excess power generation capacity and of redundancy in the distributed energy resources.

An important finding is that redundancy can improve resilience at little to no cost under the assumption that costs are proportional to kW. Adding excess capacity beyond the expected total load initially leads to large increases in resilience and then experiences diminishing improvements. The cost of power generation is mostly linear, and it is for the decision makers to determine how much resilience they want depending on the costs.

The maintenance and logistical aspects such as availability of spares, trained maintainers, and so forth are important contributors to resilience. While our model made some simplifying assumptions about the logistics, the model indicated that maintenance is important to recoverability, especially when the generative capacity is only slightly more than the load. Future work should examine in greater detail the effects of logistics and maintenance on resilience.

The intent of the model is to support base commanders in determining the microgrid architecture and operational policies for the microgrid. The article demonstrated through several case studies of Navy installations on islands how the model would support the decision maker through visualization of the trade space.

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