GOING OFF THE GRID: OPTIMIZING SOLAR RENEWABLE ENERGY SYSTEMS TO MINIMIZE LOGISTICS REQUIREMENTS OF REMOTE AND ISOLATED LOCATIONS

THESIS

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AFIT-ENV-MS-20-M-247

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

AFIT-ENV-MS-20-M-247

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THESIS

Presented to the Faculty

Department of Systems Engineering and Management

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Master of Science in Engineering Management

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March 2020

AFIT-ENV-MS-20-M-247

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AFIT-ENV-MS-20-M-247

Abstract

Established electrical power infrastructure is unavailable for over 1.2 billion people worldwide at remote locations including developing nation communities, humanitarian relief camps, isolated construction sites, and military contingency bases. Powering these locations with conventional diesel generators requires ongoing fuel resupply, resulting in increased costs, negative environmental impacts, and a burdensome and exposed logistical tail. For example, at the height of the Iraq and Afghan Wars, the U.S. military delivered more than two million gallons of fuel per day to contingency bases at a fully burdened cost of $15 to $42 per gallon depending on scenario, time, and location. These deliveries are not only costly but dangerous, as research has shown there was approximately one casualty for every 24 fuel convoys in Afghanistan. These issues present generators as an obstacle for military objectives of energy resiliency and sustainability. To meet future threats identified in the 2018 National Defense Strategy of near-peer adversaries, there is a pressing need to design contingency bases that reduce reliance on external resupply of fuel. Accordingly, United States Department of Defense policies and the Air Force's *Energy Flight Plan* encourage using renewable energy when cost-effective or to increase resiliency, in order to enable long-term energy assurance.

In pursuit of this goal, this research examines the use of solar renewable energy systems to replace prime-power generators at remote and isolated locations. Despite their significant contributions, previous research studies have failed to demonstrate

optimization based on logistics concerns, including system weight and volume, and to design practical solar and energy storage systems for prime power at contingency bases. Accordingly, the research objectives of this study are to: (1) produce an innovative renewable energy system optimization model capable of efficiently determining optimum solar array and energy storage sizes based on techno-economic criteria in order to demonstrate the viability of renewable systems at remote locations; (2) develop a novel logistics-based multi-objective optimization model for solar renewable energy systems to minimize logistics variables including system weight, volume, and land area; (3) utilize this logistics criteria to select solar array (photovoltaic) modules based on weight, volume, and area power densities; and (4) determine a multi-objective optimization method for the design and planning of renewable and hybrid renewable energy systems that provides the capability of simultaneously minimizing the logistics requirements and the lifecycle costs of powering remote sites.

The performance of the developed optimization models was analyzed using case studies of hypothetical remote locations. Analyzing these case studies illustrates the novel and distinctive capabilities of the developed models in enabling designers to select optimal renewable energy design configurations based on the logistics requirements and characteristics of the remote site. These capabilities can be used in the development of renewable energy systems that create energy self-sufficient and cost-effective sites and reduce the negative impacts of traditional diesel fuel logistics. The implementation of a renewable energy system to replace a single contingency base generator would result in a savings of over 500,000 gallons of fuel annually and eliminate the need for 100 fuel tanker deliveries.

Acknowledgments

I would like to express my sincere appreciation to my faculty research advisor, Lt Col (s) Steve Schuldt, for his direction and support throughout the course of this thesis effort. I really value his introduction into the world of academia and what it means to be both a student and a researcher. I think I would still be refining my thesis topic on something about physics and EMPs if it were not for his guidance. In addition, my entire thesis committee has been invaluable to this effort and I want to thank each of them for their technical assistance, meticulous editing, and wise research guidance.

I would also like to thank my sponsor, Reza Salavani, and others from the Air Force Civil Engineer Center (Tyndall Air Force Base) for both the funding and support provided to me in this endeavor. Individuals include Dr. Heather Luckarift, Rich Peck, Mike Farrington, Tom Kensky, Mike Ginger and many others. I am also sincerely thankful to the Air National Guard Civil Engineering Technical Service Center in Minot, ND (and NGB/A4OC) for their generous contributions to this research and others in the Engineering Management (GEM) program.

To my classmates in the 20M GEM class: you have been sincere friends and I learned so much from each of you. Thank you and hope to see you around the world.

Finally, I want to thank my family who have always encouraged me to be a better student and truly blessed me during this process. Thanks to my sister for the amazing illustration. To my girlfriend, sorry this effort took so much time away from you. Thanks for encouraging (and dealing with) me during the long thesis days.

Nathan J. Thomsen

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GOING OFF THE GRID: OPTIMIZING SOLAR RENEWABLE ENERGY SYSTEMS TO MINIMIZE LOGISTICS REQUIREMENTS OF REMOTE AND ISOLATED LOCATIONS

I. Introduction

Background

At remote and isolated locations around the world, including communities in developing nations, humanitarian disaster relief camps, isolated construction sites, and military contingency bases, access to electric power grids is frequently unavailable or unreliable. To provide power at these isolated locations, over 10,000 MW of off-grid diesel generators are presently installed worldwide [1]. Locations that operate using generators face numerous challenges, including the constant need for fuel resupply, local air and noise pollution, and required regular maintenance to keep these generators running. The negative aspects of diesel power generation make these remote locations ideal candidates for the use of renewable energy. While small-scale examples of renewable power exist, renewable energy has yet to enter substantial service for prime power applications at remote locations with capacities greater than 100 kW [1].

The Department of Defense (DoD) currently uses diesel generators to power nearly all deployed Forward Operating Bases (FOBs). The fuel expense for diesel generation is a significant issue because the cost is much higher than traditional domestic grid power generated from fossil fuels, nuclear plants, and renewables. A conservative estimate puts generator power at \$0.17/kWh vs. \$0.10/kWh grid production, based on a fuel price of only \$1.70/gal [2]. This estimate does not take into account the much higher and more comprehensive fully burdened cost of fuel (FBCF). DoD estimates on the

FBCF start at a minimum of $15/gal up to $42/gal (in 2008 dollars), according to the Government Accountability Office [3].

Furthermore, the logistics chain required to supply fuel to these FOBs is a significant issue of concern. Massive quantities of fuel must be transported via air, sea, or land—except in rare cases where pipelines are available. At the height of the Iraq and Afghan Wars, the U.S. military delivered more than two million gallons of fuel per day to contingency bases [3]. For FOBs not collocated with a port, land convoys are the only viable option since the airlift of fuel is extremely expensive. These fuel convoys are very dangerous, requiring troops or contractors to travel potentially hundreds of miles through uncontrolled territory that is vulnerable to attack. One study from the Army Environmental Policy Institute showed that there is "one casualty for every 24 fuel resupply convoys in Afghanistan [4]." In addition to attack, these convoys are also vulnerable to embargos, border closures, corruption, local supply issues, and bridge and road collapses. Because of this, FOB energy resiliency is low. Recent examples of outposts in Afghanistan that required fuel be airlifted in prove that this is a serious concern [5]. With the rising threat identified in the 2018 National Defense Strategy of near-peer adversaries, contingency bases in the future need to be more self-sustaining, agile, and easy to maintain, and all while requiring reduced logistical support without restricting operations or capabilities [6].

These issues present generators as an obstacle for DoD ambitions toward energy resiliency and sustainability. According to the DoD Strategic Sustainability Performance Plan for 2016, the military seeks to assure the continued availability of energy through the reduction of fossil fuel use [7]. Similarly, the U.S. Air Force's energy goals to

"Improve Resiliency, Optimize Demand, and Assure Supply," as stated by the Air Force's *Energy Flight Plan 2017-2036,* are supported by activities promoting, developing, and utilizing clean energy technologies as part of the Air Force's energy supply [8]. DoD Instruction 4170.11 on installation energy supports these goals with the policy that the DoD will utilize renewable energy when shown to be cost-effective or to enhance energy resiliency [9]. According to Executive Order 13693, resiliency can be defined "as the ability to anticipate, prepare for, and adapt to changing conditions and withstand, respond to, and recover rapidly from energy disruptions" [8]. Despite these goals, diesel generators are still utilized by the DoD nearly exclusively at FOBs and other remote and isolated locations.

The recent rapid improvement of renewable energy technologies is expanding the potential power options for isolated sites. Engineers can design renewable energy systems (RES) that utilize solar, wind, energy storage, and other alternative power sources to provide electricity. Solar cell arrays, also called photovoltaics (PV), produce electrical power from sunlight, which is abundant, free, and available during daylight hours over nearly the entire globe. The distinct advantage of PV arrays over generators is that they produce power nearly 365 days per year with no fuel resupply requirements, no noise, no air pollution, and minimal maintenance over their lifespan. These advantages make them viable candidates to replace generators at remote locations such as FOBs and improve DoD energy resiliency and sustainability. However, solar arrays only produce power during daylight hours and are dependent upon the weather conditions. Therefore, energy storage solutions such as batteries are required to supply electricity at night and are a necessary part of any RES involving PV that seeks to replace generators. While other renewable energy power sources are available, Air Force Research Laboratory (AFRL) technology analysis has shown that PV may be the best candidate for alternative energy power generation in the deployed environment versus wind [10]. These reasons include PV's availability, reliability and relative portability and adaptability versus wind or other alternatives [10], [11]. In the civilian sector, PV is also the fastest-growing and most-promising renewable technology for generator replacement at remote locations [12].

Several previous research studies have examined: (1) Hybrid and PV systems for remote locations; (2) DoD use of renewable energy at FOBs; and (3) potential DoD prototypes of renewable systems. In the first category, previous work considered optimizations between PV and generators in similarly austere civilian environments. This includes hybrid power systems utilizing: wind and solar [13], diesel generator and PV [14], and PV as the sole power source [15]. Because FOBs require mobile, rapidly deployable power systems, logistics factors such as weight and volume are vital for any replacement systems; however, studies that consider these factors are rare, and only a single example was discovered [16].

DoD-focused research has examined the economics and optimization of PV arrays for use by the DoD. Schill (2015) investigated the advantages and difficulties of nearly every possible energy source for military installations [2]. Wagner et al. (2018) published important results of the time-phased nature of PV arrays and the optimal configuration of a RES to replace entire FOB power grids both with and without batteries [17]. On a smaller scale (5 kW), one study determined a 36% savings of fuel cost by use of battery-generator hybridization, running generators only at their peak efficiency [18]. At the scope of a full FOB, McCaskey (2010) examined supplementing existing MEP-12 generators with wind, solar, and battery storage at a notional Afghanistan FOB but focused on optimizing the addition of renewables to existing generators, instead of examining complete stand-alone replacements [19].

Other studies are beginning to evaluate the physical engineering requirements necessary to produce DoD-oriented renewable sources. The National Renewable Energy Laboratory (NREL) and the AFRL designed and built a prototype for a mobile inverter and battery platform capable of converting renewable energy from solar or wind and supplying standard alternating current (AC) power at deployed bases [20]. AFRL's design supplies 30 kW of power—too small for prime-power generator replacement, but still an advancement toward DoD hybrid energy use. These efforts have laid the groundwork for the potential future use of renewable energy at remote locations and military contingency bases but have not yet made sustainable FOB power a reality.

Problem Statement

Despite the significant contributions of the aforementioned research, these studies failed to demonstrate: 1) a practical PV and energy storage system that can replace prime-power generators used by the DoD at contingency bases; 2) optimization based on logistics concerns, including system weight and volume, which are crucial to the implementation, transport, and operation of RES at contingency bases and other remote and isolated locations; 3) analysis of PV modules to determine the best candidates for the remote sites based on logistics variables, including power density and efficiency; and 4) demonstration of an optimization model that decision-makers can utilize to select and design a RES based on the specific logistics requirements of various remote locations.

Accordingly, this research will utilize existing literature and computer simulation to design and optimize potential replacements for these large generators, develop a multi-criteria optimization method to balance logistics factors along with conventional techno-economic parameters, and discuss the potential resiliency benefits that arise out of self-sufficient, sustainable remote sites. This research is sponsored by the Air Force Civil Engineer Center's (AFCEC) Expeditionary Directorate located at Tyndall AFB, FL, and the Air National Guard's Civil Engineering Technical Service Center (NGB/A4OC), Minot, ND.

Research Objectives

The purpose of this thesis research is to present the planners of remote, isolated locations and military decision-makers a method to optimize an potential alternative energy system to replace existing FOB prime power diesel generators and evaluate the viability, sustainability, and resiliency of this proposed system. This research is organized around three key research questions:

1. Can renewable energy, specifically PV, provide a viable alternative for forward operating base prime power production?
2. What is the most efficient and effective design for this alternative system, and how can this system design best be optimized for cost, logistics, and performance requirements?
3. How would the implementation of this system affect remote location power resiliency?

To answer these questions, this research is subdivided into three major tasks of proving the viability of renewable PV at remote locations, optimizing the choice of PV modules based on logistics factors, and developing a multi-objective optimization for PV RES that utilizes performance, economic, and logistics as primary criteria for RES designs at remote and isolated locations.

Thesis Organization / The Way Ahead

This thesis follows a scholarly article format in which chapters 2, 3, 4, and 5 each serve as stand-alone academic publications. Chapters 2-4 comprise the bulk of the thesis and individually contain their own abstract, introduction, literature review, methodology, results, discussion, and conclusion. While they include DoD-focused case studies and research, due to the nature of the publications these articles appear in, this research is presented in a format accessible to civilian engineers. Chapter 5 serves as the conclusion of the thesis, containing a stand-alone article summarizing the research effort along with additional material detailing the significance of the results for DoD decision-makers and potential future work.

In Chapter 2, "A Sustainable Prototype for Renewable Energy: Optimized Prime-Power Generator Solar Array Replacement," the viability of a PV and battery storage RES replacement for a single 800 kW Air Force diesel generator is examined. This is accomplished through a MATLAB simulation of a PV RES operating using one year of solar insolation data and a techno-economic optimization method to balance cost-performance tradeoffs. The purpose of this paper was to answer the first research question of whether PV-based renewable energy can present a reasonable alternative to traditional generators. This paper was published in the *International Journal of Energy Production and Management* and presented at the 8th International Conference on Energy and Sustainability held in July 2019 in Coimbra, Portugal.

Chapter 3, "A Multi-Criteria Logistics Analysis of Photovoltaic Modules for Remote Applications," presents the need for and method to optimize the choice of PV module technologies based on logistics factors. These factors include weight, volume, and land area of the modules and reflect the available power density of each module. For remote locations, RES systems should be optimized for minimal logistics, in additional to considering the customary economic factors, performance, and environmental impacts. As part of this optimization, 29 PV modules are considered based on these objectives, providing planners with logistics-centered PV panel choices for use at remote and isolated sites. Both Chapters 3 and 4 pursue the goal of the second research question, to answer how RES engineers can best design and optimize these systems. This paper has been submitted for the 47th IEEE Photovoltaics Specialists Conference to be held in June 2020 in Calgary, Canada.

In Chapter 4, "A Multi-Criteria Logistics Optimization Method for Stand-alone Photovoltaic Renewable Energy Systems at Remote Locations," gaps in existing RES and hybrid RES literature are presented, and a multi-criteria optimization method for RES is developed, allowing logistics to be balanced with economic and mission concerns. This journal article includes a brief, systematic review of RES optimization in the last two years, recognizing that logistics is not considered as a primary optimization variable in previous studies. Accordingly, this paper develops a multi-objective optimization method to select, size, and design a PV RES for remote locations. This method utilizes the results from Chapter 3 to select the optimal PV module and examines appropriate energy storage solutions. The optimization method is then implemented through a MATLAB simulation that is greatly expanded from Chapter 2. Both PV RES and hybrid RES and solutions are modeled and compared against conventional diesel generators. To demonstrate the use of the model, case studies at three locations are presented. The target publication for this full-length article is *Renewable and Sustainable Energy Reviews*, a journal published by Elsevier with an impact factor of 10.556.

Chapter 5, “Going off the Grid: Sustainable Contingency Bases through Solar Power,” summarizes the background, results, significance, and conclusions of this research. This article has been accepted for publication in *The Military Engineer* March/April 2020 “Energy Issue,” published by the Society of American Military Engineers. The purpose of this article is to present to decision-makers and military and civilian engineers the potential use of PV RES to surmount generators in supplying electrical power at contingency bases at remote locations and illustrate the significant benefits of these sustainable energy solutions to military and civilian applications. This article serves as the summary and conclusion for the thesis. In addition to the article, Chapter 5 also includes additional conclusions relevant to the Air Force and recommendations for future research.

II. A Sustainable Prototype for Renewable Energy: Optimized Prime-Power Generator Solar Array Replacement

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Published in: *International Journal of Energy Production and Management* (2019)

Abstract

Remote locations such as disaster relief camps, isolated arctic communities, and military forward operating bases are disconnected from traditional power grids forcing them to rely on diesel generators with a total installed capacity of 10,000 megawatts worldwide. The generators require a constant resupply of fuel, resulting in increased operating costs, negative environmental impacts, and challenging fuel logistics. To enhance remote site sustainability, planners can develop stand-alone photovoltaic-battery systems to replace existing prime power generators. This paper presents the development of a novel cost-performance model capable of optimizing solar array and Li-ion battery storage size by generating tradeoffs between minimizing initial system cost and maximizing power reliability. A case study for the replacement of an 800 kilowatt generator, the U.S. Air Force's standard for prime power at deployed locations, was analyzed to demonstrate the model and its capabilities. A MATLAB model, simulating one year of solar data, was used to generate an optimized solution to minimize initial cost while providing over 99% reliability. Replacing a single diesel generator would result in a savings of 1.9 million liters (500,000 gallons) of fuel, eliminating 100 fuel tanker truck

deliveries annually. The distinctive capabilities of this model enable designers to enhance environmental, economic, and operational sustainability of remote locations by creating energy self-sufficient sites, which can operate indefinitely without the need for resupply.

Keywords: *renewable energy, photovoltaic, solar array, optimization, energy storage, diesel generator, battery, standalone, isolated sites.*

Introduction

At locations around the world, many isolated sites lack access to reliable power grids, requiring them to rely on diesel generators in order to produce power. Examples of these locations include developing nation villages, disaster relief camps, isolated arctic communities, and military forward operating bases. While as many as 1.2 billion people still do not have any access to power, over 10,000 megawatts (MW) of off-grid diesel generators are presently installed at other isolated locations [1]. Locations that operate using generators face challenges including the constant need for fuel resupply, local air and noise pollution, and regular maintenance to keep these generators running. The negative aspects of diesel power generation make these remote locations ideal candidates for the use of renewable energy. While small-scale examples of renewable power exist, renewable energy has yet to enter substantial service for prime power applications at remote sites with greater than 100 kW of capacity [1].

One such type of remote location is military FOBs, which range in occupancy from a few hundred to a few thousand personnel. These isolated bases form an ideal case study for potential renewables. To power nearly all FOBs, the United States Department of Defense (DoD) currently uses prime power plants, consisting of several large diesel generators. The operating cost of diesel generation is higher than traditional domestic grid power. A conservative estimate puts generator power for U.S. FOBs at $0.17/kWh vs. $0.10/kWh grid production based on a diesel cost of $0.44/L ($1.70/gal) [2]. This estimate does not account for the fully burdened cost of fuel, which includes the expense of transportation and logistics. DoD estimates on this quantity start at a minimum of $4/L ($15/gal) according to the Government Accountability Office [3]. Therefore, the actual cost for power at FOBs is likely close to $1.50/kWh. Generator maintenance provides an additional cost burden, requiring a dedicated team of technicians on standby at all times [2].

Furthermore, the logistics chain required to keep these FOBs supplied with fuel is an issue of great concern. Massive quantities of fuel must be transported via air, sea, or land—except in rare cases where pipelines are available. For FOBs not collocated with a port, land convoys are the only viable option since airlift of fuel is cost prohibitive [21]. Fuel convoys are dangerous, requiring troops or contractors to travel hundreds of miles through uncontrolled territory vulnerable to attack. One study noted that in Afghanistan there is one additional fatality per each 24 fuel convoys [4]. These convoys are also vulnerable to embargos, border closures, corruption, local supply issues, and bridge and road collapses. Because of this, current FOB energy resiliency is low. Due to the aforementioned issues, FOBs are an ideal test case for renewable energy.

This paper develops two photovoltaic-battery storage system models of increasing realism and complexity that can be used to design an optimized system based on performance, cost, and logistics. As a case study, these models will be applied to design a stand-alone photovoltaic (PV) replacement of a typical prime power generator used at military FOBs. This design will then be compared against existing diesel generators, examining the lifecycle cost and logistics requirements. If demonstrated to be workable, this PV design model can then be applied to other types of remote sites.

Literature Search

Previous research studies have examined: (1) hybrid and renewable systems for remote locations; (2) DoD use of renewable energy at FOBs; and (3) potential DoD prototypes of renewable systems. For hybrid and PV systems, previous research considered optimizations between PV and generators in non-military austere environments to include power systems utilizing wind and PV [13], diesel generator and PV hybrids [5], and PV only [6]. There is also a study comparing the weight of various types of PV panels for logistics analysis [16]. Perera et al. [22] examined a renewable hybrid system showing that, to minimize initial costs, when beginning the use of renewables it is optimal to add renewable components to existing non-renewable systems. Therefore, for initial testing at remote locations, a potential renewable replacement should be modular, allowing it to be used in conjunction with other generators. For the purpose of this model and system design, the renewable energy resource is confined to PV, as it is currently the fastest growing and most promising renewable technology for generator replacement at remote locations [12].

In the second category of studies, DoD-focused research has examined the economics and optimization of PV arrays and battery storage for use by the DoD. On the scale of a full-size base, Schill [2] investigated the advantages and difficulties of 12 possible energy sources. At a smaller scale (5 kW), one study demonstrated a 36% savings of fuel is possible through battery-generator hybridization, thereby operating generators only at peak efficiency [18]. On the scale of a single FOB, Wagner et al. [17] published results of the time-phased nature of PV arrays and the optimal configuration both with and without batteries to replace entire FOB power grids. Furthermore, McCaskey [19] examined the supplementation of existing 750 kW MEP-12 generators with wind, solar and battery storage and proposes a test case at a base in New Mexico. His research focuses on optimizing the addition of renewables to existing generators in a hybrid form, instead of examining possible stand-alone replacements [19].

In the third category, other studies have begun to investigate the physical engineering requirements necessary to produce DoD-oriented renewable sources. NREL and AFRL designed and built a prototype for a mobile inverter and battery platform capable of converting renewable energy from solar or wind sources to supply AC power for FOBs [20]. AFRL's design supplies 30 kW of power—too small for a prime-power replacement, but still an advancement for hybrid energy use. From 2008 to 2012 AFRL also experimented with a variety of temporary shelter designs that incorporated integrated PV shades, improved insulation, and reconfigured HVAC systems to provide a 35-65% reduction in energy demand [23].

Despite the significant contributions of the aforementioned research, these studies have not yet demonstrated a workable design of a stand-alone PV-energy storage replacement for prime-power generators at remote locations while considering cost & performance. Additionally, weight, volume, and shipping configuration of PV have been only cursorily examined but have a major impact on decisions to implement such systems. Accordingly, this paper presents the development of an optimization model for PV-battery systems, illustrating the key tradeoffs and logistics considerations involved and outlining a potential replacement system. Such a replacement solution could provide benefits for military FOBs, remote communities and other isolated sites.

Method

To develop and demonstrate a practical PV-battery storage system design and optimization model, it was necessary to select a specific requirement and location to model. For this study, the United States Air Force (USAF) Basic Expeditionary Airfield Resources (BEAR) Power Unit generator, known as a BPU, was selected to model for replacement. For location, a notional 1,100-personnel FOB in Afghanistan (similar to many other military environments) was chosen.

The BPU supplies 800 kW at 60 Hz 4160/2400 VAC across a wide range of environmental conditions using diesel fuels [24]. Approximately 6-8 BPUs can supply a 1,100-personnel FOB with sufficient surplus generation available for generator downtime due to maintenance and repair [19]. The average load for a theoretical base of this size is 4.8 MW [19]. Prime power generators frequently operate at up to rated capacity for extended periods of time. Therefore, a replacement PV system must be capable of providing a consistent 800 kW for each removed BPU removed. However, PV arrays do not provide power at a constant rate, but instead the power produced changes depending on weather conditions and solar intensity [12]. Therefore, meeting a constant demand is difficult for PV systems. To offset the time-phased nature of PV-supply, batteries are necessary to provide power when solar intensity is insufficient. While many other energy storage methods are possible, this paper focuses on developing an optimization model; therefore the design assumption was confined to lithium-ion batteries.

Due to the remoteness of FOBs, it is often necessary to transport generators and other power system components long distances via air, ground, or sea transport. Given the practice of military operations, the USAF BPU is provided in a mobile, palletized configuration, enabling the transportation and setup of FOB power grids in a matter of days. Similarly, a renewable replacement system must keep transported size and weight to a minimum since all components of the power system may need to be airlifted to the remote location or FOB. The installed area required for a PV array compared to diesel generators is another factor since available land can be limited. While not the only factor, the initial purchase and ongoing system costs are important, so the total lifecycle cost was included in the model.

Once a PV replacement system is designed using the model, its performance must be compared with current BPU generators. Performance was measured based on (i) lifecycle cost, (ii) total initial cost, (iii) ability to meet the power demand, (iv) system size, and (v) system weight. Key assumptions were that the lifecycle of the system is short enough that generator, battery, and PV panel degradation and replacement can be ignored. For the purpose of this study, the first few years of system lifecycle were considered. For the BPU, we assumed military forces will handle installation as part of base setup and the regular preventative maintenance costs are ignored. This makes the model slightly conservative by underestimating the generator costs.

In order to analyse and develop a model for the PV replacement system, certain parameters and assumptions were chosen, as shown in Table 2.1. Because weight and size are major concerns for the logistics of these remote sites, lithium ion batteries were selected in the design despite their higher cost. Generator fuel consumption is from the comparable 750kW MEP-12 [25]. Costs shown in the table were adjusted to 2018 values using the U.S. Bureau of Labor Statistics' CPI rates [26]. In order to model logistics considerations, Table 2.2 displays the estimated weights and volumes for each of the power system components.

Table 2.1 System Cost and Model Parameters

Component	Parameter	Reference
PV Array Cost (installed)	\$1.50/W	Wagner et al. [17]
PV System Losses	15%	Wagner et al. [17]
PV Panel Efficiency (Fixed, Latitude-Tilt)	15%	Wagner et al. [17]
Inverter Cost	\$0.42/W	McCaskey [19]
Lithium Ion Battery System Installed Cost	\$310/kWh	Diorio et al. [27]
Battery Storage Losses	8%	Diorio et al. [27]
Generator Cost	\$587K	USAF [24]
Fuel Consumption / Generator Efficiency	55 gal / hr (750 kW) = 3.59 kWh/L	USAF [25]
Fully Burdened Cost of Fuel	\$4.69/L (\$17.74/gal)	US GAO [3]

Table 2.2 Logistics Performance Parameters

Component	Parameter	Reference
PV Array Deployed Footprint	9.29 m^2 / kW	McCaskey [19]
PV Panel Thickness	38 mm (1.5 in)	-
PV Array Packed Size	0.35 m^3 / kW	-
PV Array Weight	0.04 kg/W	Yilmaz et al. [16]
Weight of Batteries	10 kg / kWh	Diorio et al. [27]
Volume of Batteries	0.0287 m^3 / kWh	Diorio et al. [27]
Weight of Generator	18,651 kg (41,118 lbs)	USAF [24]
Weight of Fuel (JP-8)	0.81 kg/L (6.8 lbs/gal)	-

The PV array panels are assumed to be 38 mm thick, and stacked for shipment, providing an estimated energy density of 2.86 kW/m^3 for the PV array. Because weight density is also a major factor for transport, thin-film silicon PV panels were selected due to their lighter weight [16].

Analysis

For this project, we created simplified and detailed models of an energy system that can meet the constant 800 kW power requirement of the BPU. Insolation estimates for the selected location were obtained from the NREL Geospatial Toolkit [19].

Figure 2.1 shows the available ground solar insolation, which peaks at approximately 1.16 kW/m2 and averages 0.24 kW/m2.

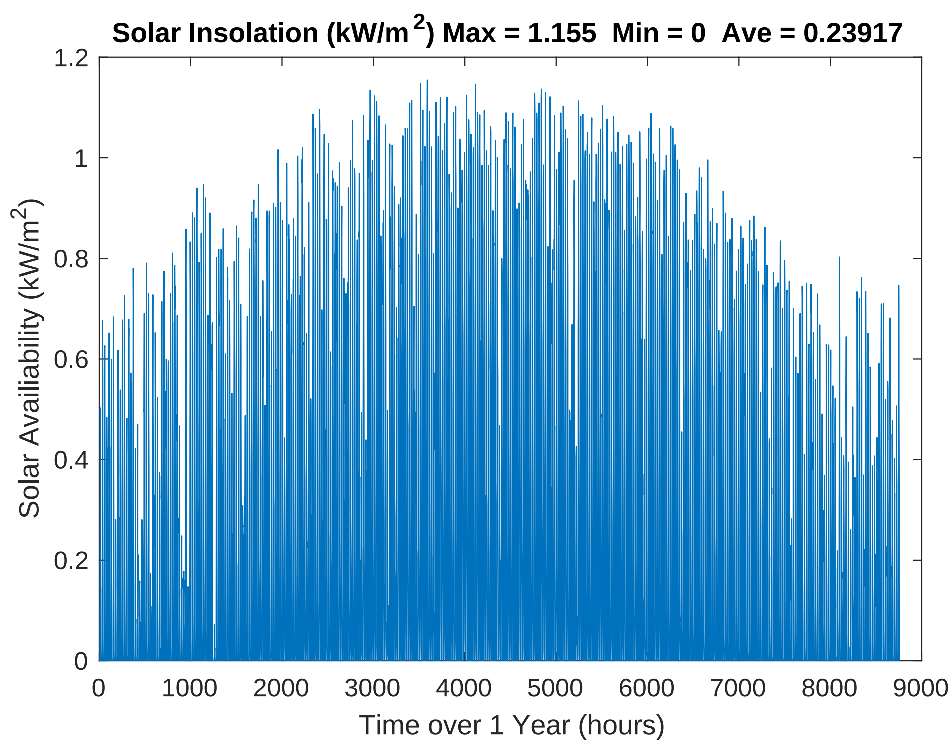

Figure 2.1. Notional FOB Solar Insolation

This average solar density is used to calculate the area for a solar array that can produce 800 kW of power on average like the BPU generator, as shown in equation (2.1). The calculated size of the array for an average 800 kW output is 26,233 m^2 (282,372 sq ft) or about 6.5 acres.

$$Array\ Size\ (m^2) = \frac{planned\ output\ (kW)}{avg\ solar\ density_{(kW/m^2)} * \ panel\ efficiency_{(\%)}\left(1 - solar\ sys\ loss_{(\%)}\right)} \tag{2.1}$$

Using this solar data and an array size of 26,233 m^2, the overall power production minus demand per hour at the hypothetical FOB was calculated (called excess power in this model) and is described by Equation (2.2).

$$ExcessPower_{(kW)} = ArraySize_{(m^2)} * insolation_{\left(\frac{kW}{m^2}\right)} * panel\ eff_{(\%)}\left(1 - solar\ sys\ loss_{(\%)}\right) - P_{demand} \tag{2.2}$$

where, P_{demand} = 800 kW.

Figure 2.2 shows the instantaneous power surplus or shortage (each hour) and the total energy surplus or deficiency stored, assuming unlimited storage. From this figure note that there are daily power shortages during hours of darkness that will have to be supplied through battery storage or other production methods.

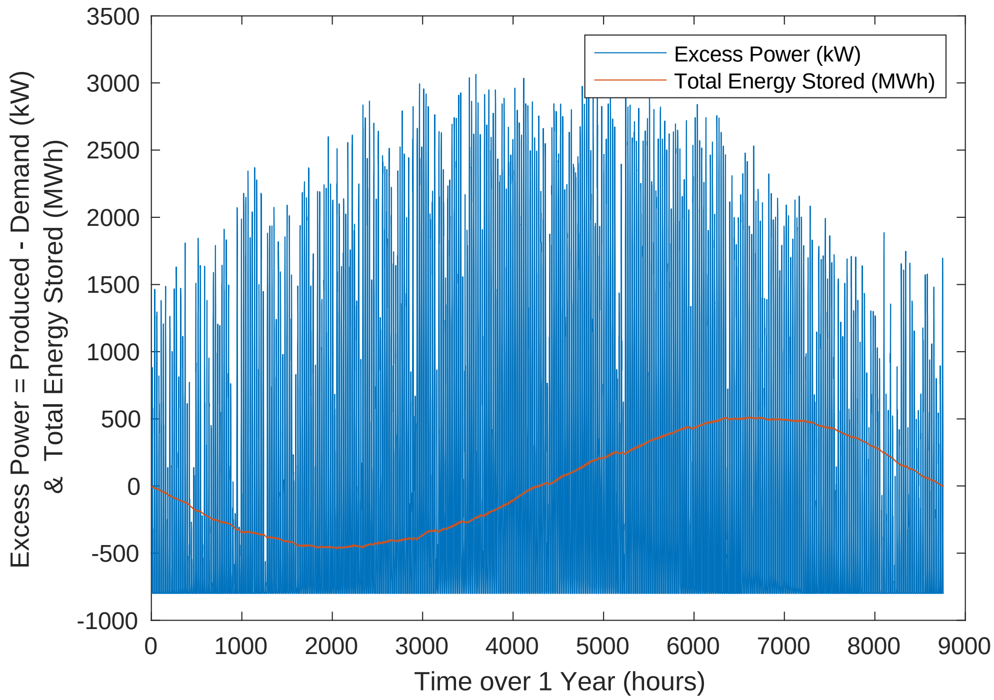

Figure 2.2. Power Production and Total Energy Stored over Year

The energy stored is calculated by integrating the excess power (power produced minus the demand) over the year as described in Equation (2.3). Because the battery losses and over/under charge conditions are not considered, this is only applicable to the simplified model.

$$Energy\ Stored_{(kWh)}(t) = \sum_{t=0}^{8760} Excess\ Power_{(kW)} * 1hr \qquad (2.3)$$

The trough and peak of total energy stored show that a 470 MWh battery would be necessary to store enough power to meet the 800 kW demand during the darker, winter months. A battery this size would meet the demand for over 24 days without any power generation. At a rate of $310/kWh for energy storage, $146 million is an unreasonable cost to replace a single generator. To reduce the size of the battery, additional solar panels can be added to provide additional power every day, reducing the required energy storage during winter months and cloudy days. By optimizing this PV array size and battery size combination, a much lower cost system can be achieved.

To conduct this optimization, a simplified MATLAB model was created using Equations (2.2)-(2.3) to simulate the PV-battery storage system, and a sweep of PV sizes ranging from 800 kW to 2,000 kW and battery sizes from 0 to 500 MWh was performed. Figure 2.3 shows this sweep along with the excess energy produced by PV that is not required to meet the 800 kW demand. Through this two-variable optimization, 1,471 kW was found to be the ideal array size with an 11.6 MWh Li-Ion battery bank for minimum total system cost. With decreasing battery sizes, the overall cost of the system decreases rapidly until reaching the optimal cost point where the cost slightly rises as additional PV is added. The reason for this plateau is that the total system cost is impacted more by the battery costs than by the size of the PV array itself. It is crucial to note that this simplified model assumes a perfect battery with no over or under-charge energy losses. This is not realistic but was used for the initial approximation of optimal sizes for the system.

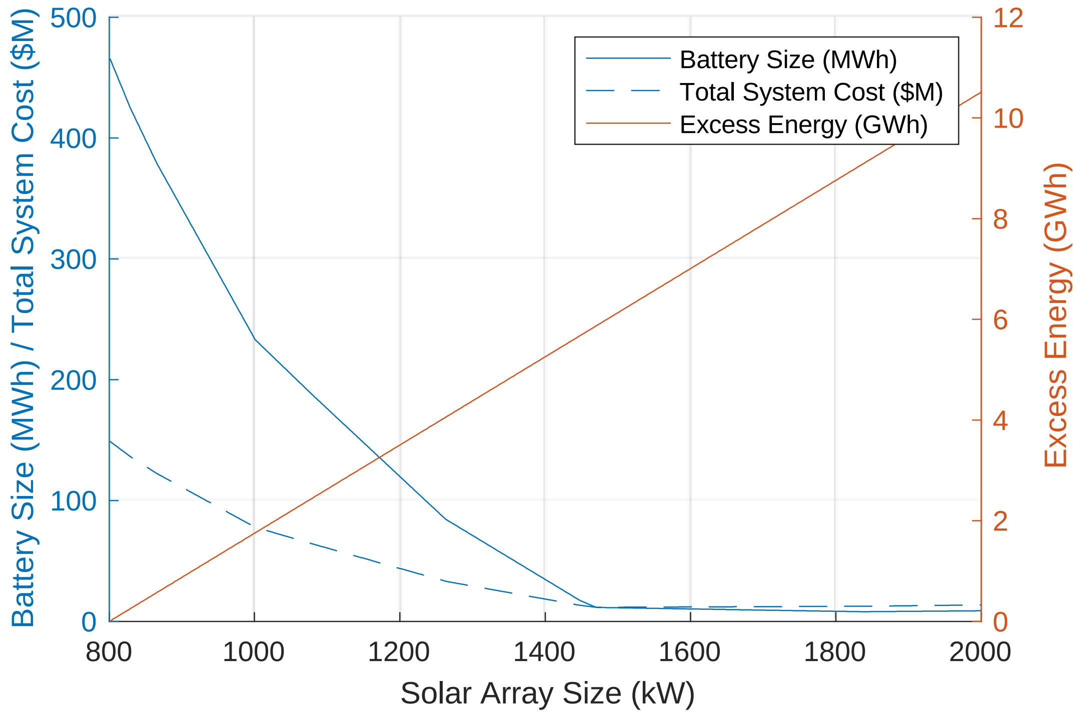

Figure 2.3. Simplified Model System Cost and Battery vs. PV Array Sizes

Next, a detailed model for the PV-battery system was created in the form of a MATLAB objective function, which we simulate to perform one- and two-variable optimizations. In this model, battery efficiency and over/undercharging losses from Table 2.1 were included. The objective function produced an output of the total cost and the hours that the system could not meet the required demand, by simulating a year of PV operation based on a given system size. Additionally, a penalty cost was added to the objective function output. The penalty cost places a dollar value on negative performance, such as when the system fails to meet the 800 kW demand. For this model, each hour (in a typical year) that the demand was not met was considered a $1,000 additional cost, which is roughly equivalent to the fuel cost of running the BPU generator for an hour. The operation of this model is described in Equations (2.4)-(2.6).

$$Objective\ function = f\left(PVsize_{kW}, Battery\ Size_{(kWh)}\right) \rightarrow \text{minimize}\ [Penalty\ Cost] \quad (2.4)$$

Where: *Penalty Cost* = (\$1,000 * $Hours\ Not\ Met$) + Total System Cost.

$$Hours\ Not\ Met = \sum_{t=0}^{8760\ hrs} \left[BattCharge_{(kWh)}(t) \leq BattDepthOfDischarge_{(kWh)}\right] \quad (2.5)$$

$$BattCharge_{(kWh)}(t+1) = BattCharge(t)_{kWh} \pm (1 - battLoss_{\%}) * ExcessPower_{(kW)}(t+1) * timestep \quad (2.6)$$

Equation (2.4) describes the goal of this model which is to minimize penalty cost based on battery and PV array size. Equation (2.5) defines a loop that iterates through an entire year of solar data (8,760 hours) to count the hours of failure criteria where the battery is completely discharge to the 10% minimum depth of discharge for the Li-Ion battery bank. Equation (2.6) explains the battery charge/discharge model where the battery is charged when Excess Power is positive and discharges when it is negative. During the charge cycles the round-trip battery loss factor $(1 - battLoss_{\%})$ is applied. Not shown in this equation is MATLAB logic that also prevents overcharging the battery beyond 100% capacity.

Two sweeps of battery size and PV array size were completed, while holding the other parameter (PV or battery, respectively) constant at the optimal size found in the previous optimization. In the detailed model, the key operational factor to consider is the failure condition or “Hours Demand Not Met.” This parameter measures all the hours in a typical 8,760-hour year where the 800 kW demand would not be met and a power outage would occur. This scenario assumes the demand would require the full 800 kW 100% of the time, which is conservative.

The penalty costs are highly dependent on the chosen cost of each failure hour. At the $1,000/hr penalty rate, penalty cost is not the best choice for system optimization as minimizing it results in over 2,000 hours of failure per year in the PV size sweep and 800 hours for the battery size sweep minimum penalty costs—at 23% and 9% failure rates, respectively, these are unacceptable levels of performance. Figure 2.4 shows the output sweep for PV sizes 0-5,000 kW with an 11.6 MWh battery.

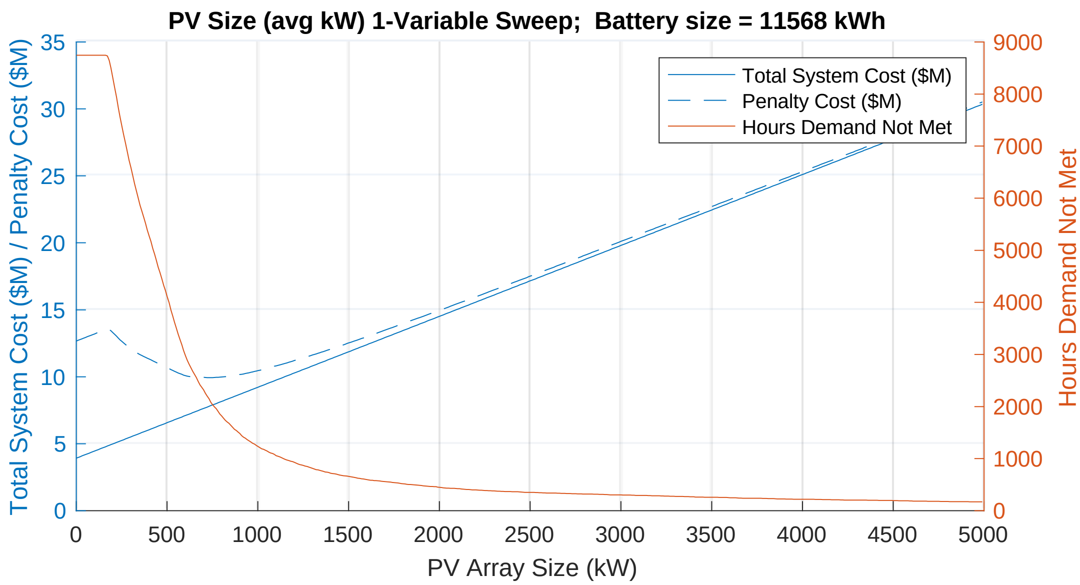

Figure 2.4. PV Array Size Sweep with Costs and Hours Not Met (Detailed Model)

The sweeps revealed that, at the current fixed battery/PV array size starting point, no optimal point of minimum total cost and failure hours is apparent; therefore, the optimization parameters were modified to enable optimization of both battery size and PV array size simultaneously.

A two-variable optimization was then performed using the detailed model to minimize the total cost and hours of failure. Because penalty cost failed to be an accurate representation of system performance, we instead minimize both system cost and failure hours, as shown in Equation (2.7).

Figure 2.5 shows two surfaces comparing the resulting total cost and hours of failure for various battery and PV sizes.

$$\begin{aligned} \mathit{Model\ 3\ Objective} = f\left(PVsize_{kW}, Battery\ Size_{(kWh)}\right) \\ \rightarrow \text{minimize}[Cost, Hours\ Not\ Met] \end{aligned} \tag{2.7}$$

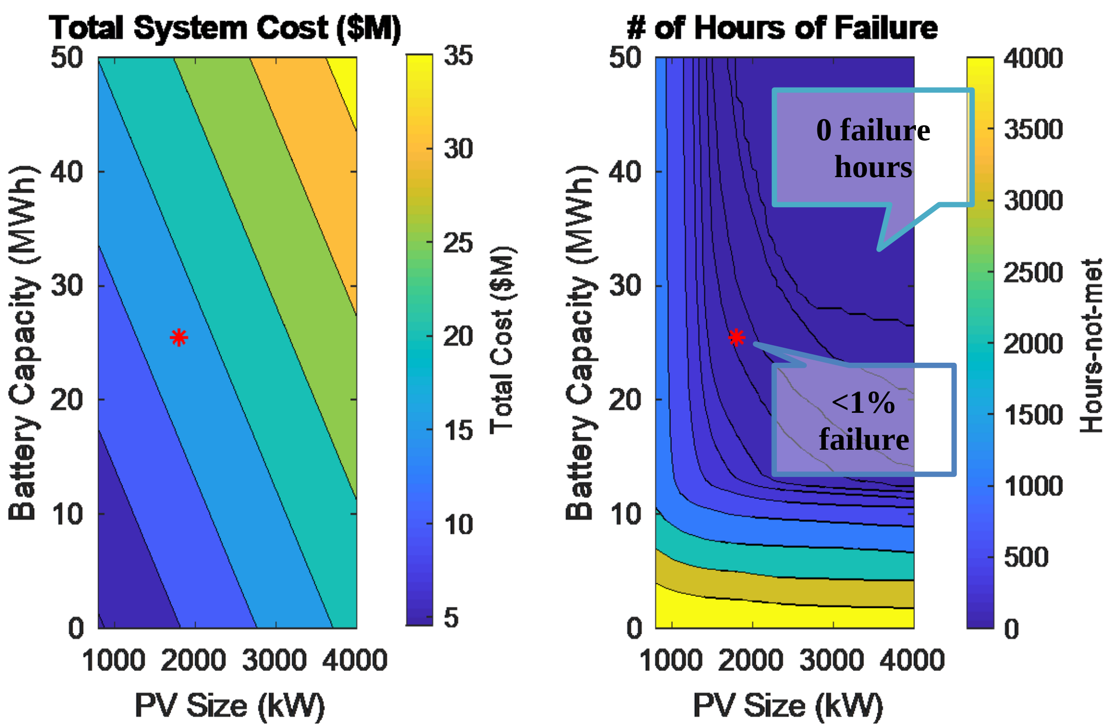

Figure 2.5. PV and Battery Size Sweep with Costs and Hours Not Met.
The red dot represents optimal cost point with <1% failure rate.

The upper right contour in the right subplot shows the area where no hours of failure occur. This chart clearly demonstrates the tradeoff between performance and cost. As hours-not-met decreases, the total cost of the system increases rapidly. In comparison, the minimum system cost for no failure hours is $22.7M vs. $17.8M for a 1% failure rate.

For this system, a 1% failure rate is acceptable, as even generators have to allow downtime for maintenance and failures. At a 1% failure rate the optimal system size is 1,800 kW of PV array and 25.5 MWh for the battery size. This optimal size is plotted as a red point on Figure 2.5. At this optimal size, a solar year was plotted showing the instantaneous power and the battery charge. Figure 2.6 shows the time series generated PV power and battery state of charge for approximately 10 days of this year.

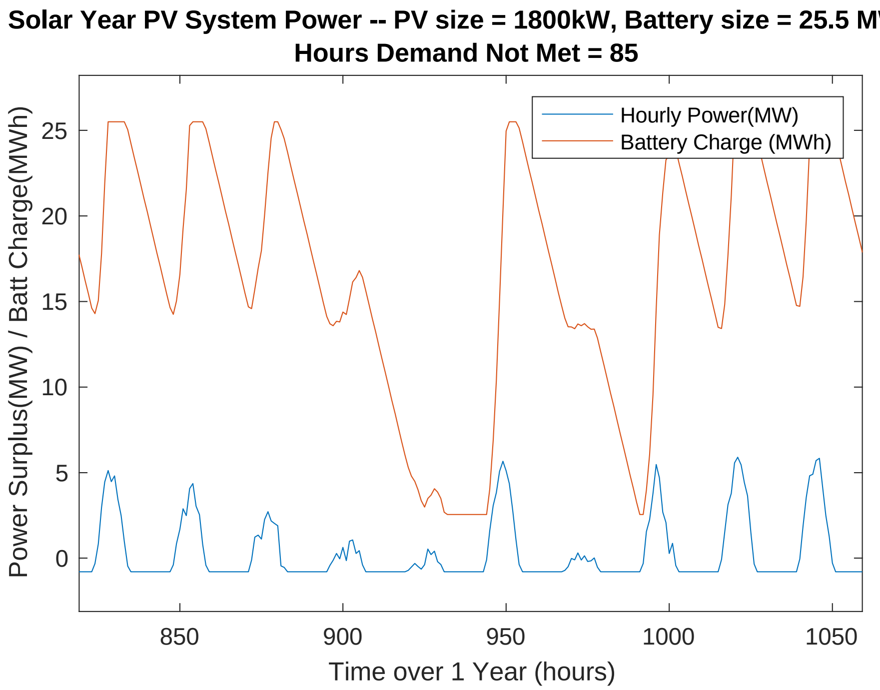

Figure 2.6. PV System Power and Battery Charge over Time

Figure 2.6 demonstrates a period during the winter months where two nights of power failure occur and the battery dips to minimum capacity at a 10% state of charge remaining. The solar input is significantly lower than normal, likely due to cloudy days. To get past these power shortages the FOB could run backup generators, reduce energy usage, or authorize using the batteries up to 100% depth of discharge, which is possible for a limited number of cycles for Li-ion batteries [18].

Using the component weights and volumes in Table 2.2, the total system shipping volume and weights were examined and compared against various battery and PV design sizes. The inverter weight and volume were considered negligible, which is reasonable [16]. Figure 2.7 shows this analysis with the same optimal system size again marked.

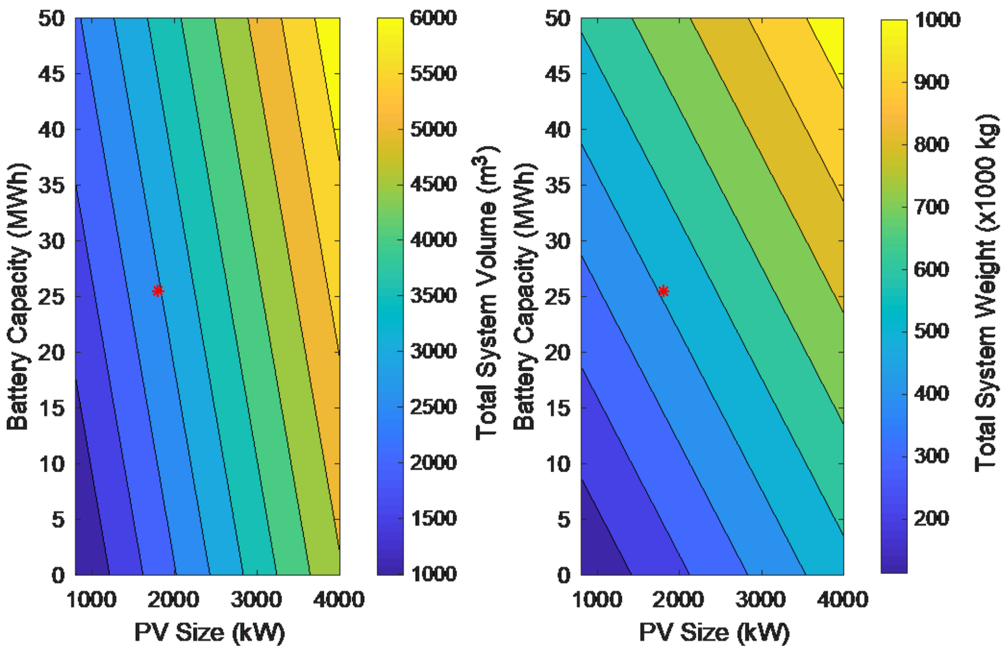

Figure 2.7. PV System Transport Volume and Transport Weight.
Red point denotes previously optimized system size (for min cost and <1% failure).

This analysis shows that system volume is impacted more by the size of PV array while the system weight is affected more by the battery capacity. At the 1% failure rate optimal system size, the total volume for PV array and batteries was found to be 3,000 m^3 and the system weight 509,000 kg (1.12M lbs). These are roughly 50x larger and 27x heavier than the BPU that is 60 m^3 and 18,651 kg (41,118 lbs). The fact that these quantities are much larger than the BPU is a significant logistical challenge, but not insurmountable, since this additional cargo required may be offset by the reduction in fuel used.

Finally, the lifecycle costs and logistics of both the PV + battery replacement system and the BPU were compared. To do this, a time series cost model was created to calculate energy system component cost and BPU fuel cost. The total weight transported, to include fuel, was also included. Figure 2.8 shows these results over a period of two years.

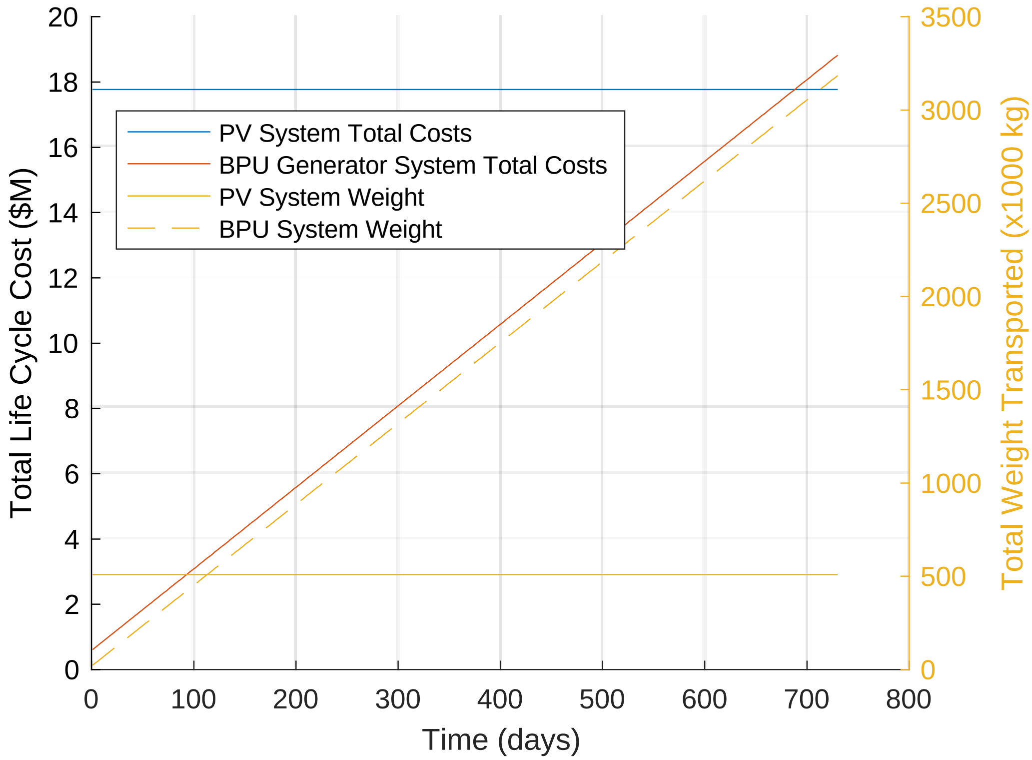

Figure 2.8. PV System and BPU Lifecycle Cost & Transport Weight

This time series cost model demonstrates that, in spite of significantly higher initial cost, the renewable replacement system becomes cost effective in a period of less than 700 days. While the PV system is 27 times heavier than the BPU, the total required transport weight for the PV replacement will be offset in just over 100 days by the weight of fuel.

Conclusions

This research has shown that a PV array and battery storage system could be a cost-effective replacement for diesel generators at remote locations as modelled by the 800 kW USAF BPU generator currently used at FOBs. The logistics required to transport these renewable replacement systems are substantial, but fuel savings quickly outweigh these initial challenges. If implemented, this PV system will reduce current military FOB reliance on diesel and reduce or eliminate the need for fuel convoys. Replacing a single diesel generator with the optimized case study PV system as modeled here would result in a savings of 1.9 million liters (502,000 gallons) of fuel each year and eliminate the need for 100 fuel tanker deliveries. This study can easily be applied to other types of remote locations, enabling them to operate without continuous fuel resupply.

III. A Multi-Criteria Logistics Analysis of Photovoltaic Modules for Remote Applications

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Submitted for publication and presentation at the *47th IEEE Photovoltaics Specialists Conference,* Calgary, Canada (June 2020)

Abstract

Reliable electrical power grids are frequently unavailable or inaccessible in remote locations, including developing nation communities, humanitarian relief camps, isolated construction sites, and military contingency bases. This often requires sites to rely on costly generators and continuous fuel supply. Renewable energy systems (RES) in the form of photovoltaic (PV) arrays and energy storage present a rapidly improving alternative to power these remote locations. Previous RES literature and PV optimization models focused on economics, reliability, and environmental concerns, neglecting factors of importance for remote installations.

This paper proposes additional optimization variables applicable to remote PV systems and compares PV module technologies based upon these criteria. Logistics requirements such as system weight and volume are critical for shipment to remote applications. Furthermore, PV module efficiency and area power density are essential because available land area can be limited in constrained sites. These factors must be considered, in addition to conventional economic and performance variables, to design an optimal RES for remote locations.

The present study evaluates 29 PV modules utilizing manufacturer datasheets and supplier pricing. For each module, cost, efficiency, panel weight, and volume were collected to calculate the proposed logistics variables: area power density, weight power density, and volume power density. These variables were plotted against module costs per watt, demonstrating cost-performance tradeoffs and enabling planners to select the best PV module for their application. Monocrystalline modules appear to provide the best balance of these factors, but developing technologies may challenge crystalline cells as they continue to mature. The best conventional panels had efficiencies of approximately 20%, costs of $0.60/W, and power densities of 17-18 W/kg, 200 W/m^2, and 5,500 W/m^3. By comparing the logistics variables of PV modules as presented here, RES planners can develop more efficient designs better suited to the logistics of installing and operating at remote sites.

Keywords: *renewable energy systems, photovoltaics, PV, solar module, logistics, optimization, power density, remote, isolated sites.*

Introduction

At remote locations around the world where reliable access to power grids is unavailable, reliance on diesel generators is commonplace, with at least 10,000 MW installed worldwide [28]. Examples of these locations include developing nations, humanitarian relief camps, isolated construction sites, and military forward operating bases. The challenges of operating on diesel generators include undesirable air and noise pollution, continual maintenance, and an ongoing fuel supply. This logistical requirement results in high transportation costs and presents a threat to energy resilience and power reliability. Renewable energy, in the form of solar arrays and energy storage, presents a potential solution to the logistics issues that arise from traditional diesel fuel generation.

Decision-makers for renewable energy face the challenging task of selecting photovoltaic (PV) array and energy storage sizes to meet operational requirements at the lowest cost. Inherent tradeoffs between cost, performance, and other variables result in different system size solutions depending on the solution set desired [29]. Previous studies have analyzed renewable energy systems (RES) with various optimization methods and key variables selected. Several review articles demonstrate that the most common methods and goals of optimization are cost, reliability, and environmental impact [30]–[32]. However, system weight and volume are "highly critical" to remote PV applications [11].

Despite the significant contributions of the aforementioned research, there are little to no proven optimization methods that incorporate weight, volume, land area, and other logistics concerns vital to RES applications at remote and isolated locales. Accordingly, the purpose of this paper is to examine the key variables required for the use of photovoltaics at remote locations, compare current and emerging PV module types using these variables, and determine the best candidates for remote and isolated applications.

Methodology: Defining Key Logistic Variables

This paper defines and examines the key logistics variables of cost, efficiency, area, weight, and volume power densities for various selected PV module types, technologies, and manufacturers.

Cost

Cost is the nearly universal primary variable optimized in PV system design and selection. RES design engineers can consider cost based on the lowest initial capital cost, lifecycle cost, or levelized cost of energy [15], [22]. This paper defines cost as the portion of initial capital cost composed of the module purchase price, neglecting the balance-of-system (BOS) costs, including inverters, switches, and mounting hardware, which should be approximately the same for any panels used.

The National Renewable Energy Laboratory (NREL) evaluates PV pricing based upon cost per power produced ($/W), which must be calculated from absolute costs given by solar pricing data ($/module) [33]. This dollars per watt method allows for comparison of power production across PV technology types that may possess very different efficiencies. For this analysis, 2019 US dollars were used.

Efficiency

The efficiency of the PV modules and technologies is measured in percent of power produced for a given solar insolation (efficiency = $P_{out}/P_{insolation}$) and is measured in percent of insolation recovered. Module efficiencies and power outputs used in this study were assumed to be obtained at Standard Test Conditions, which are AM 1.5G sunlight at an irradiance of 1,000 W/m^2 and a temperature of 25°C [34]. Module efficiencies were used versus solar cell lab research efficiencies since this analysis is at a practical, system level.

Area Power Density

The area of PV panels required to produce a certain amount of power is determined by the area power density (W/m^2), which can be calculated from PV panel specifications. However, this quantity is proportional to PV module efficiency for a given insolation level or location. Therefore, this value will be estimated but will not need to be compared individually as the efficiency variable above already accounts for this factor.

PV Panel Weight (Power Weight Density)

Because of the logistics emphasis of this study, PV panel weight is an important variable to consider. Weight data is often provided by module manufacturers in terms of kg and were converted to W/kg to enable a comparison of overall power weight density. Weight density can be a vital factor in cases where transportation is very limited or expensive, such as aircraft cargo. In actual PV installations, there will be additional weight from the BOS equipment, such as mounting hardware and cables, but these weights are not considered in this study.

PV Panel Thickness and Volume (Power Volume Density)

PV panel volume is an essential logistics factor and distinct from weight since some methods of transport such as sea shipment depend on volume rather than weight. Because PV module volumes are directly dependent on the panel thickness, that is an important attribute to consider. Using the panel thickness, size, and efficiency, an estimated power per PV unit volume was determined (W/m^3). Similar to weight, the volume contributed from BOS components is not considered in this study.

PV Technologies and Data Collection

As PV technology improves, more economical and high-efficiency options are becoming available for PV modules. This section will briefly describe each type of PV module and the potential advantages or concerns of each.

Monocrystalline Silicon (mono-Si)

Monocrystalline silicon is one of the most widely produced solar technologies today. It boasts high efficiencies but higher cost largely due to the need to create a nearly perfect, single-crystal structure in the Si wafers, which comprise as much of 40% of the manufacturing cost of the cell [35]. However, this structure creates a more efficient single-junction cell than many other types. Many of the PV modules studied in this review are mono-Si. According to the Fraunhofer ISE PV report, mono-Si makes up 32% of the global annual PV production [36].

Polycrystalline Silicon (poly-Si)

Polycrystalline is now the largest produced type of PV module worldwide, with over 60% of the market share according to Fraunhofer [36]. Polycrystalline, also called multicrystalline, cells are formed in a similar process as mono-Si; however, there is no need to produce a single, pure crystal of silicon. Instead, the silicon is formed into rectangular ingots and allowed to cool naturally. This creates small, crystallized areas but not an entire single-crystal wafer. Cells produced with polycrystalline silicon material typically have lower efficiencies than mono-Si cells; however, poly-Si continues to improve and boasts a higher usable area for modules due to the square ingots vs. round mono-Si wafers which utilize cut corners. Peak mono-Si modules reach 24.4% efficiency while the best poly-Si currently only reach 19.9% efficiency, so the efficiency difference of mono-Si over poly-Si is around 4% [36].

Amorphous Silicon (a-Si) and HIT Cells

Amorphous silicon cells are formed with raw silicon that does not possess a long-range crystal structure like crystalline silicon. This means that a-Si has a much lower power conversion efficiency as compared to mono-Si or poly-Si. A-Si boasts a high absorption coefficient and can be formed into very thin films that can be flexible. This study looks at a hybrid of a-Si and crystalline silicon called HIT—Heterojunction with Intrinsic Thin-Layer modules. These cells are formed with a layer of p-type a-Si and intrinsic a-Si added the top and bottom of a traditional n-type crystalline Si layer. Cell efficiencies of 25% have been reached with these types of cells by the Sanyo/Panasonic corporation [37]. Traditional a-Si thin-films were not considered due to their very low conversion efficiencies.

III-V Group Devices

III-V type solar cells are formed with elements of groups III and V on the periodic table and are recognized for their outstanding efficiency and extremely high cost. According to NREL estimates, commercial III-V cell prices range from $100 to $300/W, which largely confines the use of the cells to space applications [38]. One experimental GaAs thin-film prototype blanket was included in this study, but its cost is too large to consider for practical prime-power applications ($100/W) [39].

Thin-films (CIGS)

CIGS are Copper Indium Gallium Selenide solar cells, one of the most popular choices for thin-film materials that can be deposited on flexible substrates. CIGS has a high absorption coefficient, making the material ideal for thin-film applications. The only thin-films included for this report are the CIGS solar thin-film blankets MiaSole Aurora Charger 97 and Brunton Solaris 62, which are both commercially available for a cost of $606 and $1500, respectively [39]. There are several other types of emerging solar cells, including other thin-films, Perovskites, and organic solar cells; however, they are excluded from the study because of their current experimental nature.

Results and Discussion

This study evaluated 29 PV panel modules of several types: 18 monocrystalline, six polycrystalline, two a heterojunction design of crystalline and amorphous silicon (HIT cells), and three experimental thin-film solar blankets. The following criteria were required for each chosen module: cost, weight, module efficiency at standard test conditions, volume, and wattage. This data was collected from manufacturer datasheets and solar panel distributor pricing [39]–[44].

Figure 3.1 shows the relationship of cost per watt versus module efficiency and power/area. The relationship is largely flat, with most solar cell modules around $0.60 to $0.80 ($/W) with an efficiency of 18-20%. Efficiency does increase with extra cost; however, a large increase in cost is needed for only a small efficiency increase. Power per unit area tracks very closely with module efficiency, confirming that only one variable will need to be considered in PV module selection. A few data points show a slight variance, likely due to the border around each module that does not contain PV cells (despite being included in the panel area). Note that due to their high costs (greater than $6/W), the three thin blanket solar modules are not shown in the figures.

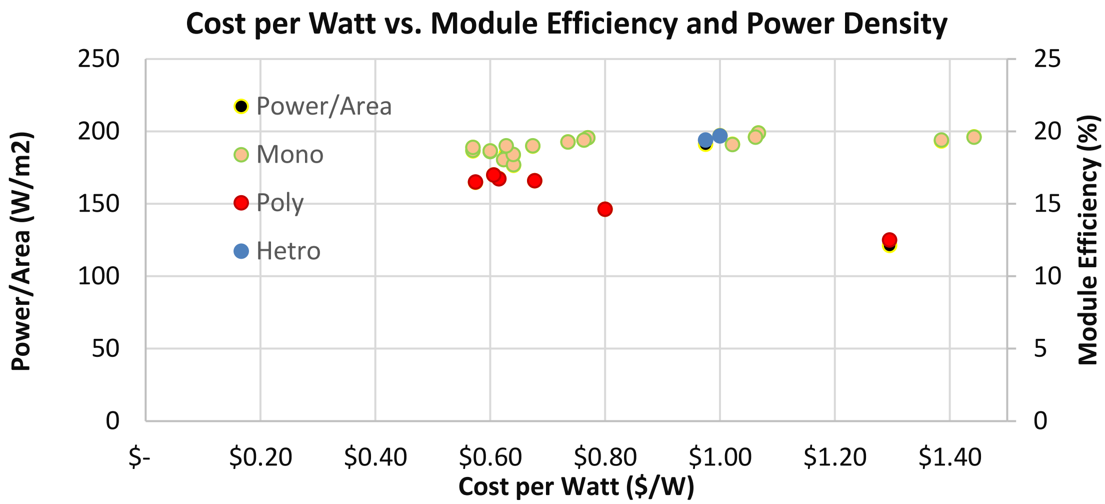

Figure 3.1. PV Module Efficiency Compared with Unit Cost for Three Types of PV. Power per unit area is also graphed on the figure (black dots), but nearly all points coincide when mapped based on efficiency.

A comparison of weight density and cost per watt is shown in Figure 3.2. The majority of the solar panels weigh 15-20 kg each, resulting in weight power densities of 10-18 W/kg. The lighter modules are polycrystalline, but those modules were smaller in size. The typical size of most modules was 1,550-1,700mm (length) x 990-1,100mm (width) x 35-40mm (thickness).

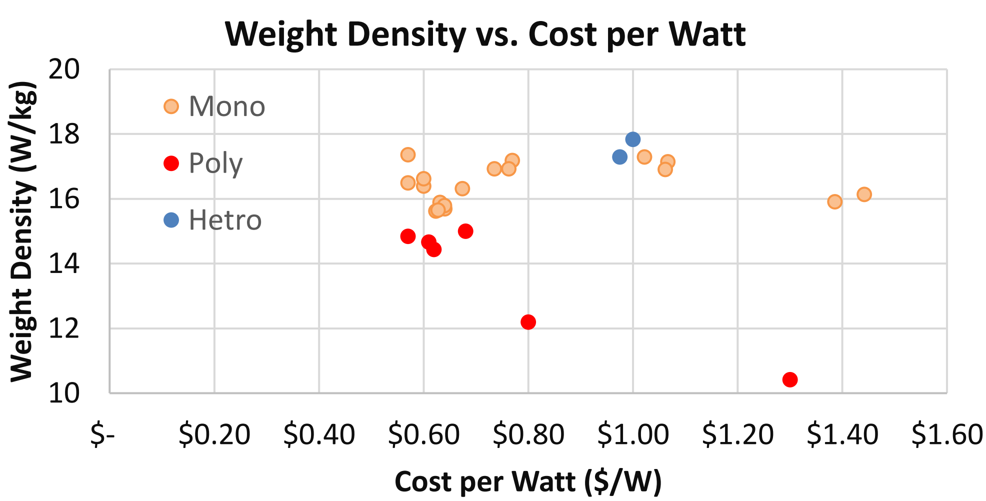

Figure 3.2. PV Module Power Weight Density Compared with Cost. Notice the correlation between weight density and efficiency comparing Figures 1 and 2.

Figure 3.3 displays a comparison of cost per watt and volume power density, with typical values ranging from 4,000-5,800 W/m^3. Monocrystalline modules have a consistently higher volume density, likely due to their higher efficiencies. It is apparent that volume power density correlates with weight density for some but not all modules, so it may be necessary to consider both of these variables based on system requirements.

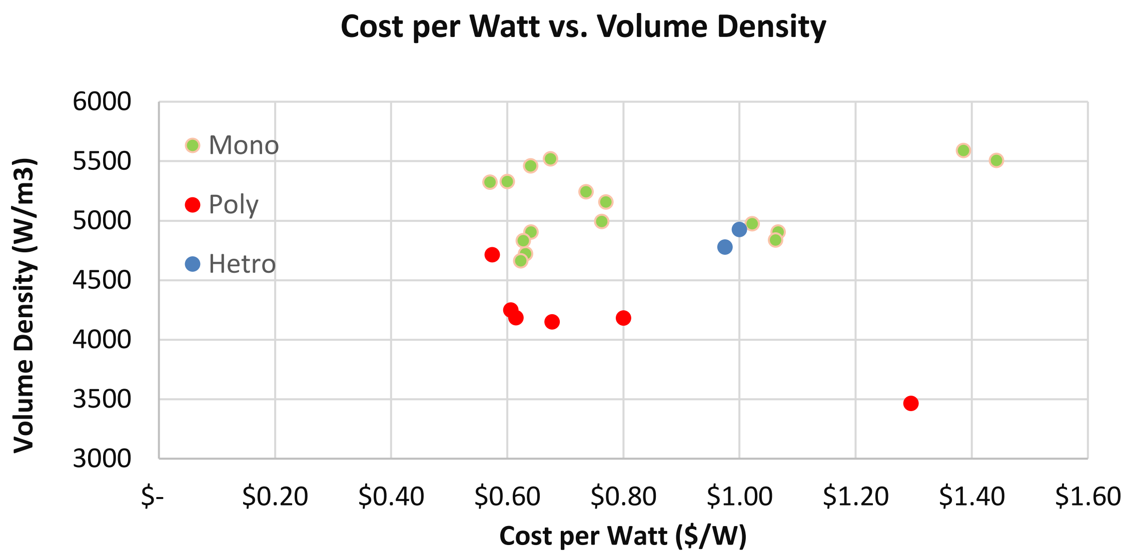

Figure 3.3. PV Module Volume Density Compared with Cost.
Notice the similarities and differences between volume and weight densities comparison.

Figure 3.4 presents a 3D scatter plot of power volume density, weight density, and cost. From this graph, the ideal solar module in regard to these parameters can be visualized: the solar cell that has the lowest cost per watt, the highest power weight density, and the highest power volume density. Note area power density and efficiency are not shown on this graph but are still valid considerations.

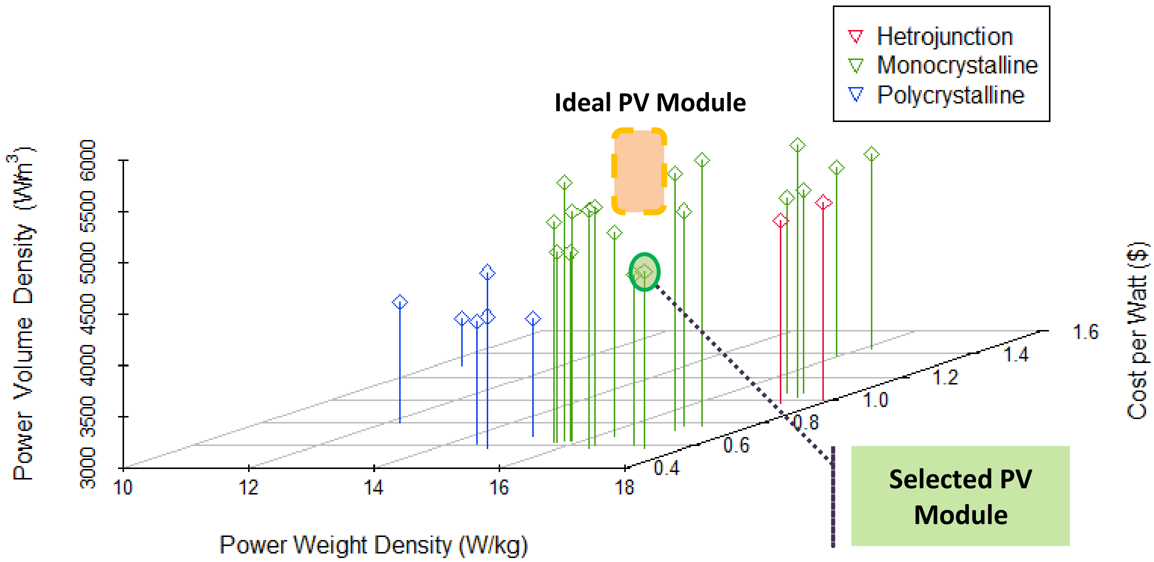

Figure 3.4. 3D Scatter Plot of Weight and Volume Density Mapped Against Cost. Ideal modules with the lowest costs and highest power density are located in the top center front of the figure.

If weight density and cost are the primary considerations, the ideal solar cell in this figure is Mission Solar MSE PERC 72. Should different variables be selected as optimization factors, another module would be preferred.

Conclusion and Significance

For the purposes of remote applications, logistics concerns such as weight and volume are critical in addition to cost. This review utilized cost, efficiency, land area, weight, volume, and panel thickness as parameters for the selection of PV modules for remote installations. It was shown that low-cost monocrystalline modules are prime candidates for this application, though the actual selection of the model will depend on the relative importance of each variable. In future research, additional factors could be incorporated into the analysis, such as installation costs, temperature dependence, and temporal degradation rates of the PV modules. Finally, thin-film blankets are a possible future technology that possess an increased power volume density, weight density, and efficiency (for III-V types) over single-junction mono and polycrystalline solar cells, but are currently prohibitively expensive for large, prime power applications.

Through use of this research and methods presented here, PV RES planners can improve their designs to for better logistics. This can enable more efficient shipping and installation (and therefore operation) of these systems at remote locations where transport proves extremely difficult such as remote islands, mountain villages, natural disaster relief camps, and military contingency bases. For the traditional modules in this study, the best showed an improvement over the worst of 71% on weight power density, 64% on area power density, and 42% on volume power density. This means that by selecting the right modules for an application, the PV portion of RES weight could be reduced by a factor of 41.5%, for example. This can make a significant difference for RES installed at locations that require expensive, non-conventional transport.

IV. A Multi-Criteria Logistics Optimization Method for Stand-alone Photovoltaic Renewable Energy Systems at Remote Locations

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Intended Journal for Publication: *Renewable and Sustainable Energy Reviews*

Abstract

Remote and isolated locations including communities in developing nations, humanitarian disaster relief camps, isolated construction sites, and military contingency bases are often located far from exiting electrical infrastructure grids, requiring reliance on diesel generators for power. These generators, installed worldwide at greater than 10,000 MW capacity, result in numerous logistics challenges and harmful environmental effects. Renewable energy systems (RES) have shown promise in providing power at these locations. Solar energy in the form of photovoltaics (PV) boasts several advantages over other renewables at remote locations including better portability and worldwide availability. However, use of the renewable resource requires energy storage in order to provide power during hours of darkness.

Planners of renewable systems face the challenging task of optimizing the size of both the PV array as well as the energy storage required to meet the power demand, while minimizing cost and environmental impact. While many aspects of this space are well-explored by previous research, what is relatively unexplored is how the logistics requirements impact the RES optimization for use at remote and isolated locations. These

logistics requirements include the initial weight, volume, and land area required for renewable systems, as opposed to the logistics of fuel resupply required for diesel generators.

Accordingly, there is a need for a RES optimization model capable of selecting the optimal configuration of PV size and energy storage that incorporates the logistics associated with RES installation. This is accomplished by the development of a multi-objective decision analysis optimization model that can simultaneously minimize logistics and cost, while achieving required levels of performance. To accomplish this, a Logistics Index is defined to weigh the importance of transport weight, volume, and land area required for the system. This index can then be optimized against cost or other objectives.

The performance of the developed logistics model was analyzed using three case studies designed to illustrate the use of the model and demonstrate its unique capability to optimize design configuration based on the local climate and the different needs of each location. The locations were chosen to show climate zone, transportation method, fuel price, and solar insolation variation. The results show that, in a variety of situations, both PV renewable energy systems and hybrid energy systems result in lower long-term costs and logistics requirements than traditional diesel generators. Notably, payback times for PV RES occur in much less than one year when examined from a logistics viewpoint. For remote locations with limited or expensive supply routes, these results greatly strengthen the case for implementation of RES.

Keywords: *renewable energy systems (RES), photovoltaics (PV), logistics, multi-objective, multi-criteria, optimization, power density, remote, isolated sites, battery, energy storage, renewable energy, solar array, stand-alone, hybrid renewable energy systems (HRES).*

Introduction

At many remote and isolated locations around the world, access to grid-based electrical power infrastructure is unavailable or unreliable. These locations include communities in developing nations, humanitarian disaster relief camps, isolated construction sites, and military contingency bases located far from traditional power grids. This problem is conventionally solved with diesel generators, presently installed worldwide with over 10,000 megawatts (MW) of capacity [1]. Operating with diesel generation results in numerous issues, including noise, negative environmental impacts, required maintenance and the need for a continuous supply of fuel. For example, to provide electricity for a population of only 15,000 living in remote communities in Northern Ontario, 22.9 million liters (6.0 million gallons) of fuel are required annually—the equivalent of 1,200 average-size fuel trucks—costing an estimated $28.3 million and releasing over 65,000 tons of CO_2 [45]. Remote locations like these are ideal candidates for the use of renewable energy, which can avoid the massive ongoing logistics demands of fuel. Renewable energy systems (RES) produce clean energy from naturally occurring, sustainable resources and are available in many forms as diverse as solar [46], wind [13], hydropower [47], ocean thermal [48], and many others [49]. These renewable resources do not require the constant resupply of diesel fossil fuels that creates challenges to living and working at remote and isolated locations.

Logistics Challenges of Remote Site Power Generation

Remote and isolated locations face multiple issues associated with operating on diesel generators including high fuel costs, limited access to skilled maintenance personnel, difficult transport to install new power production capacity, and the potential threat of fuel supply shortages or embargos. One specific example of these types of locations is military contingency bases, which require massive amounts of fuel and other supplies to be transported long distances across potentially difficult terrain. For example, at the height of the Iraq and Afghan Wars, the U.S. military delivered more than 7.6 million liters (2 million gallons) of fuel per day to contingency bases at a fully burdened cost of $15 to $42 per gallon depending on the supply scenario, time, and location [3]. This fully burdened cost of fuel (FBCF) includes the additional costs for logistics, transport, and security. Furthermore, diesel generators form the single, largest consumer of fuel at these remote bases [3]. Because of these challenges and extremely high costs, numerous studies have demonstrated the need to optimize or reduce reliance on fossil fuels for power at these sites [3], [4], [21], [50]. Numerous civilian locations face similar challenges, including villages in developing nations, inaccessible construction sites, disaster relief locations, humanitarian aid camps, and remote islands. For instance, the microeconomies of small Pacific islands are largely influenced by the price of oil, as much of their economy is dependent on electrical power from diesel or heavy fuels and the energy cost forms a large portion of their Gross Domestic Product (GDP) [51].

Acknowledging the challenges stemming from diesel power generation, RES presents an innovative solution to eliminate the need for continual fuel supply. However, while a RES can minimize the ongoing logistics of fuel transport, there is the need to consider both the initial cost and logistics required to install these systems [52]. Therefore, any RES design at a remote or isolated location must optimize for logistics, as well as cost. System transport weight, transport volume, and PV land area required are all significant factors that comprise logistics and affect the viability of new RES installations, especially at locations difficult to access, such as remote mountain bases or African communities [53].

While there are numerous renewable energy technologies available, solar has distinct advantages that make it attractive in remote, mobile, and isolated environments. The first is that it has been established as a maturing energy technology that continues to rapidly advance. Photovoltaics are the fastest growing renewable energy resource and show promise as research continues, technologies improve, manufacturing costs decrease, and worldwide employment increases—demonstrated by a 50% expansion of PV in 2016 alone [12]. The International Energy Agency (IEA) projects that by year 2022, solar photovoltaic (PV) production will reach 740 GW, more than the power production capacities of India and Japan combined today [12]. Meanwhile, the cost of PV continues to decline rapidly, with the National Renewable Energy Laboratory (NREL) projecting that the average selling price for PV modules will drop to $0.20/Watt by 2022 [54]. These developments suggest that PV will continue to improve in efficiency, quality, and in cost, making it much more competitive when compared with diesel generators and even traditional grid power.

From a practical standpoint, other renewable options like utility-scale wind require large rotors that are heavy, bulky, and difficult to transport. Other options are very location specific as they require access to hydroelectric, geothermal, or ocean thermal resources not universally available. Hence, they are not practical for the majority of locations where remote access to electrical power is required. Solar energy has the advantage of frequent availability at nearly all populated locations on earth and arrives without cost in a quantity such that less than a month of global solar energy is equivalent to all fossil fuel reserves [55]. Furthermore, technical assessments comparing renewable and other power technologies, have recognized that solar may be the best candidate for remote applications [10].

A significant issue with solar PV is the uncertain, time-phased nature of this resource, which is only available during daylight hours and is effected by cloudy or inclement weather and dust [17]. This is similar to other renewable energy sources (e.g. wind), which are also impacted by atmospheric conditions [56]. To overcome these difficulties and to ensure a reliable supply of energy, RES designers utilize energy storage of various types. Batteries, including lead acid and lithium-ion, are the most common choice; however, many others exist including electrolyzing hydrogen, pumped-hydro storage, flywheels, flow-batteries, supercapacitors, and other developing technologies [57].

Designers of RES face the challenging task of selecting PV array and energy storage sizes to meet operational requirements at the lowest cost. Inherent tradeoffs between cost, performance, and other variables result in different system size solutions depending on the location, load demand, and desired configuration. Existing studies typically design RES to optimize for cost, reliability, and occasionally environmental impact; however, prior work has largely ignored the logistics challenges of accessing, transporting, and installing RES. For RES installation at remote sites, these logistics concerns are not negligible. Accordingly, there is a need for a RES optimization model capable of selecting the optimal solution based on objectives specific to remote and isolated locations.

Therefore, the purpose of this paper is to: 1) define the specific characteristics of and requirements for power production and PV RES at remote locations; 2) explore literature in RES optimization to determine frequently used strategies and variables to optimize; and 3) present a logistics-based multi-criteria model for PV RES optimization based on system weight, volume, and land area. The performance of the developed optimization model is analyzed using three case studies designed to demonstrate the model's unique capability to optimize design configuration based on the local climate, power demand, site lifespans, and logistics requirements. For these scenarios, the competitiveness of these optimized solar RES and hybrid solar RES is measured against the time-dependent cost and logistics burden of traditional diesel generators to demonstrate the value of RES power generation for remote and isolated locations.

Systematic Review of Recent RES Optimization Research

The problem of renewable energy system (RES) selection and optimization is not new and numerous papers exist detailing various optimization methods and key variables selected. However, the optimization variables traditionally selected are cost, reliability and/or environmental impact, with little emphasis given to weight, volume, required land area, or other logistics concerns vital to RES applications at remote locations. To further explore PV RES optimization and these concerns, the following research questions were proposed:

1) How do RES designers and engineers optimize their designs?
    a. What optimization methods do they use?
    b. What are the primary variables optimized?
2) Are there journal articles in the literature of PV RES that consider optimizing logistics variables for use at remote or isolated locations?

To provide an initial answer to these questions and outline the basic research of the field, several review articles on RES optimizations were examined. These reviews demonstrate the most common methods and goals of optimization are cost, reliability, and environmental impact. By analyzing many solar and wind RES optimization examples, Khare et. al. (2016) showed that cost—in terms of net present value or lifecycle cost—and reliability—measured as the loss of power supply probability (LPSP)—were the only optimization objectives utilized [30]. Another review demonstrated that the indicators examined can be divided into reliability, economic, environment, and social criteria categories [31]. Similarly, Guo et. al. (2018) showed that economic and reliability objectives dominate RES optimization [32]. Table 4.1 summarizes the optimization variables considered in the papers examined by these reviews.

Table 4.1: Summary of RES Optimization Reviews

Review Article	Primary Optimization Variables	Logistics Considerations	Ref.
Khare et al. (2016)	Techno-Economic (cost-performance)	No logistics variables mentioned.	[30]
Al-Falahi et al. (2017)	Reliability, economic, environmental, and social criteria.	No logistics variables mentioned.	[31]
Guo et al. (2018)	Techno-economic	No logistics variables mentioned.	[32]
Liu et al. (2018)	Techno-economic, environmental	Examines isolated location uniqueness. Logistics not mentioned.	[58]
Dawoud et al. (2018)	Techno-economic, weather-based reliability	No logistics variables mentioned.	[56]
Khan et al. (2018)	Techno-economic (cost-reliability)	No logistics variables mentioned.	[59]
Alsadi and Khatib (2018)	Techno-economic (system cost-reliability)	No logistics variables mentioned.	[60]
Vera et al. (2019)	Techno-economic, environmental, energy storage lifetime	No logistics variables mentioned.	[61]

In order to achieve a wide perspective on recent RES optimization literature, a robust review was conducted. This review utilizes a methodical search method with explicit inclusion and exclusion criteria to discover all relevant work addressing the research questions and present the results following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method [62], [63]. A systematic search was conducted in January 2020 for all relevant journal articles in the field of PV RES optimization in the last two years. The search reviewed 6,000 unique journals using the Scopus tool [64]. The search string utilized in the standard title, abstract, and keywords search included:

- PV RES keywords
- Optimization keywords
- Location stand-alone, remote, or isolated keywords
- Battery or energy storage keywords

- Document type included Journal articles
- Published in the timeframe January 2018 to January 2020.

The inclusion and exclusion criteria included:

1. Must be focused on RES optimization (design and sizing) as opposed to solely operation or control techniques including solar maximum power point tracking or energy dispatching.
2. Must include Photovoltaics (PV) as an energy source.
3. Must be applicable to remote, isolated, or stand-alone locations.
4. Must include energy storage (i.e. batteries); therefore, grid-tied only case studies are excluded.
5. Scale must be greater than a single residence with power > 5 kW as defined by peak demand or system capacity, whichever is larger.

The search revealed a total of 93 articles, which was reduced to 58 based on full paper reviews and application of the inclusion and exclusion criteria. Two full-text articles could not be obtained after pursuing them through three college libraries, two interlibrary-loan applications, and sending requests to the authors. Figure 4.1 shows the systematic review PRISMA diagram explaining the search method [63].

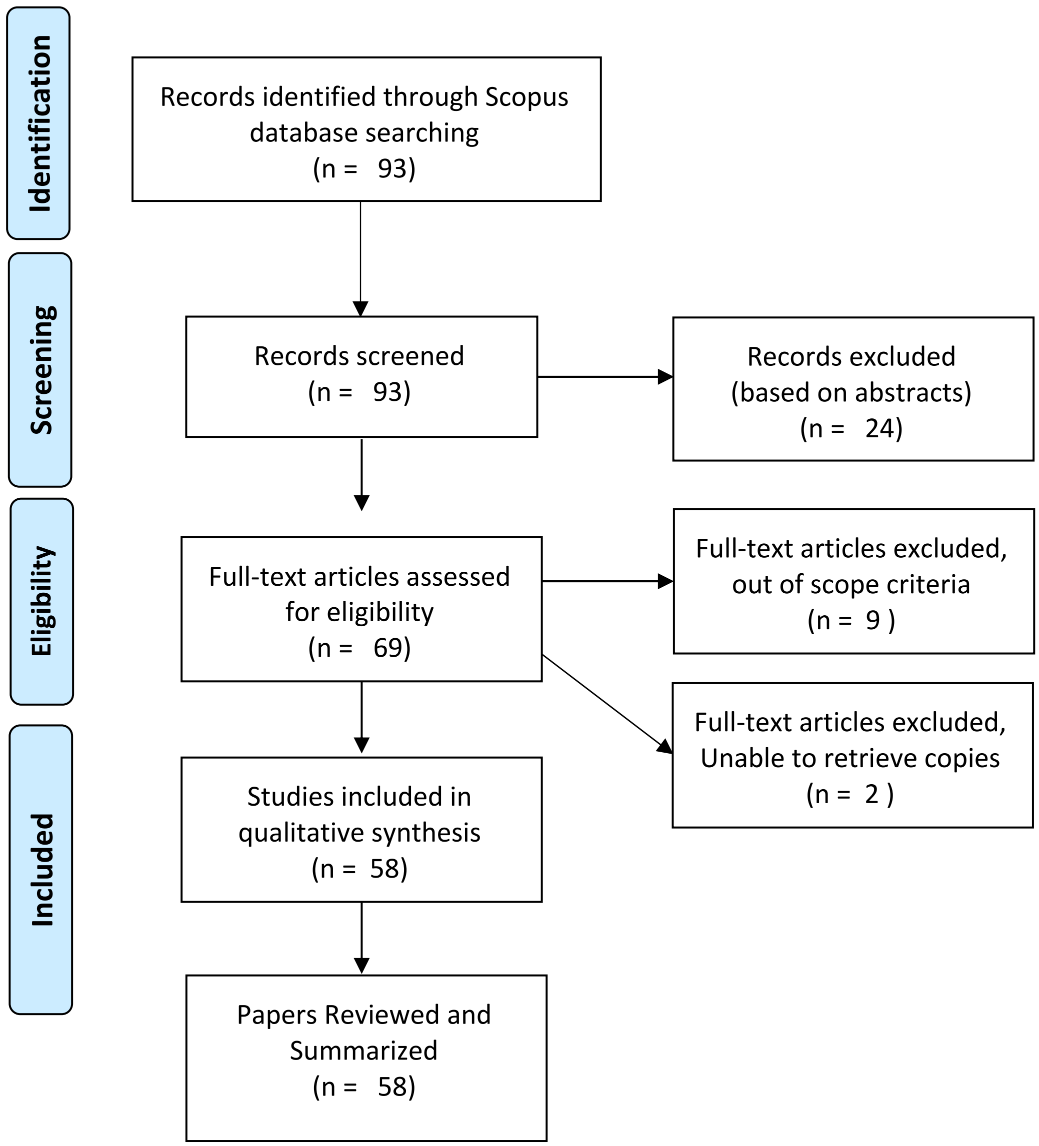


Figure 4.1: PRISMA Flowchart for RES Systematic Review [63]

A number of key data points were collected from these 58 articles, which include the optimization goals, other variables reported (performance indicators), energy sources, type of energy storage selected, hybrid / stand-alone / grid-tied scheme, location, scale, demand load profile, and optimization methods utilized. Selected data on system types and methods are summarized in Table 4.2.

Table 4.2. PV RES Systematic Review Summary of Materials & Methods

Energy Source	Energy Storage	Hybrid/ Stand-alone	Optimization Method		
			HOMER	Meta-Heuristic[1]	Deterministic[2]
PV	Battery	Hybrid	[65]–[68]	[69], [70]	[71]
		Stand-alone			[72], [73]
	VRF/Battery	Hybrid	[74]		
	H_2 Fuel Cell + Battery/ Supercap	Hybrid	[75]		
		Stand-alone	[76], [77]	[46]	[78]
PV, wind	Battery	Hybrid	[79]–[85]	[53], [86]–[94]	[88], [95]–[97]
		Stand-alone		[98]–[101]	[102]
	H_2 Fuel Cell + Battery	Hybrid	[103]		
		Stand-alone		[104]	
	Flywheel/ battery/other	Hybrid		[105]–[108]	[109]
	Batt/Supercap	Stand-alone		[110]	
PV, wind, fuel cell	Battery	Hybrid		[111]	
PV, wind, hydropower	Pumped storage	Hybrid	[112]		
		Stand-alone/ utility-scale		[47], [113], [114]	
PV, hydro	Battery	Hybrid	[115]	[115]	
PV, CSP[3]	Thermal	Utility-scale		[116]	
	Thermal/Batt	Hybrid			[49]
PV, ocean thermal	H_2 Fuel Cell	Stand-alone			[48]

[1]Meta-heuristic methods include various evolutionary and other random search techniques including particle swarm optimizations (PSO), multi-objective PSO (MOPSO), genetic algorithms (GA), weighted superposition attraction (WSA), fuzzy satisfying method, and others.
[2]Deterministic methods include mathematical approaches, mixed integer linear problems (MILP), exhaustive/parametric search, and other techniques.
[3]Concentrating solar (thermal) power

In this analysis, different categories of optimization goals were considered, including economic, environmental, performance (reliability), and technical. The majority of the goals can be considered techno-economic, which attempt to determine an RES size with the lowest cost while maximizing reliability of the power delivered or minimizing the unmet load [46]. There are various specific variables, also called performance indicators, that typically fall into techno-economic or environmental categories. These include net present cost (NPC), cost of energy or lowest cost of energy (COE/LCOE), and loss of power supply probability (LPSP) [47]. Other performance indicators are examined and reported but not utilized as primary optimization objective. These reported variables often included environmental variables such as carbon dioxide (CO_2) and other operational particle emissions [75], [89], [105]. This is also the case with many sensitivity analyses, which consider the effects of changing various criteria, parameters, and variables, including such examples as fuel cost (such as FBCF), interest rates, and system type selection. By grouping the primary optimization categories and reported variables some trends become apparent, as shown in Figure 4.2. First of all, techno-economic factors alone are widely used to optimize most RES, acting as the primary optimization objectives in 27 studies [46], [47], [49], [70]–[72], [77], [82], [83], [89]–[91], [95], [96], [98], [103]–[105], [113], [117]. Solely economic considerations were the focus of 15 papers including [65], [69], [74]–[76], [102], [106]. Environmental and environmental with technical or economic factors were the focus of 11 studies including [86], [88], [90]. Other factors included thermodynamics (due to use of ocean solar thermal) [48] and other technical aspects [87].

Some of these studies utilized renewable resources alone as a pure, stand-alone RES, while others operated in a hybrid RES configuration by utilizing a supplementary non-renewable power source. Of the 58 papers reviewed, 39 used a hybrid RES while 19 used pure RES in a stand-alone configuration. In this study use of multiple renewable sources without a traditional generation source is not considered a hybrid RES. Almost all hybrid RES used diesel generators with the exceptions of the use of bio-fuel generators [79], [112] and fuel cells (for power generation vs. energy storage) [111].

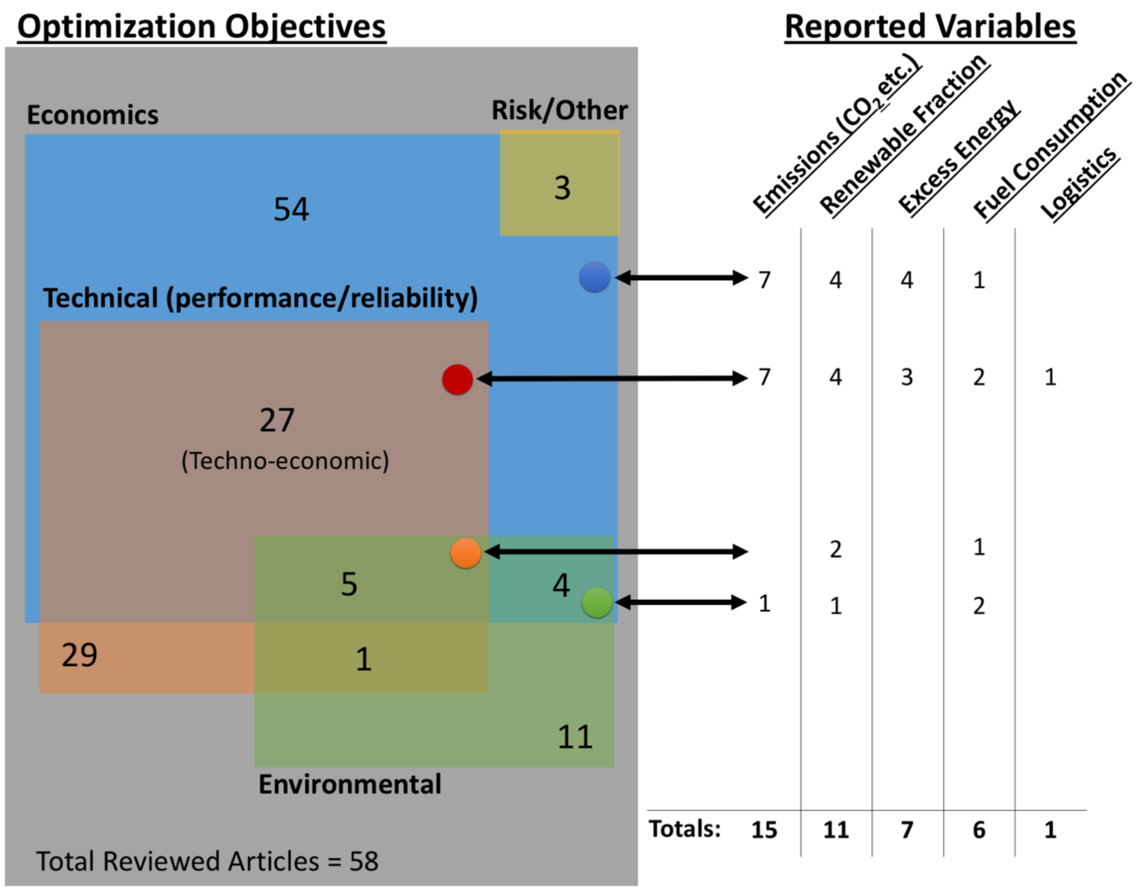


Figure 4.2. Optimization Primary Objectives and Other Variables Reported
Dots and arrows indicate connections of the primary optimization objectives (colored squares) with the reported variables on the right.

From examination of these 58 papers and review articles, it is clear there is a gap in PV RES literature related to logistics. Of these papers, only two examined logistics and did not optimize primarily for logistics factors in those cases. The first is Roth et al., who utilized PV minimum and maximum area constraints in order to ensure panels could fit on a building rooftop [71]. Second, the present authors previously used a techno-economic RES optimization to report the logistics variables of weight and shipping volume of the selected systems, but these factors were not included in their optimization [72].

The paucity of articles dealing with the logistics of installing RES at remote sites illustrates the need to consider these effects, which are highly critical to remote RES applications, where transport weight and volume must be minimized [11]. Additionally, as far as the authors are aware and as confirmed by this review, there are no papers which use logistics as a primary optimization objective and none address logistics to the level of optimizing the RES specifically for weight, volume, and land area of PV required. Accordingly, this paper will explain and demonstrate a multi-objective decision-making model that can be used to balance economic, performance, and logistics factors to design an optimal PV RES for remote and isolated locations.

The remainder of this work is organized as follows: Section 2, Methodology, discusses the proposed RES, its components, and the methods used to gather solar radiation and power demand data. This section also outlines the development of the logistics-cost-performance optimization method. In Section 3, Results and Discussion, the multi-objective optimization is demonstrated using the case of a military contingency operating base. Several tradeoffs are demonstrated in the analysis, including between cost-performance, cost-logistics, and RES component sizes. Two additional case studies are exhibited, one for a remote Caribbean island and one located at a small remote African community, demonstrating differing climates, fuel prices, power demands, and logistics transport concerns in two diverse candidate situations for remote RES. Finally, Section 4, Conclusions, summarizes the uniqueness of this study and the implications from a multi-criteria cost-logistics-performance model for RES planners and engineers.

Methodology

In this research, a set of logistics criteria are developed that can be compared against traditional cost and performance variables through a multi-objective decision analysis (MODA) optimization approach. To test these criteria and this optimization method, a RES simulation was created in MATLAB and tested with three different case studies.

Development of Logistics Criteria for Remote and Isolated RES

Whether the power system is a RES, traditional generator, or a hybrid RES-generator system, it is necessary to minimize both the initial and the lifecycle logistics. When utilizing a RES to achieve more sustainable remote sites, there is a tradeoff between the increased initial logistics cargo that must be transported to install an RES, and the relatively lower initial logistics requirement when using conventional diesel generators [52], [72]. This tradeoff makes optimizing the initial PV RES vital to ensuring that renewable energy can be viable at these locations. The logistics criteria used in this research include the system weight, volume, and PV land area required, which should be minimized in an optimal solution to reduce the logistics burden faced by remote locations. Different RES location requirements will weight each of these factors differently, as shown in the case studies.

As described in Section 1, the majority of RES studies utilize techno-economic optimization variables that simultaneously strive for the lowest cost and highest reliability. Several optimization methods can be used to resolve these two-variable approaches, including programs, such as HOMER, that allow multiple RES architectures to be rapidly considered. However, these programs lack the capability to optimize for three or more variables simultaneously.

To accomplish this multi-objective optimization, an additive linear numeric model will be used to assign scores and weights to each individual variable in order to create a single index [118]. This creates a hierarchy of variables that can now be weighed against one another, illustrated in Figure 4.3.

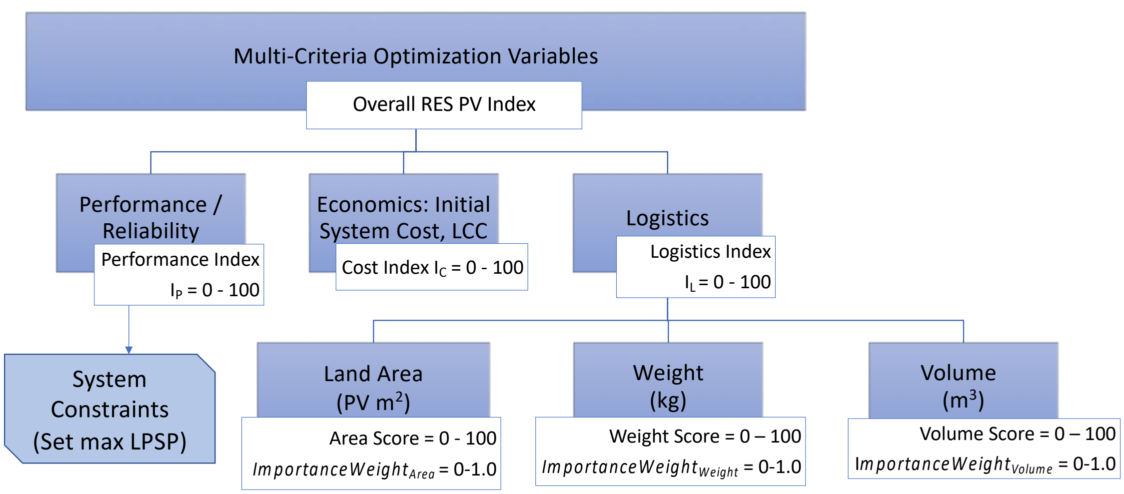


Figure 4.3. Hierarchy of Optimization Variables for RES Logistics

Note that these parameters can be viewed as constraints (such as reliability), direct optimization variables (for example, cost in dollars), or weighted scores. Unitless scores are indexed from 0-100 where 100 is the largest (or heaviest, most costly, etc.) and 0 the smallest value expected. The equation used to calculate the scores or indexes is as follows (adapted from [118]):

$$Score\ (x) = 100\ (x - MinValue)/(MaxValue - MinValue) \tag{4.1}$$

Where:

x = value of variable considered
$MinValue$ = minimum value expected of variable type
$MaxValue$ = maximum value expected of variable type

The minimum and maximum expected values are chosen from the extents of the RES optimization search range as discussed later. This method allows easy comparison between variables of different units and scales. For example, system packed volume, weight, and land area required all have incompatible units. These can be combined by multiplying by weighted factors (which sum to 1) and adding to create an overall Logistics Index that can then be weighed against techno-economic parameters, which will also range from 0-100, as shown in Equation (4.2).

$$\begin{aligned} Logistics\ Index \\ &= ImportanceWeight_{PVarea} * PVareaScore \\ &+ \ ImportanceWeight_{Volume} * VolumeScore \\ &+ \ ImportanceWeight_{weight} * WeightScore \end{aligned} \tag{4.2}$$

An overarching PV RES Index of suitability can also be created in a similar fashion adding weighted performance (reliability) and cost scores into a single weighted index that can be globally minimized. Either of these indexes can then be used for optimization or to illustrate tradeoffs in RES sizing and design selection.

In addition to these tradeoffs, constraints can also be imposed on the RES optimization. The most common are performance or reliability demands such as setting a maximum LPSP, which is the portion of time that energy consumers can expect to be without power. Combining multi-objective tradeoffs will allow optimization of a system that meets set performance requirements while optimizing for lowest cost, most-efficient logistics, and lowest environmental impact.

Typical PV RES System Components and Modeling

PV renewable energy systems are composed of a renewable power source(s), energy storage, AC-DC inverters, and control systems. In this paper, the renewable power source is constrained to PV due to its advantages in remote location applications, as identified in the introduction. A typical PV-energy storage RES is depicted in Figure 4.4.

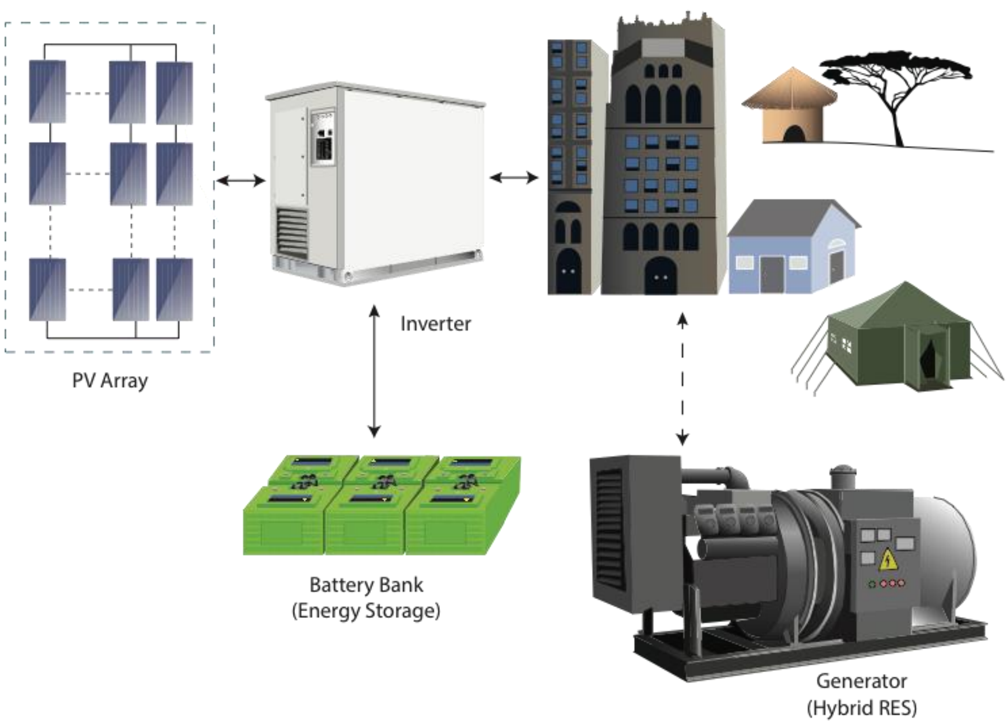


Figure 4.4. Illustration of the Proposed PV RES and Hybrid RES

Photovoltaic Power Modeling and Selection

The power output from a solar PV array can be modeled by equations (4.3)-(4.4) from [119]. Equations (4.3) and (4.4) allow for determining the power in watts produced by a PV module based upon its rated power, solar insolation received, and the ambient temperature. In these equations, the parameters are determined from standard test conditions (STC) which are AM 1.5G sunlight, 1,000 W/m^2 irradiance, and 25 °C.

$$P_{PV}(t) = P_{rated}\left(\frac{G(t)}{G_{STC}} - \gamma\ [T_{cell}(t) - T_{STC}]\right) * \eta_{sys} \tag{4.3}$$

Where:

$G(t)$ = current solar irradiation (W/m^2)
G_{STC} = solar irradiation at STC = 1,000 W/m^2
T_{STC} = temperature at STC (25° C)
η_{sys} = Combined efficiency of power controller, wires, and inverter
γ = temperature coefficient of the PV module (% power loss/°C)
$T_{cell}(t)$ = operating temperature of PV module;

And:

$$T_{cell}(t) = T_{ambient}(t) + \frac{NOCT - 20\ ℃}{800\ W/m^2} G(t) \tag{4.4}$$

Where:

$NOCT$ = Nominal operating cell temperature (°C)
$800\ W/m^2$ = Nominal irradiance .

Solar cell temperature effects can also be accounted for by applying a fixed temperature efficiency derating, instead of the time-dependent model from equations (4.3)-(4.4). Based on three different estimates of average summer ambient temperatures, PV module temperature coefficients and nominal operating temperatures, and utilizing equation (4.4), a 6 - 11% loss was calculated [40], [41], [119]. The present study uses an estimate of 10% for the temperature derating. Applying this factor simplifies equation (4.3) above to:

$$P(t) = PVRatedP * G(t) * \left(1 - TempLoss_{(\%)}\right) * \left(1 - solarSysLoss_{(\%)}\right) \tag{4.5}$$

Where:

P(t) = output of the solar array in kW
G(t) = current solar irradiation in kW/m^2
$PVRatedP$ = rated (max) power of array in kW
$TempLoss_{(\%)}$ = temperature adjustment and derating factor = 10%
$solarSysLoss_{(\%)}$ = total electrical system losses.

Selection of the PV module type is a critical aspect of optimizing any remote PV system application and impacts the economic and logistics of the RES. As demonstrated in Chapter 3, RES designers can select various PV technologies and manufactures which will affect cost-efficiency-logistics tradeoffs. This chapter demonstrated that low-cost monocrystalline PERC modules are potentially the best candidates for many remote and will be selected here as a base case. Table 4.3 displays the base case model parameters. Time-based PV degradation is assumed to be negligible in this model. Note that due to a wide variance in BOS components, their weights and volumes are ignored for the purpose of this study. Furthermore, transport cost of the RES is assumed to be included in the purchase cost of the RES.

Table 4.3. PV Module Parameters

Parameter	Value / Unit	Reference
PV Module	MSE PERC 72 Mono-crystalline	Mission Solar
PV Module Cost	$0.57/W	Dec 2019 Pricing [40]
System Electrical Losses	15%	Wagner et al. [17]
PV Panel Efficiency	18.89%	Datasheet
PV Panel Thickness	40 mm (1.6 in)	Datasheet
PV Array Packed Size	0.21 m^3 / kW	Datasheet
PV Array Weight	0.058 kg/W	Datasheet
Balance-of-System Costs	$0.35/W	Woodhouse et al. [120]
Inverter Cost	$0.15/W	Woodhouse et al. [120]
Installation Cost	$0.20/W	Woodhouse et al. [120]
Total PV Array Cost	$1.27/W	-

Energy Storage and Modeling

In order to provide power during hours of darkness or insufficient solar insolation, it is necessary to utilize energy storage. Several studies have considered available options and the cost, performance, and logistics parameters, similar to Chapter 3's analysis of PV types but for the energy storage RES component [57], [121], [122]. Key to analyzing these solutions are the parameters of peak power output, time of storage, cost per energy stored ($/kWh), energy volume density, and energy weight density. Table 4.4 displays these specifications for several different current and emerging energy storage system technologies.

Table 4.4. Energy Storage Technology Specifications (adapted from [57], [121])

Technology	Cost ($/kWh)	Energy density (Wh/kg)	Volume Density (Wh/L)	Power density (W/kg)	Volume Density (W/L)	Power rating (max)	Storage time (max)	Life-time (yrs)	Round -trip eff (%)	Tech Maturity
Flywheel	1000–5000	10–30	20–80	400–1500	1000–2000	250 kW	min	15	85-95	Comm
Pumped-hydro	5–100	0.5–1.5	0.5–1.5	-	-	MW	months	40–60	65-87	Mature
CAES	2-50	30–60	3–6			MW	months	20-60	50-89	Developed
Hydrogen FC	10,000/kW	800–10,000	500–3000	500+	600	MW	weeks	5–15	20-45	Comm
Super-capacitor	300–2000	2.5–15	40,000-120,000	500–5000	10-20	300 kW	hour	Indef.	90-95	Developed
Batteries:										
NaS	300–500	150–240	150–250	150–230	120-160	MW	hour	10–15	80-90	Comm
Zn-Air	10–60	150–3000	500–10,000	100	-	10 kW	months	N/A	50-55	Demo
Li-ion	600–2500	75–200	200–500	500–2000	1,300-10,000	MW	days	5 - 15	85-98	Comm
Lead Acid	255	30 - 50	30 - 80	75-300	-	MW	days	3 - 20	70 - 90	Comm
VRF (Flow)	150–1000	10–30	20 - 70	-	0.5 - 2	MW	months	5–10	60 - 85	Demo
SNG (Nat Gas)	N/A	-	1800	-	0.2 - 2	MW	Indef.	30	25-50%	Experiment

CAES: Compressed air energy storage, FC: Fuel Cell, VRF: Vanadium Redox Flow battery, SNG: Synthetic natural gas.

Figure 4.5 illustrates the types of energy storage available by the power rating and capacity (discharge time) with colors showing the round trip efficiency. This figure demonstrates the narrow range that can be used to provide long-term power for RES sites that are operating in the 100 kW – 10 MW capacity ranges, typical of some of the locations previously discussed. These systems will require 2-3 days of energy storage to account for weather events, which gives most RES at remote locations the choice between conventional batteries, flow batteries, and hydrogen fuel cell storage. Hydrogen storage has a very low efficiency compared with batteries which are now reaching efficiencies of 95% or better [121].

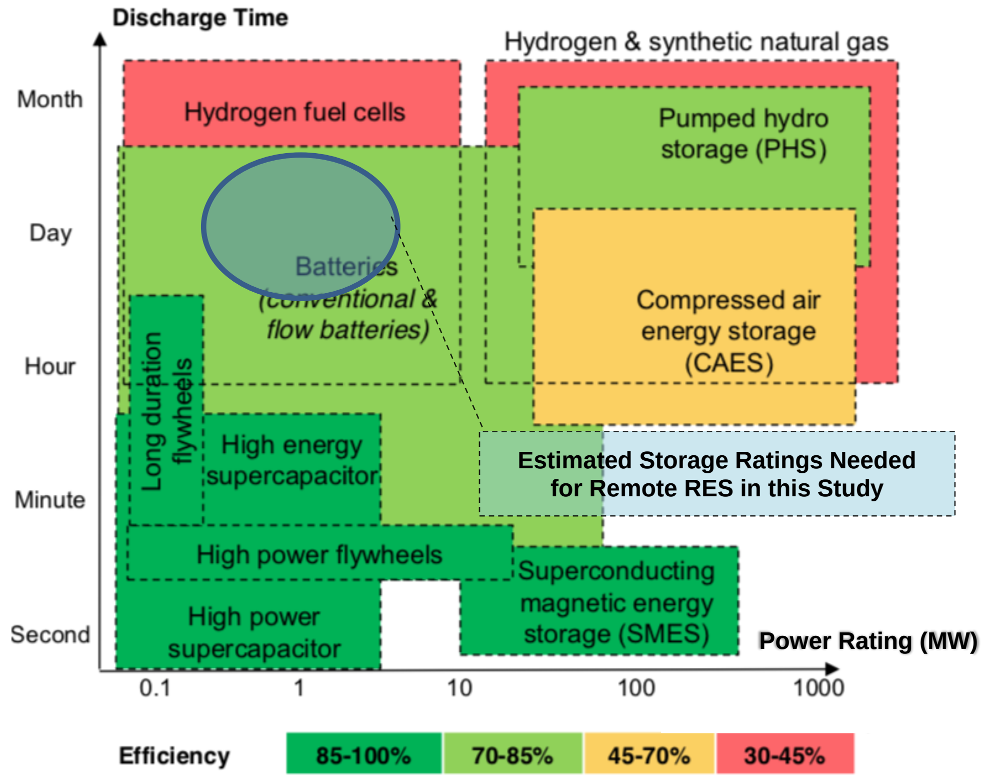


Figure 4.5. Energy Storage Options: Power (MW), Storage Time, and Efficiency. The recommended parameters for remote RES in this study are highlighted in blue [121].

Among the numerous energy storage solutions available to RES planners, Lithium-ion batteries appear to be the most effective strategy for remote systems and are rapidly becoming dominant, being used in several recent studies [65], [69], [72], [76], [86], [95], [113] as well as the majority of new installations, and make up 35% of overall stored battery energy [57].

For the purpose of this study, lithium-ion batteries will be used as the base case. RES system planners can select alternative choice based on the needs of each scenario. Utilizing Lithium-ion batteries also allows for a much larger maximum depth-of-discharge, or minimum allowable state-of-charge (SOC). To model the lithium ion battery equation (4.6) will be used from [72]. Note that the battery losses are only applied on charging in the MATLAB simulation since they are round trip losses.

$$BattCharge_{(kWh)}(t+1) = BattCharge(t)_{kWh} \pm (1 - battLoss_{\%}) * ExcessPower_{(kW)}(t+1) * dt \tag{4.6}$$

Where:

$ExcessPower_{(kW)}(t+1)$ = PV supplied power – load demand (kW)
$battLoss_{\%}$ = battery round trip storage losses

Parameters for the selected, base-case lithium ion battery banks are shown in Table 4.5. Note that energy storage BOS costs are included in these parameters, however energy storage BOS weights/volumes are ignored in this study. Furthermore, the transport cost is assumed to be included in the battery system installed cost.

Table 4.5. Lithium Battery Performance Parameters

Parameter	Value / Unit	Reference
Battery System Installed Cost	\$310 / kWh	Diorio et al. [27]
Battery Storage Losses	8%	Diorio et al. [27]
Weight of Batteries	10 kg / kWh	Diorio et al. [27]
Volume of Batteries	0.0287 m^3 / kWh	Diorio et al. [27]
Battery Maximum Depth of Discharge	10% Rated Capacity	Das et al. [65]

Model Generator for Conventional Comparison and Hybrid RES

For this study, an 800 kW diesel generator is used for comparison against the new PV RES as well as selected to supply alternate power in a hybrid RES configuration. This generator is sized to meet the peak demand modeled. Because the nature of this study is for remote and isolated locations, the United States Air Force (USAF) Basic Expeditionary Airfield Resources (BEAR) Power Unit generator, also known as a BPU, was selected. This generator is used at remote locations worldwide to supply long-term prime power in a wide range of environments and is capable of air transport [24]. The parameters for the generator are shown in Table 4.6.

Table 4.6. Generator Performance Parameters

Parameter	Value / Unit	Reference
Generator Cost	$587K	USAF [24]
Fuel Consumption / Generator Efficiency	55 gal / hr (750 kW) = 3.59 kWh/L	USAF [25]
Fully Burdened Cost of Fuel (FBCF)	$4.69/L ($17.74/gal)	US GAO [3]
Weight of Generator	18,651 kg (41,118 lbs)	USAF [24]
Weight of Fuel (JP-8)	0.81 kg/L (6.8 lbs/gal)	-

To model the fuel consumption of this generator, a linear function for fuel use as a function of power demand was created using fuel curves for similar generators [19], [25]. This function is shown in Figure 4.6. Note that the y-intercept on the fuel curve at 0 kW demand accounts for the efficiency loss in generators when run at less than full load.

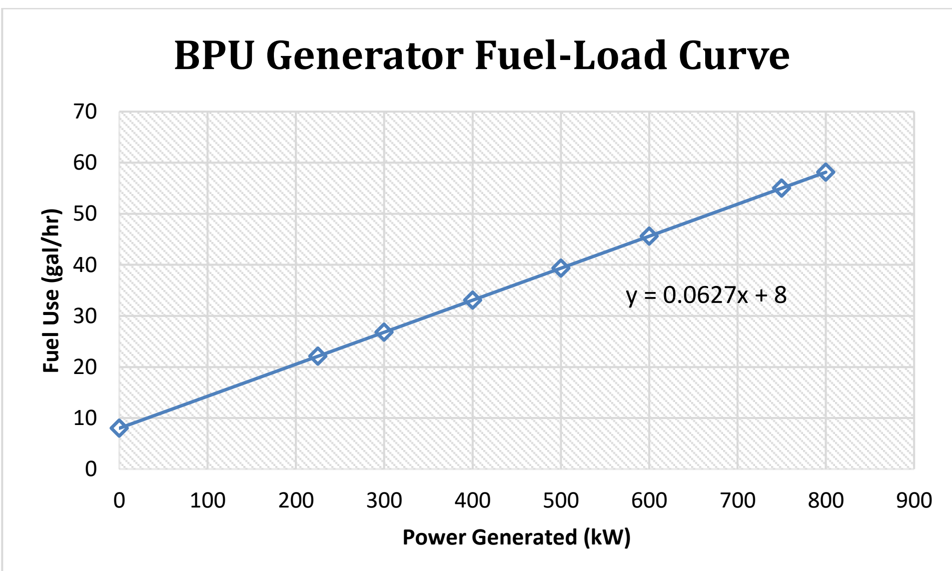


Figure 4.6. Generator Fuel Use (gal/hr) Curve based upon Power Demand (kW)

In the model, the minimum operating load for the generator is assumed to be 225 kW as its power demand range is limited [19]. Maintenance costs for the generator and PV system will be ignored for the purpose of this study, however it should be noted that generators require regular preventative maintenance that requires them to be taken offline every 400 operating hours for 6 man-hours of overhaul. This results in an LPSP of around 1% for conventional diesel generation. To overcome this, traditionally multiple backup generators must be purchased, maintained, connected and made available to supply the load as required [19]. The additional cost of these backups is not accounted for in this study, but is an additional advantage of RES.

Modeling Load Demand

For each scenario, annual power load profiles containing hourly power demands in kW are created using two different models. For the military contingency base examples, a load profile was used that assumes a constant operational load with 5% variability and an additional temperature-dependent heating and cooling load for a notional military camp in Afghanistan [19]. Figure 4.7 shows the demand profile for the Afghanistan military base scenario.

For the other two locations, a method was developed to utilize available U.S. Department of Energy residential and commercial hourly power data for U.S. cities and towns [123]. This method utilized a synthesis of residential and commercial building data to model the loads of a generic city at a specific location. Because the data is only available for domestic U.S. locations, the closest similar location based on the Köppen-

Geiger climate classification system will be used [124]. This method is very similar to that utilized by the commercial HOMER program [125].

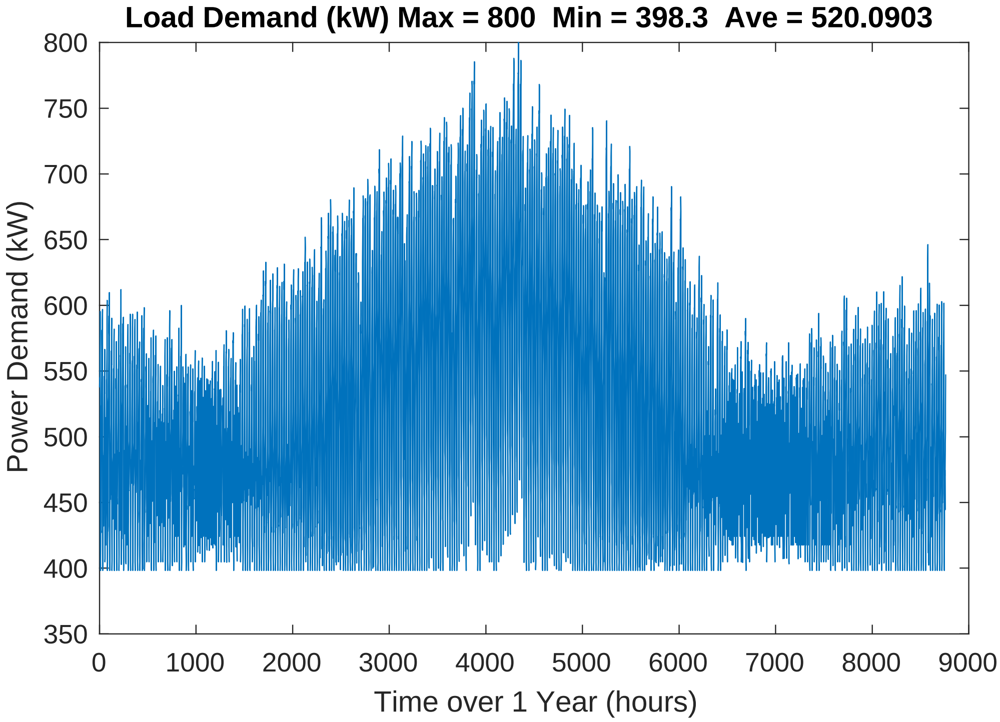


Figure 4.7. Hourly Load Demand for Afghanistan Military Base Over 1 Year

Modeling Hourly Solar Irradiation

Solar irradiation data for most locations on earth can be modeled through National Air and Space Administration's (NASA) Modern-Era Retrospective analysis for Research and Applications (MERRA) satellite weather data [126]. Using this data, an estimated solar irradiance for a specific tilt of an array was calculated via methods developed by Pfenninger and Staffell (2016), taking into account a fixed latitude-tilt array and weather data for the area [127]. Figure 4.8 shows the hourly latitude-tilt solar irradiation as measured in kW/m^2 for the Marjah, Afghanistan location.

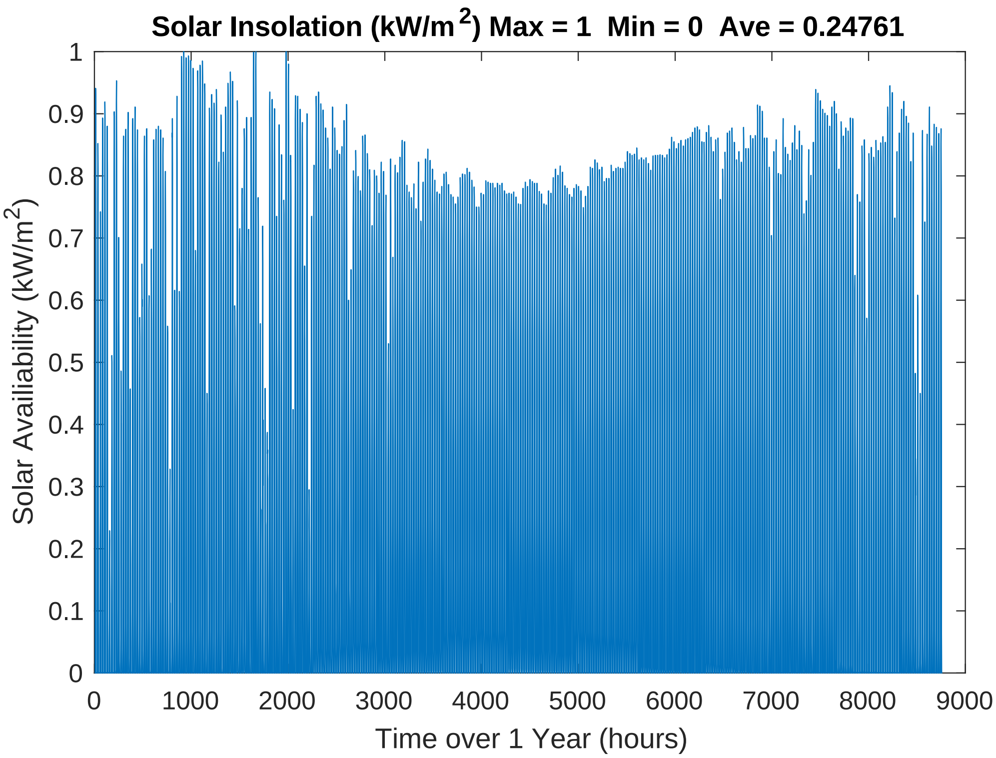


Figure 4.8. Hourly Fixed-tilt Solar Insolation Data for one year at Marjah, Afghanistan

From this figure, it appears abnormal that the peak irradiance can be lower during the summer months, especially when compared to Figure 2.1 from Chapter 2 showing solar data for the same location. However, this change is due to the fixed latitude tilt of the array in this updated model which improves PV power output during the winter months. By tilting the fixed array towards the equator at an angle from horizontal equal to the latitude of the location, a near-balanced power output can be obtained, minimizing seasonal variation. Nevertheless, during the cloudier winter months, it is clear there are longer periods of less sunlight, requiring significant energy storage to meet the demand during these periods of inclement weather.

MATLAB Simulation and Modeling

To model a RES as well as a hybrid RES-generator system, a MATLAB computer simulation was developed. This simulation uses a year of demand and solar insolation data to optimize the system sizing for variables of cost, performance (LPSP), and logistics. This simulation is built around an objective function that operates using the following equations:

$$Objective\ function = f\left(PVsize_{kW}, Battery\ Size_{(kWh)}\right) \rightarrow \text{minimize}\ [System\ Cost, Hours\ Not\ Met, Logistics\ Index] \quad (4.7)$$

Where:

$PVsize_{kW}$ = Size of PV Array in Rated kW
$Battery\ Size_{(kWh)}$ = Size of Energy (battery) storage in kWh
System Cost = RES Initial Cost or Hybrid RES total cost.

And:

$$Hours\ Not\ Met = \sum_{t=0}^{8760\ hrs} \left[BattCharge_{(kWh)}(t) \leq BattDepthOfDischarge_{(kWh)}\right] \quad (4.8)$$

Where:

$BattDepthOfDischarge_{(kWh)}$ = Minimum battery depth of discharge in kWh

Note that the reliability performance factor, which can be considered the probability of power supply loss, is equivalent to the percent of hours in a year when the demand is not met: LPSP = $Hours\ Not\ Met/8760$ (%). The objective function in Equation (4.7) analyzes a year of hourly solar and demand data for a given rated size (kW) of solar array and a given energy storage size in kWh and provides the system costs, hours-not-met (failure criteria), and the Logistics Index value for the RES system. This allows the MATLAB program to utlize an exhaustive search method through all possible design combinations to determine the optimal solution, depending on the desired requirements of RES planners. Because this is a three variable multi-objective function, it is unlikely there will be single optimum point. Instead a Pareto front, Pareto surface, or series of Pareto fronts will be created where the goal is to select the optimum non-dominated tradeoff, such that no other solution is better on any variable, given that the others are fixed.

The system size search range is determined by the minimum estimated rated PV size that could meet the load. This is determined as *PV Size Estimate = average load demand (kW)/capacity factor*, where the capacity factor is the average PV insolation received as a percent of STC (1kW/m^2). This size estimate is then tripled to determine the maximum rated PV size to search. For battery sizes, through inspection and numerous models, 0 - 50 MWh was specified as an appropriate range for most RES scenarios [72].

Results and Discussion

To demonstrate the function of the multi-objective RES logistics optimization, the Afghanistan military contingency base scenario will be used. This scenario is then compared with the two other case studies included in this paper, a Caribbean island without energy reserves and a remote African community with no current access to power.

Logistics Scoring Models

Operating the MATLAB RES simulation over one year for all possible system size configurations, the values of the Logistics Index and its component scores for weight, volume, and PV array area can be determined. Figure 4.9 and

Figure 4.10 demonstrate the expected values of each parameter based on system size. Note that PV Land Area score is only based on the PV array size, since batteries require minimal area compared with solar arrays. The Logistics Index shown here is based on an equal weighting (33% each) of volume, weight, and area. These index importance weights can be changed based on RES design requirements for the scenario, as demonstrated in the case studies. These figures illustrate the evident fact that the most compact and lightest PV system possible is the RES with the smallest PV and battery size; however, this system could never meet the load demand. Therefore, constraints such as performance-reliability (i.e. LPSP) must be included in the optimization.

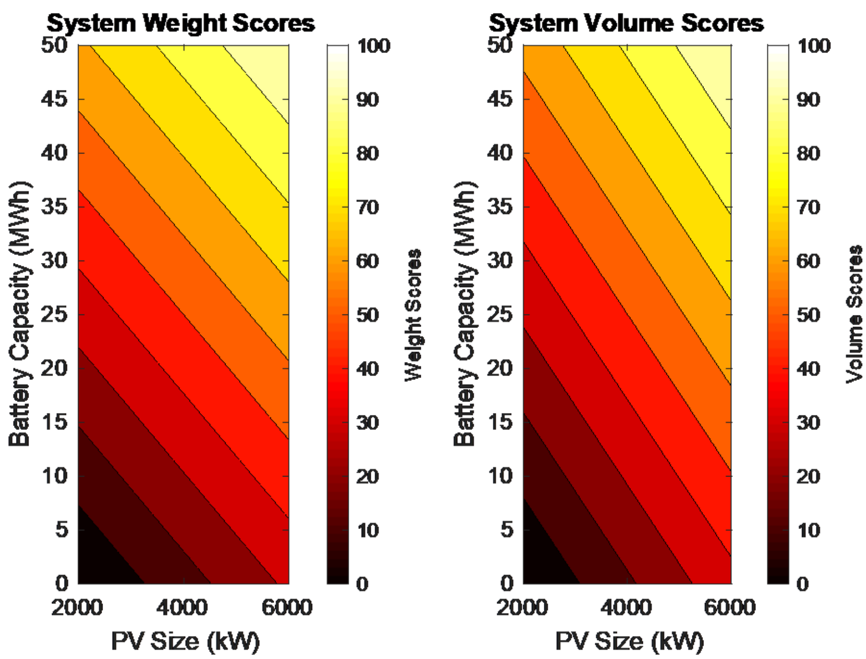


Figure 4.9. RES Weight and Volume Scores 0-100 based on PV & battery sizes

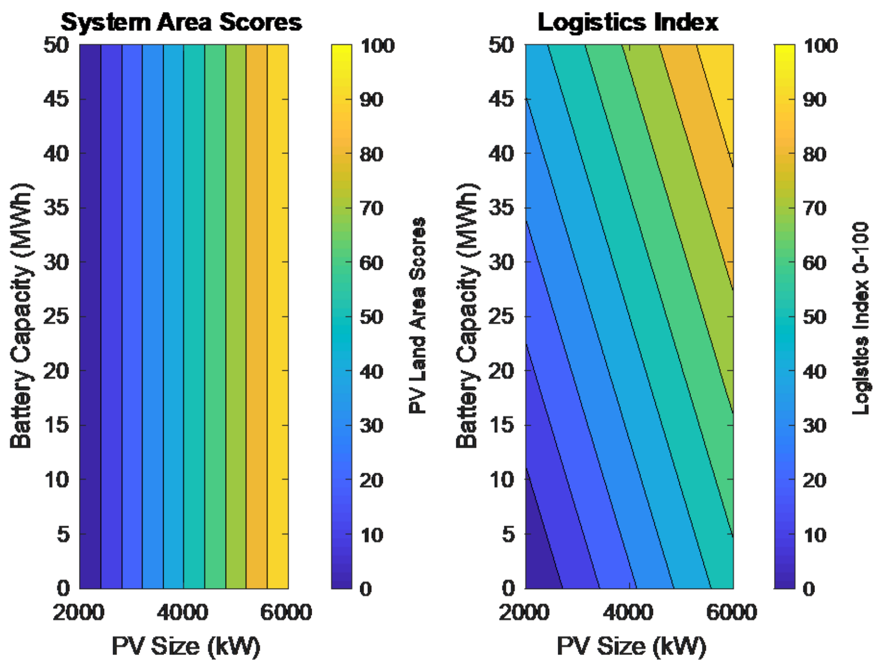


Figure 4.10. RES PV Area Scores and Overall Logistics Index

Optimizing PV RES for Minimum Cost and Logistics

If a desired system power reliability is known, this constraint can be applied to enable optimization on a number of other variables. In this case, to model the preventative maintenance requirements of traditional generators, a maximum LPSP of 1% is chosen. Applying this constraint allows the MATLAB simulation to optimize another key objective variable while attaining 99% reliability or better in the performance variable. To accomplish this, the MATLAB model simulates a year of solar data for each possible system size and then the optimal sizes are scored to minimize a single variable. Figure 4.11 shows the system costs and hours of failure plotted for various system sizes. Overlaying this data is a Pareto-front curve that illustrates the system size solutions meeting a LPSP of less than 1% (87.6 hours/year). In the right subplot, the upper right quadrant has 100% reliability (LPSP = 0%) and decreases to nearly 50% power loss for the smallest PV size and no battery (approximately 4,000 hours-not-met per year).

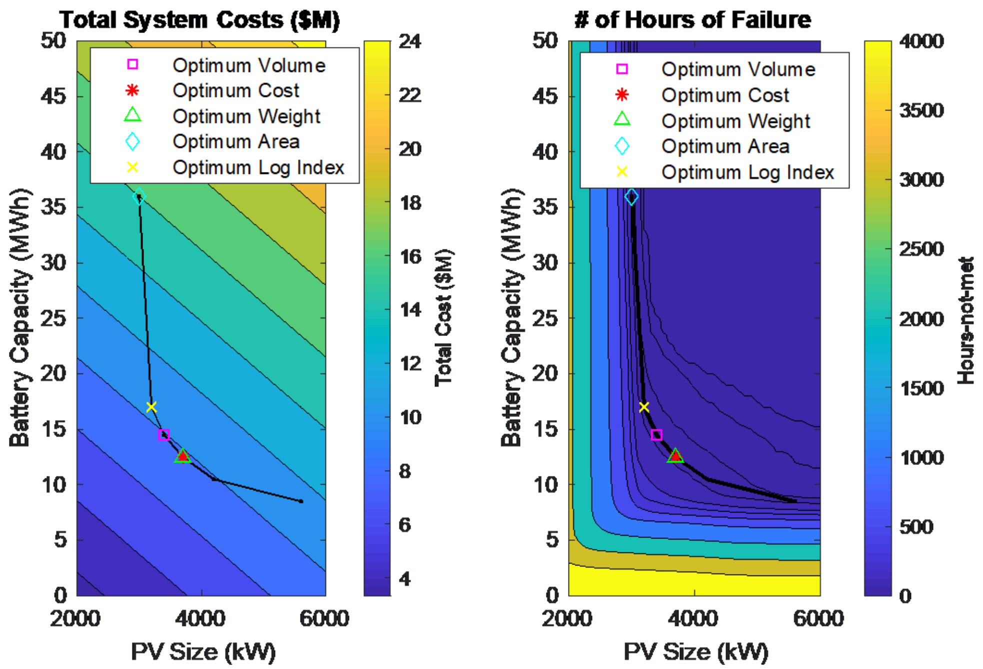


Figure 4.11. RES System Costs and Failure Hours vs. PV and battery sizes. Optimum points are plotted for cost, weight, volume, area, and Logistics Index. The LPSP=1% Pareto curve is plotted as a dark line.

Figure 4.12 shows two logistics criteria, system transport (packed) volume and system weight, shown for each RES PV and battery storage size. These figures illustrate that the optimal system sizes are different based on the chosen primary optimization variable. At one extreme, for optimal area, the smallest PV and largest battery are used. Conversely, for optimal weight a large PV array and smaller battery should be used due to the heavy mass of batteries. Note that due to the high cost of batteries, the cost-optimum system very nearly coincides with the weight-optimized RES. For optimum volume and logistics index, moderate points are selected with medium amounts of array and batteries. With the notable exception of minimum area, all of these optimal RES sizes have comparable total initial costs.

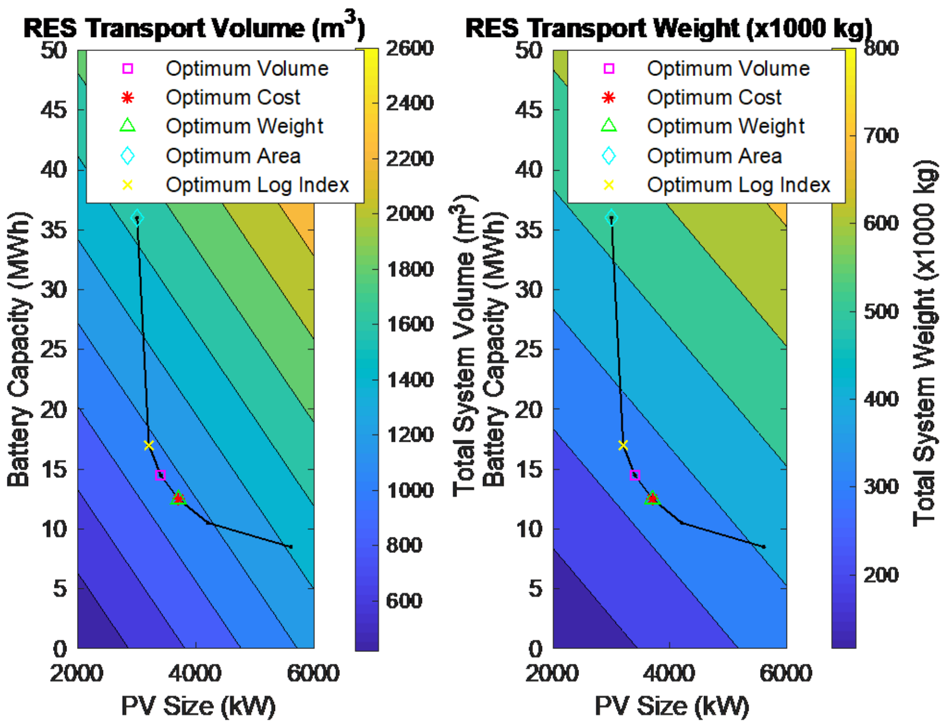


Figure 4.12. RES Weight and Volume vs. PV and battery sizes.
Optimum points are shown for cost, weight, volume, area, and Logistics Index. The LPSP=1% Pareto curve is plotted as a dark line.

Utilizing this method, RES designers can select the optimal configuration given a primary optimization objective and a reliability-performance constraint (LPSP). For RES engineers seeking to optimize a number of variables such as weight and volume simultaneously, the Logistics Index can be used to balance these factors. The choices of importance weights for volume, weight, and PV area will determine the extent each of these variables are minimized.

Most often, RES planners desire the most economical system at the minimized cost point. Should the goal be to minimize both logistics and cost at a given reliability constraint, a tradeoff decision will have to be made between them. Figure 4.13 illustrates all potential system solutions by comparing the Logistics Index with RES initial cost at a maximum LPSP of 1%. Figure 4.14 shows the Cost-Logistics Pareto front for all system solutions with LPSP = 1%, which shows only the much smaller, non-dominated range of solutions from Figure 4.13. Outside of these ranges no optimal cost or logistics points exist. This Pareto front illustrates that small changes in system cost can allow flexibility with logistics parameters.

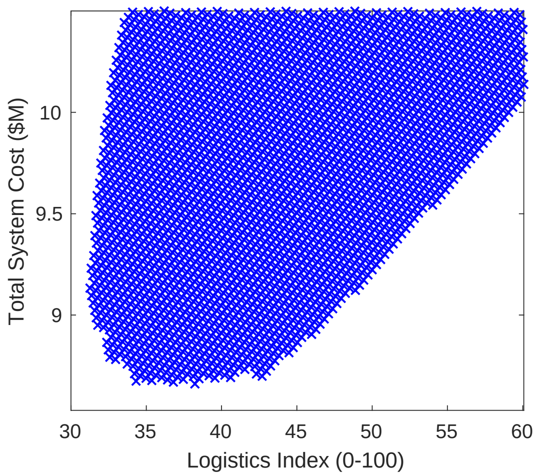


Figure 4.13. Cost v. Logistics Plot of All System Solutions (LPSP <= 1%)

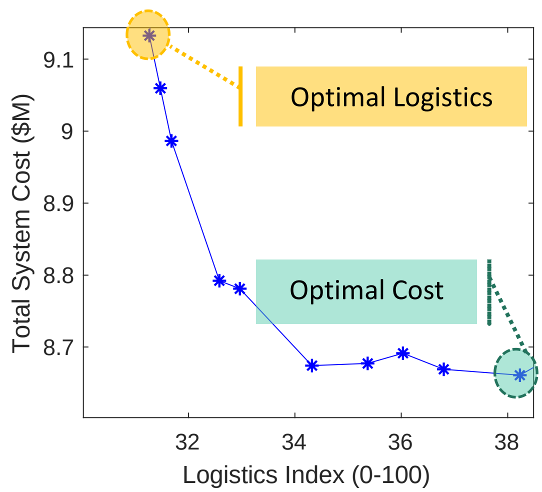


Figure 4.14. Pareto front for Cost-Logistics at LPSP = 1%

Another potential method as described above is to extend the MODA model to include an overall "PV RES Index" for suitability that takes into account the three factors of logistics (Logistics Index), cost ($ millions), and reliability (hours-not-met or LPSP). By weighting all three factors, a balanced system can be created. Figure 4.15 shows this optimization with all factors evenly weighted. The issue with this optimization is there are few scenarios where there is no minimum reliability performance requirement (maximum LPSP). Many power customers including military contingency bases, hospitals in remote areas, or simply commercial buildings, are unlikely to accept time without power greater than a small fraction. The alternative methods above appear to be more effective for most RES planners, where logistics and cost are measured independently, and a constraint of performance can be applied. However, this overall system PV Index could be used in situations where a range of reliability performance is acceptable or where power demands can be deferred for a period of time. One example of this situation includes developing nation communities where no power access is currently available; therefore, no minimum level of reliability is expected. Another example might be electric vehicle charging stations, where users can utilize another location in days of solar energy shortage or charging can be deferred by the system for a period of time.

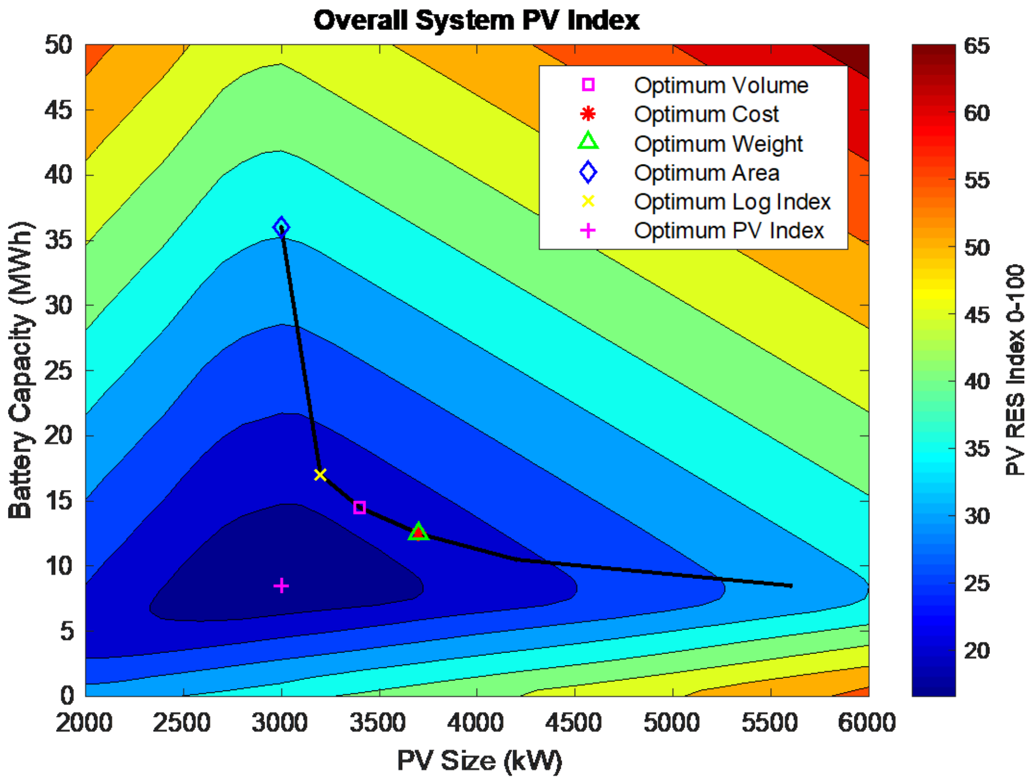


Figure 4.15. Optimization Utilizing Overall PV RES Index.
Performance (LPSP = 1%) Pareto front and points optimized based on individual variables are also shown.

One key variable not optimized as a primary objective but instead used as a constraint in the above cases is the performance reliability of the RES system, measured in LPSP or hours of failure (hours-not-met). To examine various levels of LPSP the optimized minimum cost solutions at each LPSP were found and plotted as shown in Figure 4.16. This figure illustrates the large premium required of RES systems in order to attain 100% reliability (0% LPSP). The cost of a 0% LPSP RES is roughly twice that of a 10% LPSP system. Logistics can be added to this optimization using a 3D plot. This is shown in Figure 4.17 where cost, performance (LPSP), and Logistics Index are compared together. The figure uses a colored surface to visualize the intersection between these three primary variables.

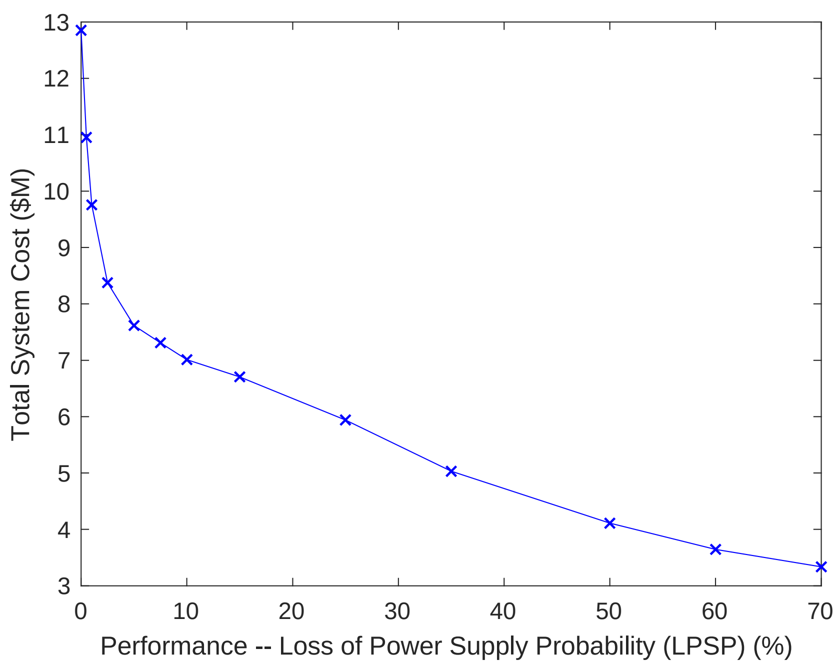


Figure 4.16. RES Initial Cost vs. Performance (LPSP)

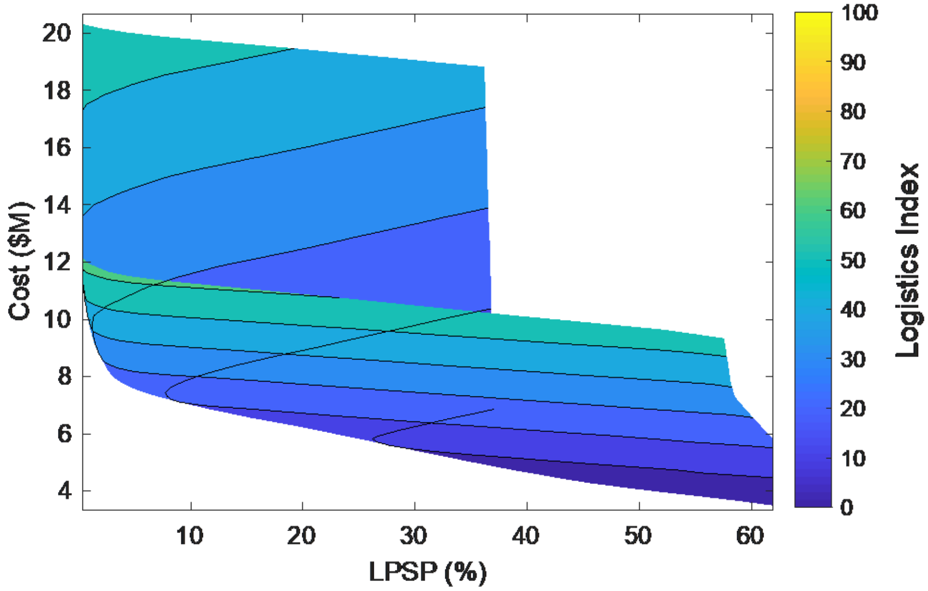


Figure 4.17. Logistics vs. Cost vs. Performance.
Colors denote the Logistic Index for each point.

To make this Cost-Logistics-Performance tradeoff easier to visualize, optimal fronts for three performance levels were plotted (LPSP = 0%, LPSP = 1%, and LPSP = 2%), shown on Figure 4.18.

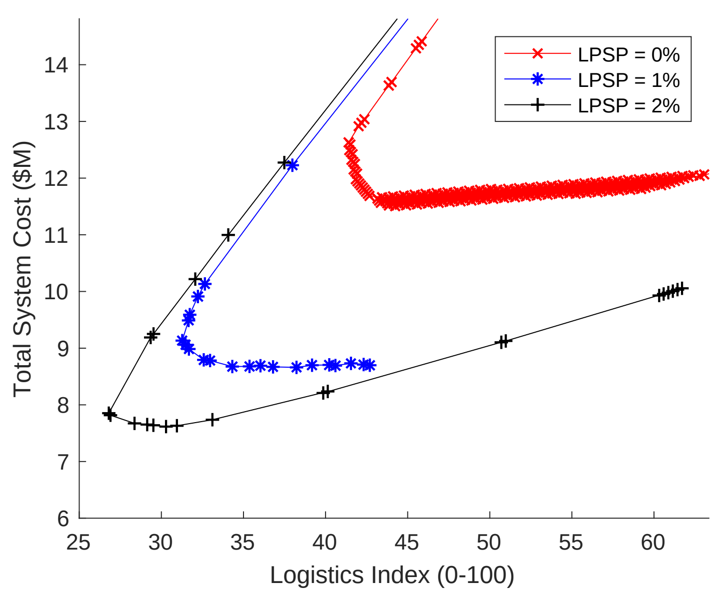


Figure 4.18. Cost-Logistics Curves Plotted for Different Levels of Performance (LPSP)

This demonstrates that as required reliability decreases (and unmet load increases), lower costs and smaller, more efficient logistics for the RES become available.

These figures illustrate the difficulty for pure PV and energy storage RES to possess high reliability at a low initial cost. The high reliability demanded of most forms of electrical power incurs a high initial cost for purchase and installation of the RES components. While initial cost for pure PV RES can be overcome when the lifecycle cost of fuel is considered, another alternative is a hybrid RES, where the required reliability—and therefore size—of the RES can be reduced by utilizing a diesel generator to augment the RES.

Considering Hybrid RES for Minimum Cost and Logistics

A hybrid RES, frequently called HRES, includes a second power generation source to provide power when the renewable system power is insufficient and the energy storage is depleted. In this case, an 800 kW BPU diesel generator will be modeled as discussed previously. By adding the opportunity for HRES to the model, RES planners can have another option versus traditional generators and the RES system proposed here. However, such systems still use traditional fossil fuels and, therefore, will not achieve completely sustainable remote sites.

To model such a hybrid system, during failure hours the demand will be met by the BPU generator and total fuel use recorded. The generator fuel curves are used to determine fuel use based on power demand for each failure hour of the annual simulation. The sum of this fuel use is then used to calculate a hybrid system total cost, which includes the RES cost, BPU purchase price, and fuel cost. The scenario is run for a number of years to determine total costs with a period of five years selected as the base case for this scenario. Figure 4.19 illustrates several possible HRES solutions and portion of the load provided by the diesel generator. This portion is equal to the LPSP (%). The lowest blue line “Optimum Initial RES Cost” shows the pure RES total costs as in

Figure 4.16. The top, green line “Total Cost RES w/Generator” demonstrates the high costs from fuel use that would occur should a generator be run for the entire portion that the load is not provided by the RES (i.e. the LPSP). The center red line “Opt. Hybrid RES Total Cost” shows the optimal cost points for an ideal hybrid system with generator operating at the LPSP or less. On this line costs decrease up to the point where decreasing PV RES size and relying on the generator results in a higher total cost; therefore, the optimization model choses to keep a higher portion of RES in the system. At approximately 5% generator energy production, the total hybrid system cost reaches a minimum, optimized configuration. Figure 4.20 exhibits similar results for 20 years of operation, but the optimized hybrid RES size is reached only 2% generator duty factor.

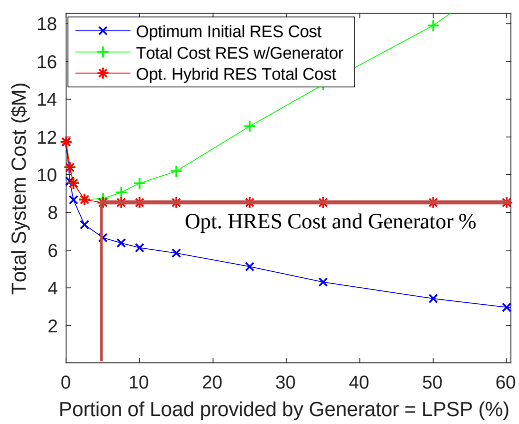


Figure 4.19. Pure RES, Hybrid RES, and Optimized Hybrid RES Compared (Scenario = 5 years)

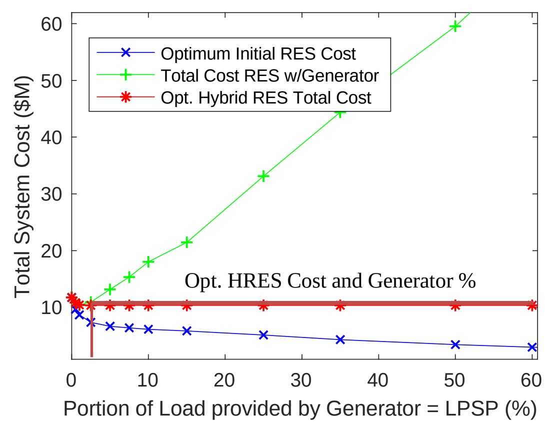


Figure 4.20. Pure RES, Hybrid RES, and Optimized Hybrid RES Compared (Scenario = 20 years)

RES engineers and designers will have to decide based on their mission requirements, whether to consider operating hybrid RES with generators instead of relying on pure PV-energy storage RES. Selecting a hybrid solution generally reduces initial system cost and provides power at the 0% failure rate (0% LPSP). Furthermore, the resiliency of this system is increased as the generator provides a backup power source if the RES system is damaged or for extended poor weather. However, a hybrid RES is not completely sustainable and must still rely on generators and a constant supply of fuel.

Comparing PV RES and Hybrid RES Against Diesel Generators

Finally, the lifecycle cost of the optimized RES and hybrid RES systems developed above was compared to the economics of traditional generators. To accomplish this, a MATLAB time-series cost and logistics model for diesel power generation and HRES generator fuel use was created. Figure 4.21 shows the lifecycle costs and logistics weight (i.e. total weight transported) for five years and for 20 years. These figures demonstrate that in only 470 days a full RES system matches the cost of diesel generators and 420 days for the hybrid RES-diesel solution.

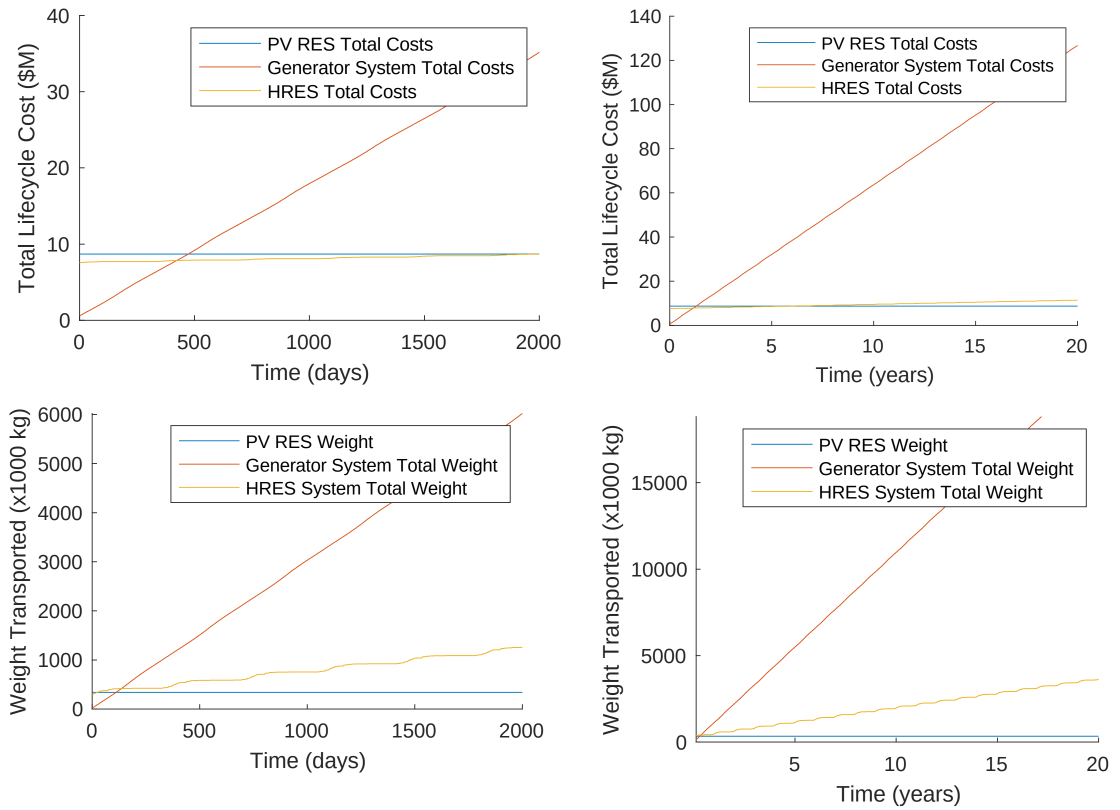


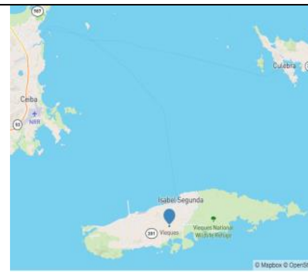
Figure 4.21. Lifecycle Costs and Transport Weights for PV RES, HRES, and Generator for 5 years (left) and 20 years (right)

For logistics, when modeled by weight, the payback times are even shorter: in only 110 days the full PV RES requires less transport than traditional generators, while the hybrid system takes longer at 140 days. These results illustrate three important considerations: 1) RES and Hybrid RES systems are more cost-effective than traditional generators in scenario horizons of only a few years; 2) Renewable systems are considerably better than generators from a lifecycle transportation standpoint in only a few months; and 3) Hybrid RES demonstrate lower costs in timelines of only a few years of operation; however, this benefit is countered by inferior logistics performance in both short and long-term scenarios.

Case Study Simulation Scenarios

To further illustrate the unique benefits of the logistics optimization model, two additional case study simulations were conducted at different regions, environments, and power demand profiles. The study parameters are given in Table 4.7.

Table 4.7. Case Study Scenario Parameters

Locations: **Parameters**	**Marah, Afghanistan** Military FOB (base case)	**Vieques, Puerto Rico** Caribbean island Community	**Biem, South Sudan** Remote African Village
Map			
Climate [124]	Hot-Dry (Class: BWh)	Hot-Humid (Class: Af)	Hot-Mixed (Class: BSh)
Power Demand (800 kW Peak)	Estimated military load demands	34% Residential, 66% Commercial [128] Based on Miami, FL	90% Residential, 10% Commercial Based on Laredo, TX
FBCF ($/gal)	$17.74 [3]	$6.00 [128]	$4.86 [90]
Scenario Time	5 & 20 years	20 years	10 years
Logistics Index Weights			
Weight:	0.34	0.10	0.80
Volume:	0.33	0.45	0.15
PV Land Area:	0.33	0.45	0.05
Optimization Priorities:	Balanced	Min Volume/Area	Min Weight
Payback Times			
Cost (years):	1.2(RES) 1.1 (HRES)	4.9 (RES) 4.3 (HRES)	5.5 (RES) 4.7 (HRES)
Weight (days):	110(RES) 140(HRES)	158 (RES) 386 (HRES)	137 (RES) N/A (HRES)

These scenarios were developed to highlight the different choices and tradeoffs RES planners can make when optimizing for logistics constraints. The results for these scenarios are shown in Table 4.8.

Table 4.8. Results for Remote Island and Village Scenarios

<table>
<tr><th>Vieques, Puerto Rico
Remote Island Scenario</th><th>Biem, South Sudan
Remote African Village Scenario</th></tr>
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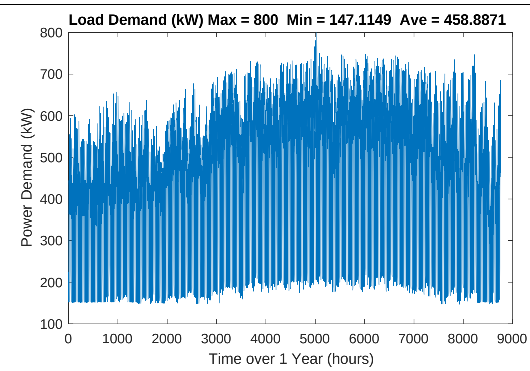

Load Demand (kW)
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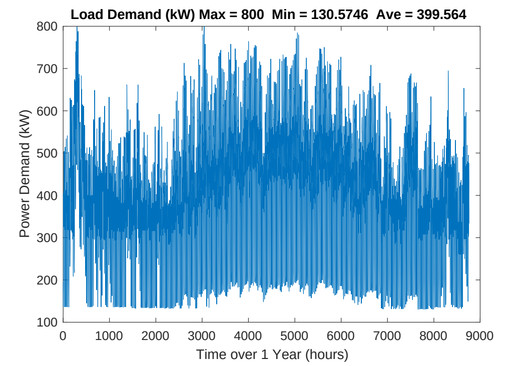

Load Demand (kW)
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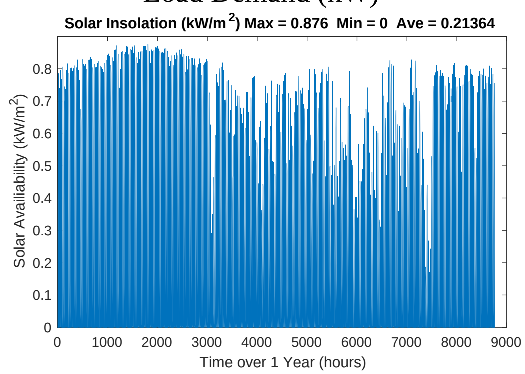

Solar Insolation (kW/m^2)
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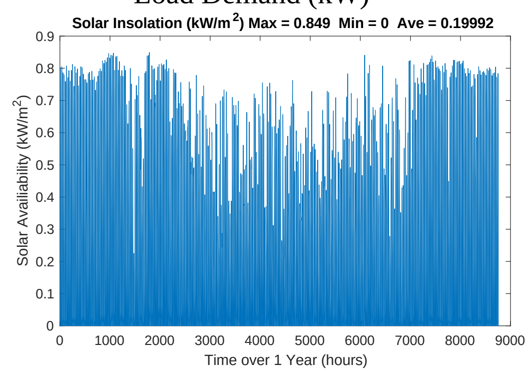

Solar Insolation (kW/m^2)
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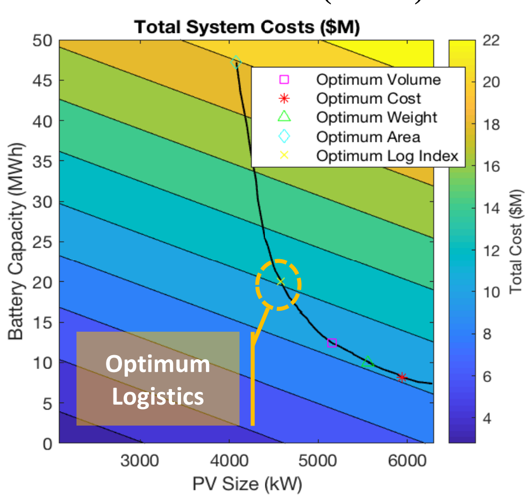

Comparison of Optimum RES Sizes
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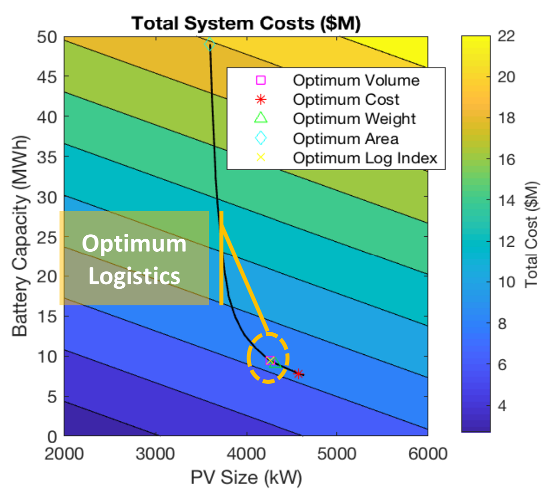

Comparison of Optimum RES Sizes
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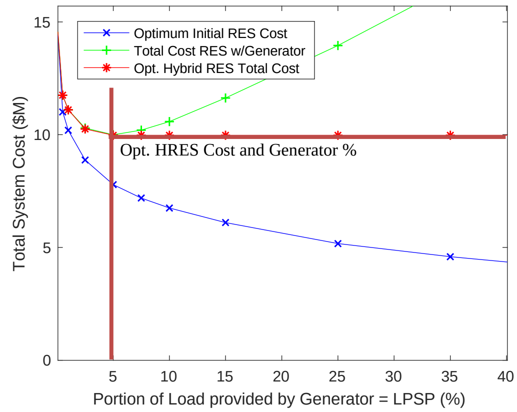
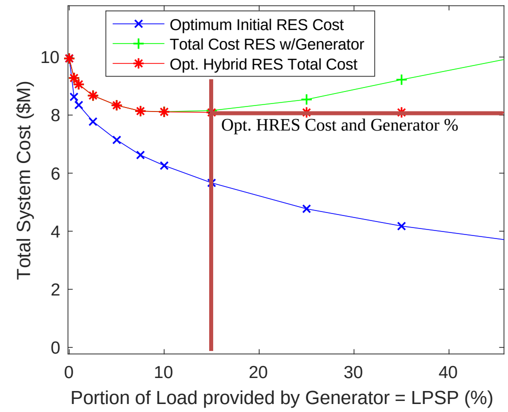
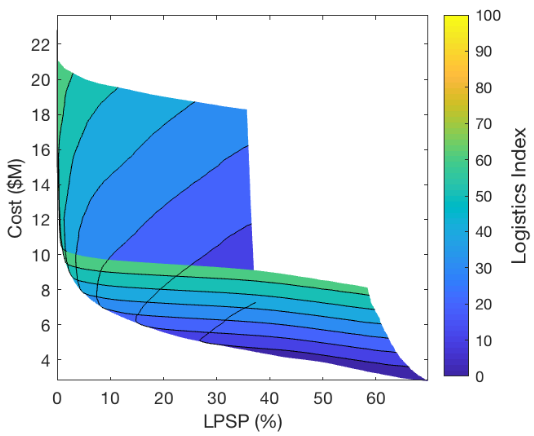


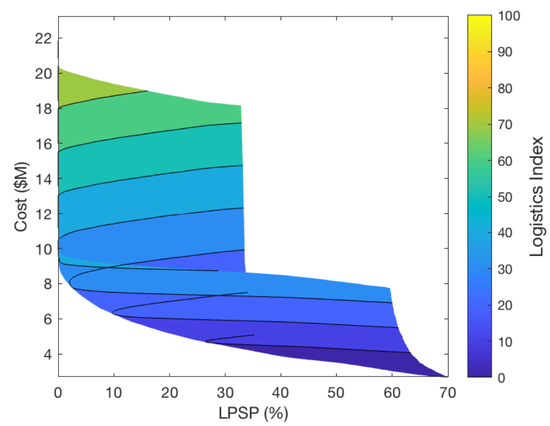
Pure RES vs. RES + Generator vs. HRES



Pure RES vs. RES + Generator vs. HRES



Cost – Performance – Logistics Tradeoff



Cost – Performance – Logistics Tradeoff

Table 4.9 shows the logistics-optimized system costs, weights, volumes, ad land area. Note that the island scenario has higher costs largely due to the high costs of batteries.

Table 4.9. Logistics Optimized System Parameters for Case Studies

Scenario:	**Island**	**African Village**
System Optimized for Logistics		
Cost:	$12.1M	$8.4M
Weight:	465,640 kg	341,080 kg
Volume:	1,536 m^3	1,164 m^3
Area:	24,552 m^2	22,552 m^2

By determining the logistics index importance weights for weight, volume, and land area, each optimization is customized to the situation. The island scenario sets a premium on volume making the RES ideal for sea shipment where volume of shipping containers determines price. Furthermore, land is expensive and may be very constrained or covered with forests on most islands. In the African scenario, available land area is plentiful, but air and land cargo are expensive. These two additional case studies demonstrate that the RES and hybrid RES optimizations here are effective at designing cost-effective solutions for each scenario, though payback times differ—only one year for the Afghanistan contingency base to over five years for the South Sudan village. This is largely a factor of the cost of fuel (FBCF) and available solar insolation, which are both lower in the village scenario than in the other two scenarios.

Furthermore, these cases illustrate that both RES and hybrid RES are more cost and logistics-effective than traditional generators in nearly every case within six years or less. The lone exception is that the hybrid-optimized solution for the African scenario which does not require less logistics to be transported than traditional generators within the 10 year scenario window. Therefore, this is a further example where the long-term logistics of pure RES are shown to be better than either hybrid RES or diesel generation.

Conclusions

This paper has demonstrated a logistics-based optimization approach for RES planners designing replacements for diesel generators at remote and isolated locations. These RES show strong promise to extend power to the 1.2 billion people currently without electricity, or to partially replace the global diesel generator infrastructure [1].

This paper proposed a novel MODA method to optimize logistics, economics, and technical concerns simultaneously to the maximum extent possible. This method is best accomplished using a Logistics Index, which balances the variables of system weight, volume, and land area required using importance weights dependent on the requirements of the scenario selected. Through the use of this index, cost and performance can be balanced against logistics.

Hybrid RES that use a diesel generator to augment PV arrays were also explored. These systems show promise with lower initial costs than pure PV RES at a high level of reliability; however, the long-term logistics, economics, and sustainability of these systems should be considered before implementation, since these systems will not eliminate the environmental and logistics impacts of fossil fuel use.

To demonstrate the effectiveness of the optimization model, a simulation of RES and HRES generator-replacement solutions was created for a military contingency operating base in Afghanistan. The cost payback period for these systems is reached in just over a year when compared to traditional diesel generators like the 800 kW BPU examined here. Concerning logistics of these systems, they require less total transport capacity (based on weight) in only four months. While HRES solutions showed lower short-term and initial costs than pure PV RES, the long-term logistics and costs for pure PV solutions are better or comparable with no requirement for fuel resupply. The two additional case studies demonstrate this model is effective in a variety of environments.

The results of this research indicate: 1) remote and isolated locations should consider use of PV RES and HRES due to their lower costs and long-term logistics requirements vs. traditional diesel generators; 2) a logistics optimization should be evaluated when designing RES and HRES for remote locations; and 3) the logistics optimization can be conducted through use of an additive multi-criteria decision analysis model presented here, with importance weights for volume, weight, and land area selected as needed based on the scenario. This work provides RES engineers and remote site planners the means and methods to reduce the overall transport requirement for new renewable energy installations. This could be further advanced through improving PV module technologies, reduction of PV BOS weights, and use of emerging energy storage technologies.

V. Conclusions and Recommendations – Going off the Grid: Sustainable Contingency Bases through Solar Power

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Accepted for Publication: *The Military Engineer*: The Energy Issue,

Society of American Military Engineers (March-April 2020)

Article Summary

Energy resiliency and sustainability are critical requirements for contingency bases and are inherent in renewable energy systems (RES). This work models photovoltaics and energy storage systems, demonstrating that recent RES improvements make them more economical than generators and eliminate the need for fuel resupply in under two years of operation.

The Need for Renewable Energy

Remote locations, such as military forward operating bases (FOBs) are disconnected from traditional power grids, forcing them to rely on diesel generators. These generators require a constant supply of fuel and result in increased operating costs, noise pollution, environmental impacts, and challenging fuel logistics. In 2009, the Government Accountability Office (GAO) recognized the massive costs of fuel use at forward deployed locations, placing the minimum fully burdened cost of fuel at $15/gallon when logistics concerns are included [3]. The fuel logistics issue creates a potential threat to FOB energy resiliency—if fuel convoys are cut-off, attacked, or depleted, base electrical power to mission essential operations is lost. Additionally, fuel convoys require security protection, which places military personnel in harm's way. One study from the Army Environmental Policy Institute showed that in dangerous locations such as Afghanistan, there was one casualty for every 24 fuel convoys. These issues present generators as a problem for Department of Defense ambitions for energy sustainability. According to the DoD Strategic Sustainability Performance Plan for 2016, the military seeks to assure continued availability of energy through reduction of fossil fuel use [7]. Similarly, the Air Force's energy goals are to "Improve Resiliency, Optimize Demand, and Assure Supply" as stated in *Energy Flight Plan 2017-2036: Enhancing Mission Assurance through Energy Assurance* [8].

Rapidly improving renewable technologies such as solar cells have expanded the potential power generation options for isolated sites. Solar cell arrays, also called photovoltaics (PV), produce electrical power from sunlight, which is abundant, free, and available during daylight hours over nearly the entire globe. The distinct advantage of PV arrays over generators is that they produce power nearly 365 days a year with no fuel resupply requirements, no noise, no air pollution, and minimal maintenance over their lifespan. These advantages make them viable candidates to replace generators at remote locations such as FOBs. However, solar arrays only produce power during daylight hours and are dependent upon the weather. Therefore, energy storage solutions such as batteries are required to supply electricity at night. Energy storage technology is rapidly improving with new developments reducing cost while increasing capacity. The advances in PV and energy storage technologies are making potential renewable replacements for generators better and more cost effective than ever before. While other renewable energy power sources are available, AFRL technology analysis has shown that PV may be the best candidate for alternative energy power generation in the deployed environment vs. wind turbines, for example [10].

Previous Air Force Research

The Air Force has examined several experimental renewable technologies for FOBs in recent years. For example, from 2008 to 2012, AFRL experimented with tent shelter designs that integrated flexible solar panel shades, enhanced insulation, and redesigned HVAC systems for a 35-65% reduction in peak energy requirements [23]. In 2010, Lockheed Martin won a contract with the Air Force to provide experimental solar microgrids. The project concluded with testing of the Integrated Smart BEAR Power System (ISBPS) at Holloman Air Force Base, NM, consisting of 75 kW of PV and 25 kW of wind power but no energy storage [129]. The ISBPS demonstrated that PV power was feasible and could be setup by Air Force engineers with minimal training. More recently, NREL collaborated with AFRL to create a 30 kW CUBE microgrid convertor, capable of integrating renewable energy sources into existing high-voltage AC grids used at FOBs [20].

Designs such as these are important steps to developing a practical renewable power grid for DoD FOBs; however, to our knowledge a complete PV replacement for prime-power generators has yet to be implemented or designed. The scale of previous designs was small, only fulfilling the requirements of localized generators or individual shelters. To power a complete FOB, multiple large, prime-power diesel generators of 800 kW or larger are necessary.

Modeling of Renewable Solutions

Recent research at the Air Force Institute of Technology (AFIT) in collaboration with the Air Force Civil Engineer Center (AFCEC) examined a case study for the replacement of a single 800-kW generator at a deployed location with a PV-based renewable energy system (RES). Marjah, Afghanistan in the Helmand province was selected as the location for this hypothetical FOB. The goal of the study was to examine, optimize, and determine the feasibility of replacing a large prime-power generator with a PV array and battery-storage system.

RES require consideration of both the power generation capacity (solar array size) and the energy storage (battery size). Industry has developed practical stand-alone PV-battery systems to replace existing generators and multiple modeling and optimization methods are available. However, military engineers need to account for logistics and land requirements in addition to cost in optimizing these systems. RES properties to optimize for military FOBs should include weight, volume, and land area required which all contribute to the logistics required to utilize these systems. In the optimization process, tradeoff decisions are made between these variables, deciding on the key factors for DoD applications. As shown in Figure 5.1, these factors should include cost, reliability, and logistics considerations.

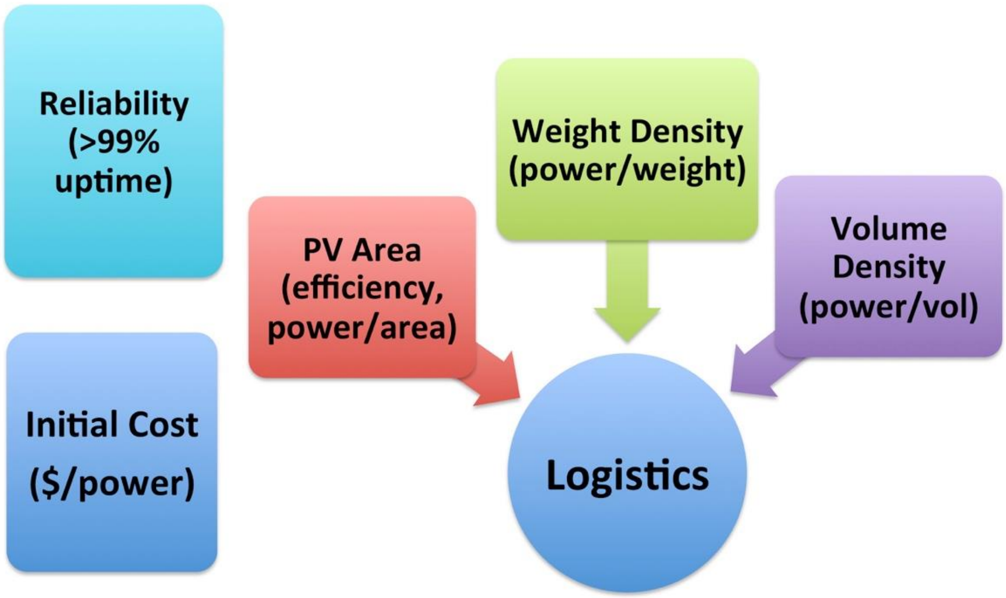

Figure 5.1. Key Optimization Factors for PV Renewable Systems at FOBs

The theoretic research at AFIT demonstrates an optimization model based on DoD priorities and generates a design solution to minimize initial cost and logistics while maintaining 99% reliability. The model utilized MATLAB software and one year of solar data for the Marjah location to examine all potential PV array sizes and battery storage capacities to determine the optimal configuration to match the continuous output of an 800 kW generator. Following GAO guidance, $17.74/gal was used as the estimated fully burdened cost of fuel.

Results of the model demonstrate a high initial cost and logistics burden for the renewable system (30x cost, 27x weight, and 50x volume compared with current generators); however, these factors are rapidly offset by the ongoing high costs and logistics of the fuel required to run the generator. In less than two years of operation, the total cost for the PV system would be less than diesel generators. Furthermore, in only

120 days the initial greater weight transport requirement is overcome by the weight of fuel required (Figure 5.2). Replacing a single diesel generator with a renewable system of this kind would result in a savings of over 500,000 gallons of fuel annually and eliminate the need for 100 fuel tanker deliveries.

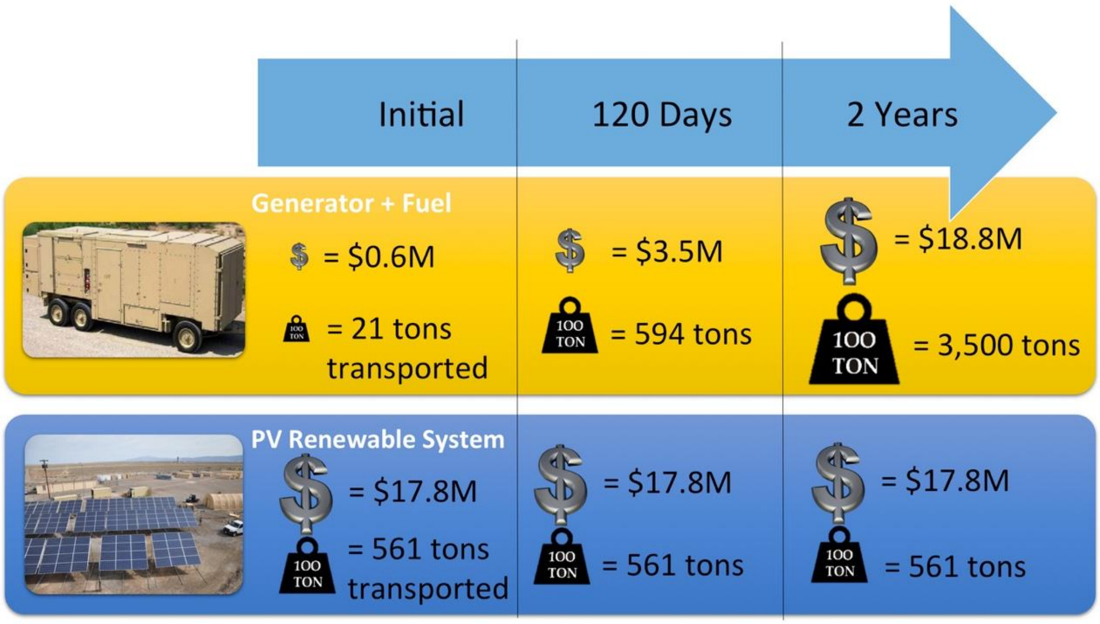

Figure 5.2. Graphic Depicting the Difference in Logistics and Costs Required for Renewable and Generator Power Systems at Remote FOBs in the first 2 years of Operation.

Conclusion - Sustainable FOBs of the Future

This research demonstrates that renewable energy systems in theory may be a viable candidate for contingency bases and are reasonable from economic and logistics perspectives in relatively short timespans when compared with typical FOB lifetimes. During initial deployment for only a few months or less, generators are lighter and cheaper to operate than RES. However, for the majority of FOBs and remote operating locations, PV and energy storage systems provide significant operational and economic advantages.

For the practical implementation of a renewable system at an expeditionary base, during the first 30 days of a beddown a FOB might utilize existing generators, with PV and energy storage following soon thereafter. Once the complete PV system is in operation, the generators could remain as backup, further increasing resiliency. A sustainable FOB operating based on this system would possess enhanced resiliency and could operate indefinitely without the need for fuel resupply—working toward military goals to assure supply and improve energy resiliency. These sustainable FOBs could be desirable in various locations, including isolated Central Command bases, remote Pacific islands, and space, communications, and intelligence assets operating at fixed locations around the world, where fuel sources are remote, but the need for power is critical.

Acknowledgements:

The authors would like to acknowledge the significant contributions to this research by Mr. Reza Salavani and Mr. Richard Peck at AFCEC and Lt Col Torrey Wagner at AFIT.

Figure 5.3. Integrated Smart BEAR Power System (ISBPS) Testing at Holloman AFB
Photo Credit: *AFCEC Expeditionary Directorate*

Figure 5.4. Air Force Engineers Assemble an Experimental PV Array at Holloman AFB, NM.
Photo Credit: *AFCEC Expeditionary Directorate*

Figure 5.5. Air Force Civil Engineers Assemble an Experimental PV Array.
Photo Credit: *AFCEC Expeditionary Directorate*

Research Significance

In recent years, research into renewable energy has greatly expanded. While numerous studies exist in the RES and hybrid RES optimization field, few are directed at military applications and even fewer approach optimizing these systems for minimum logistics. To the author's knowledge and as confirmed through a robust survey of recent PV RES optimization articles, this thesis is the first to focus on optimizing RES specifically for logistics factors, including weight, volume, and PV land area required, instead of the traditional techno-economic and environmental concerns typically considered. The novel model presented here demonstrates a multi-objective decision-making method that can be used by RES planners at remote locations to develop more compact and efficient system designs. The unique aspects of this method are demonstrated by the case studies presented here.

While significant obstacles to use of PV for contingency applications remain, including high initial costs, module degradation, and reliability concerns, this research demonstrates that renewable energy can quickly overcome these issues because of the large quantities of fuel required to sustain existing bases and remote locations. Military engineers must consider PV and RES in the development of future contingency bases.

Research Contributions

This research demonstrated the optimization, viability, and relative economy of PV RES when compared with traditional diesel generators through the case study of an Afghanistan contingency base supplied by an 800 kW generator, as well as considered the lifecycle costs and logistics of pure RES and conventional diesel generation (Chapter

2). Furthermore, this thesis developed the first known multi-criteria decision making model to include logistics factors of weight, volume, and land area along with traditional techno-economic considerations. This model was then applied to the selection of PV module types for use at remote applications by surveying and minimizing logistics factors (Chapter 3). The logistics model was then used to optimize both PV RES and hybrid RES at remote locations by simultaneously obtaining minimal logistics at minimal cost (Chapter 4). Finally, the implications of these findings for DoD energy engineers was provided in a summary article contained in this chapter.

This U.S. Air Force thesis research was dedicated to the study and analysis of PV renewable energy systems for remote, isolated locations, and contingency bases. The findings could help shape future Department of Defense expeditionary renewable energy research and testing, as well as the Air Force's decision to invest in and implement this technology at contingency bases. As part of this work, a conference paper, conference oral presentation, and two poster presentations were created. This research culminated in the development of two journal articles that demonstrate the viability of expeditionary PV RES (Chapter 2) and the multi-objective logistics optimization method for RES and Hybrid RES (Chapter 4).

Recommendations for Future Research

This research has explored PV RES and hybrid PV RES from a systems modeling, simulation, and optimization approach and has demonstrated, from a theoretical standpoint, the viability, economics, and logistics of utilizing such renewable systems to replace generators. Accordingly, there are several areas where this research could be expanded and utilized in the future:

1. Logistics Multi-Criteria Model: The model to optimize RES for logistics criteria, as described in Chapter 4, can be expanded to include optimizing the choice of PV module and energy storage types automatically. This can also include the addition of an analytical hierarchy process to select the importance-weighting criteria for each logistics variable. Furthermore, additional factors such as environmental or mission concerns could be added to the optimization model.
2. MATLAB Simulation Model Expansions: The model described here can be expanded to add additional fidelity to account for variability in power demand, weather, solar insolation, and other factors. This can be accomplished through additional sensitivity analyses and Monte-Carlo simulations based on uncertainty. Furthermore, PV degradation over time and RES shipping costs could be considered.
3. Integration with HOMER Software: Because commercial HOMER software is designed to optimize based on economics (NPC), it cannot be used to produce the logistics-based optimization presented here. However, by using the MATLAB multi-criteria model as a software back-end for HOMER, it is possible to enable this widely used program in a logistics-optimized approach, giving RES planners rapid access to the principles described here in a more familiar format.
4. Quantifying RES Resiliency: While RES systems to appear to provide additional resiliency for military FOBs and remote locations through sustainability of the mission and reduction of the logistics tail, comparisons of resiliency between RES

and existing generators were not conducted in this thesis. Such a comparison could enable planners to better design resilient future bases operating and decide between pure RES or a hybrid configuration utilizing existing generators.

5. Prototyping: Development of large-scale, logistics-optimized prototypes for PV RES of the scale discussed in this thesis (800 kW and larger) is a key first step to wide-spread deployment of PV RES at contingency bases and other remote locations. This prototyping should also include development and optimization of the BOS PV and energy storage components such as mounting hardware, cabling, protective shelters, and inverters.

These avenues, among others in the RES field, provide further research and development opportunities for PV RES and hybrid RES use at remote and isolated locations.

Appendix

List of Acronyms

AFCEC – Air Force Civil Engineer Center

AFIT – Air Force Institute of Technology

AFRL – Air Force Research Laboratory

AC – alternating current

BEAR – Basic Expeditionary Airfield Resources

BOS – balance-of-system

BPU – BEAR Power Unit

COE / LCOE – cost of energy or lowest cost of energy

CPI – Consumer Price Index

DoD – U.S. Department of Defense

FBCF – fully burdened cost of fuel

FOB – Forward operating base

GAO – (U.S.) Government Accountability Office

GDP – Gross Domestic Product

HOMER – Hybrid Optimization of Multiple Energy Resources, by HOMER Energy LLC

HRES – hybrid renewable energy systems

HVAC – heating, ventilation, and air conditioning

IEEE – International Institute for Electrical and Electronics Engineers

IEA – International Energy Agency

ISBPS – Integrated Smart BEAR Power System kW – kilowatts

Li-ion – Lithium ion (batteries)

LPSP – Loss of power supply probability

MATLAB – MATrix LABoratory, software by MathWorks

MODA – multi-objective decision analysis

MW – Megawatts

NREL – National Renewable Energy Laboratory

NPC – net present cost

PRISMA – Preferred Reporting Items for Systematic Reviews and Meta-Analyses

PV – photovoltaic

RES – Renewable energy systems

USAF – United States Air Force

Wh – Watt-hours

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REPORT DOCUMENTATION PAGE	*Form Approved OMB No. 074-0188*

1. REPORT DATE *(DD-MM-YYYY)*	**2. REPORT TYPE**	**3. DATES COVERED** *(From – To)*
06-03-2020	Master's Thesis	October 2018 – March 2020

TITLE AND SUBTITLE	
Going off the Grid: Optimizing Solar Renewable Energy Systems to Minimize Logistics Requirements of Remote and Isolated Locations	**5a. CONTRACT NUMBER**
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	**5d. PROJECT NUMBER**
Thomsen, Nathan J., Major, USAF	**5e. TASK NUMBER**
	5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S)	**8. PERFORMING ORGANIZATION REPORT NUMBER**
Air Force Institute of Technology Graduate School of Engineering and Management (AFIT/ENV) 2950 Hobson Way, Building 640 WPAFB OH 45433-8865	AFIT-ENV-MS-21-M-247
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	**10. SPONSOR/MONITOR'S ACRONYM(S)**
Air Force Civil Engineer Center 139 Barnes Drive, Suite 2 Tyndall AFB, FL 32403-5323 (850) 283-3715 Reza.salavani@us.af.mil POC: Mr. Reza Salavani	AFCEC/CXAE **11. SPONSOR/MONITOR'S REPORT NUMBER(S)** N/A

12. DISTRIBUTION/AVAILABILITY STATEMENT
DISTRUBTION STATEMENT A. APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

13. SUPPLEMENTARY NOTES

14. ABSTRACT

Grid-based electrical infrastructure is unavailable at many remote locations including developing nation communities, isolated construction sites, and military contingency bases. Powering these locations with diesel generators requires regular fuel resupply, resulting in increased costs, environmental impacts, and burdensome logistics—making generators an obstacle for energy resiliency and sustainability.

This research examines using solar renewable energy systems to replace generators at remote locations and presents a multi-objective optimization model that minimizes logistics variables. Replacing a single deployed generator would save over 500,000 gal of fuel annually, eliminating the need for 100 fuel tanker deliveries.

15. SUBJECT TERMS
renewable energy systems, photovoltaics (PV), logistics, multi-objective, multi-criteria, optimization, power density, remote, isolated sites, battery, energy storage, renewable energy, hybrid, solar array

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON** Maj Steven J. Schuldt, AFIT/ENV
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			**19b. TELEPHONE NUMBER** *(Include area code)*
U	U	U	UU	131	(937) 255-3636, ext 4645 (steven.schuldt@afit.edu)

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39-18