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Photovoltaic System Optimization for an Austere Location Using Time-Series Data

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***Abstract* — In this work we test experimental photovoltaic, storage and generator technologies and investigate their potential to meet austere location energy needs. After defining the energy requirements and insolation of a 1,100-person base, we develop a microgrid model and simulation. Cost optimizations were then performed using hourly time-series data to explore the cost and performance trade-space of a PV-battery-generator system. The work highlights the cost of resiliency and the dependencies of optimum system component sizes on duration and the fully burdened cost of fuel.**

***Index terms* — energy, energy storage, hybrid power systems, photovoltaic systems, microgrids, renewable energy sources, optimization.**

I. Introduction

Photovoltaic (PV) energy generation is currently the fastest-growing energy source and growth is projected to double by 2022 [1]. However, for most applications energy storage is required as PV is an intermittent energy source. PV and battery storage are attractive technologies for defense, humanitarian, disaster recovery and construction applications because resiliency is valuable, and liquid fuel prices can surge during these applications. The fully burdened cost of fuel (FBCF) used in this work includes the cost associated with the fuel commodity, force protection if required, generator maintenance and fuel transport to an austere location. Fortunately, rapidly increasing PV power density and battery energy density, and the decreasing cost of these technologies increases their likelihood of meeting austere location energy requirements in a cost-effective manner.

In this work we investigate ways to meet the published energy requirements of a representative contingency base located at 31° N latitude without access to an external power grid [2]. Requirements are established and a systems engineering model is developed to specify microgrid behavior. Three candidate photovoltaic, storage and generator technologies are documented, and their parameters are used in optimizations to explore the cost and performance trade-space of the system. This research meets the intent of US Department of Defense guidance, which seeks to integrate alternative energy sources into austere location bases, where cost-effective, in order to increase energy resilience [3], [4].

II. Modeling and Simulation

The electrical energy demand modeled in this work is from a hypothetical 1100-person contingency base without access to an external power grid [2], as shown in Fig. 1. A major energy load is heating, ventilation, and air conditioning (HVAC), which varied with atmospheric temperature and humidity from 0.9 to 3.3 MW. Other energy loads ranged from 1.5 to 1.7 MW and include lighting, electronics, administration, vehicle and aircraft maintenance, civil engineering, water production and meal preparation. The yearly energy requirement is 28.4 GWh, or 25.8 MWh per occupant, which compares reasonably to similar work [5].

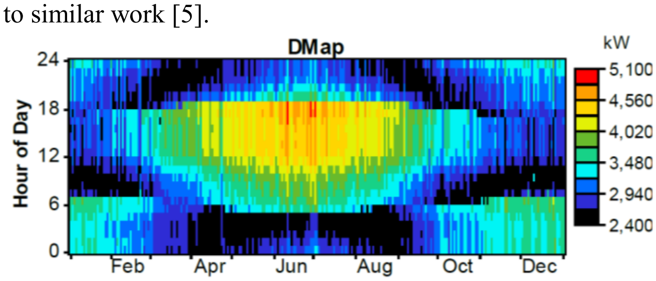

Fig. 1. Energy demand for an 1100-person contingency base [2].

Hourly solar resource data from the National Renewable Energy Laboratory (NREL) were downloaded from the NREL Geospatial Toolkit [6]. Monthly global horizontal averages ranged from a low of 3.0 kWh/m^2/day in December to a high of 8.2 kWh/m^2/day in June, using a clearness factor that ranged from 0.58 to 0.74. These data are shown in Fig. 2.

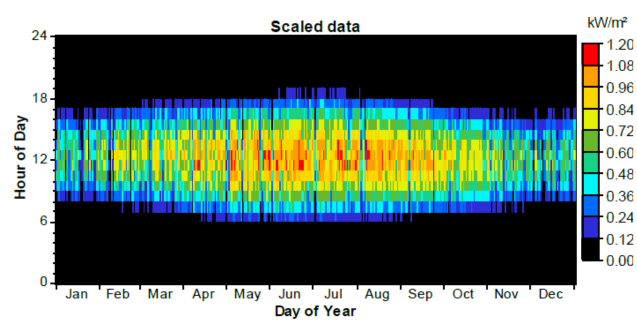

Fig. 2. Global horizontal insolation [2], [6].

For the purposes of this study, a single unified microgrid serving all loads is assumed, as shown in Fig. 3. The battery storage is accomplished through lead-acid or lithium-ion batteries. The inverter can accept DC power from the solar panels or batteries and deliver energy to the microgrid, or if necessary, pull energy off the microgrid for battery storage. Additional solar energy is provided by solar modules connected to micro-inverters that convert the DC electricity from the solar module to AC electricity of the microgrid. The frequency and voltage of the microgrid is determined by the output of the diesel generators, which provide any load that can't be met by the PV or battery storage. For simplicity and due to the duration of the simulations, we disregard battery & PV deterioration with time, and the decrease of PV efficiency with PV cell temperature, and shipping costs.

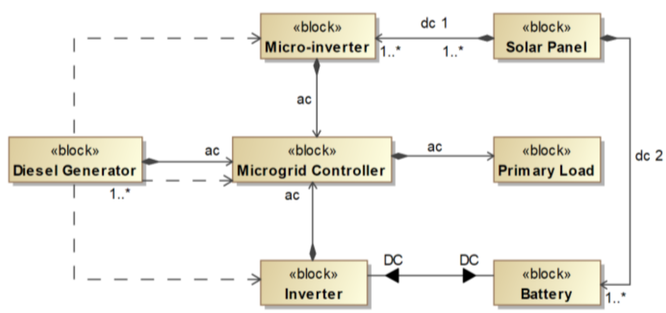

Fig. 3. Systems block definition diagram model of the simulated microgrid. Solid lines indicate power flow and dashed lines indicate frequency and voltage control flow.

An hourly simulation model of the microgrid was developed using the parameters in Table 1 for costs & performance associated with energy generation, storage, inversion, shipping and installation. System installation, deployment training and PV/battery maintenance costs were assumed to be sunk costs that are performed by military personnel. The system components include glass-covered PV panels, lead-acid or lithium-ion batteries and MEP-012A diesel generators. The cost of 4 generators is included in all simulations.

TABLE I

OPTIMIZATION PARAMETERS

Component	Parameter
Photovoltaic (PV) array, installed	\$1.50 /W
PV system loss	15%
PV system efficiency	15%
Lead-acid battery system with cooling and control, installed	\$100 /kWh [2] 70% DoD
Lithium-ion battery system with cooling and control, installed	\$400 /kWh [7] 100% DoD
Battery storage round-trip loss	8% [7]
Generator, 750 kW, installed	\$240K (750 kW) [2]
Generator average fuel efficiency	13.7 kWh/gal 3.6 kWh/L
Generator fully burdened cost of fuel	\$3-70 /gal \$1-18 /L

The price of fuel can be significant for a large encampment. If a PV system is not installed, the 28.4 GWh yearly energy requirement uses 2.1 million gallons or 7.9 million liters of fuel. If 30% generator efficiency is assumed, 13.7 kWh of electrical energy can be obtained from each gallon of Jet-A fuel, or 3.6 kWh from each liter of fuel. The cost of this fuel is \$28.4M multiplied by the cost of each kWh, which in this work was modeled from \$0.50 to \$7. The zero PV case shown on the left side of Fig. 4 shows a baseline fuel cost of \$284M, which is \$28.4M * \$2/kWh * 5 years.

III. ONE-VARIABLE OPTIMIZATIONS

The lifecycle cost is defined by the cost of components and fuel over a 1-5 year period, and in this section the cost is optimized while PV array size or battery capacity are varied.

A. Cost Optimization while Varying PV Array Size

This single-variable optimization seeks the lowest cost solution to meeting energy demands while varying the size of the photovoltaic array. The parameter values for the simulation are shown in the title of Fig. 4, which include the unit PV array cost, unit battery cost, battery depth of discharge, FBCF, years of simulation and the optimal solution.

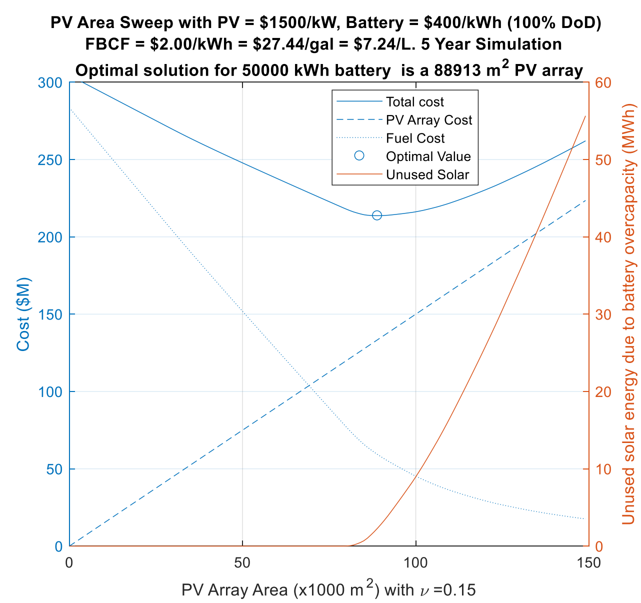

Fig. 4. Cost optimization with varied photovoltaic array size, fixed battery size and \$2/kWh FBCF.

With the given parameter values, the solid blue line in Fig. 4 shows the total cost of the system for 5 years of operation. For a 50,000 kWh battery, the optimal size of PV array is 89,000 m^2, resulting in a total cost of \$210M. The dotted line shows the cost of fuel, which decreases as the amount of PV array is increased. However, the rate of decrease slows as the PV array is increased past its optimal PV array size, because at that point the PV array is can meet the microgrid load and excess energy can't be stored in the batteries due to overcapacity. This is highlighted by the red line in Fig. 4, which shows the unused solar energy that is produced.

Figure 4 shows an optimal value of PV array size for a relatively expensive FBCF at \$2 /kWh. In Fig. 5 all parameters are the same as Fig. 4, with the exception that the FBCF is decreased to \$1 /kWh. Fig. 5 shows that adding PV is not cost effective in this case, as the optimal PV size is 0 m^2.

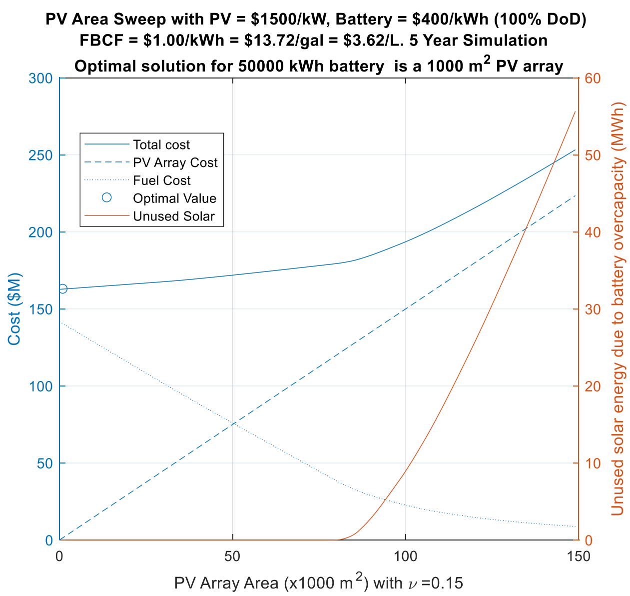

Fig. 5. Cost optimization with varied photovoltaic array size, fixed battery size and \$1/kWh FBCF.

Figure 6 is similar to Fig. 4 and Fig. 5 but instead shows the output if the PV array size is held fixed at 89,000 m^2 while the battery size is varied. In this case, the optimal battery capacity is 38,000 kWh, where it can store the majority of excess energy that the PV array produces. This is illustrated in Fig. 6 by the knee in the red curve.

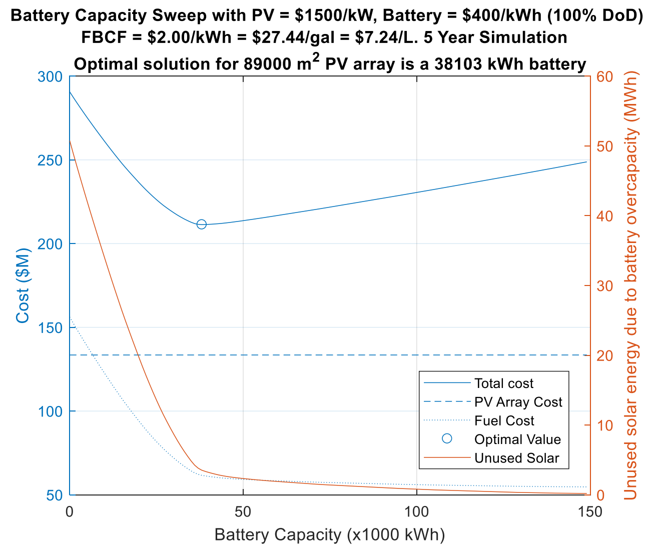

Fig. 6. Cost optimization with varied battery capacity, fixed PV array size and \$2/kWh FBCF.

Figure 7 shows the resulting cost surface for many combinations of battery and PV array sizes, and shows a single global minimum in this portion of the parameter space. In the case, the optimal combination of PV and battery storage occurs with 90,000 m^2 of PV array and a 45 MWh battery.

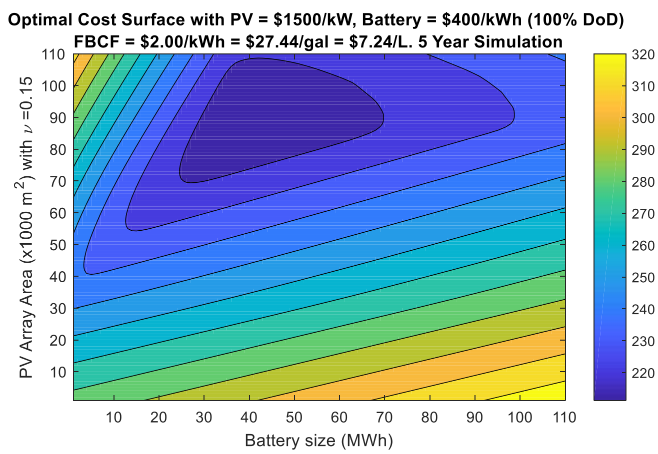

Fig. 7. Total cost surface for variations in PV array size and battery size, using \$2 /kWh fuel and lithium ion battery parameters.

III. Two-Variable Optimizations

In this section the optimal combinations of PV array size and battery capacity are determined so that the system cost is minimized. Results for lithium-ion and lead-acid batteries are presented.

A. Cost Dependence on One Year and Five Year Simulations with Lithium Ion Batteries

In Fig. 8, for both one year and five year simulations, the total cost and optimal combination of PV and Lithium Ion battery storage are shown for a wide range of FBCF. For the five year simulation, Fig. 8 shows that a PV array is cost-effective above a FBCF of $18 /gal ($4.7 /L) and battery storage is cost-effective above a FBCF of $19 /gal ($5 /L). Additionally, the blue curves shown in Fig. 8 highlight that for a one year simulation, PV is cost effective above $80 /gal and only a negligible amount of battery storage is optimal. The high FBCF for cost-effectiveness results from relatively small fuel savings when compared to the high capital cost of the system.

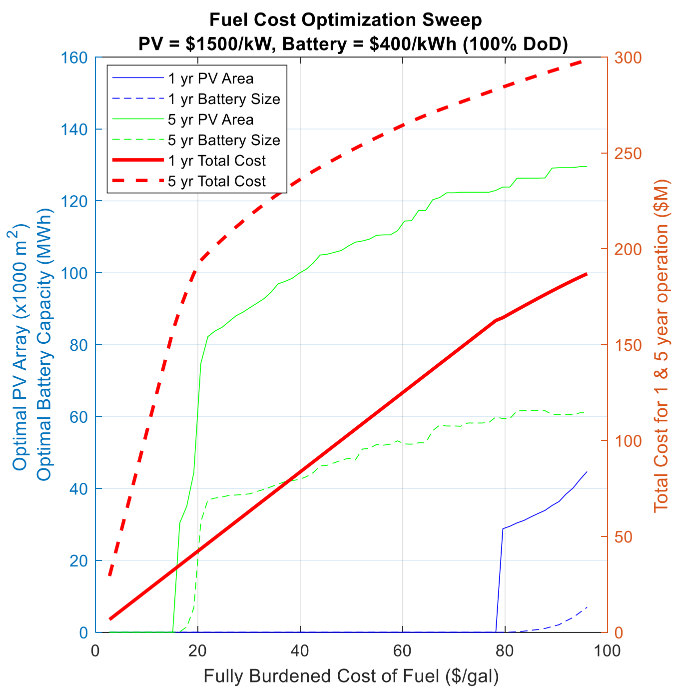

Fig. 8. 1 year and 5 year FBCF sweep using lithium-ion batteries.

B. Cost Dependence on One Year and Five Year Simulations with Lead Acid Batteries

Figure 9 repeated the method used for Fig. 8 while changing the battery parameters to reflect lead acid batteries. The cost is reduced, and a 70% depth of discharge is implemented in the model. When compared to Fig. 8, the 5 year total cost curve is lower, showing that the decreased cost of battery more than offsets the increased quantity of batteries. Even with the change in battery technology, the point at which PV and batteries become cost effective is the approximately the same for the five year simulation. For the one year simulation, the cost effectiveness threshold remains the same, however the optimal combination of PV and battery is larger than the lithium ion case.

One concerning aspect of Fig. 9 is that that the quantities of PV and battery, shown in green, vary dramatically with FBCF, and are no longer strictly monotonically increasing. In order to investigate this phenomenon, a cost surface was generated that is similar to Fig. 7 at $3 /kWh FBCF. The main differences are that lead acid battery parameters were used, and the range of batteries and PV array size was extended.

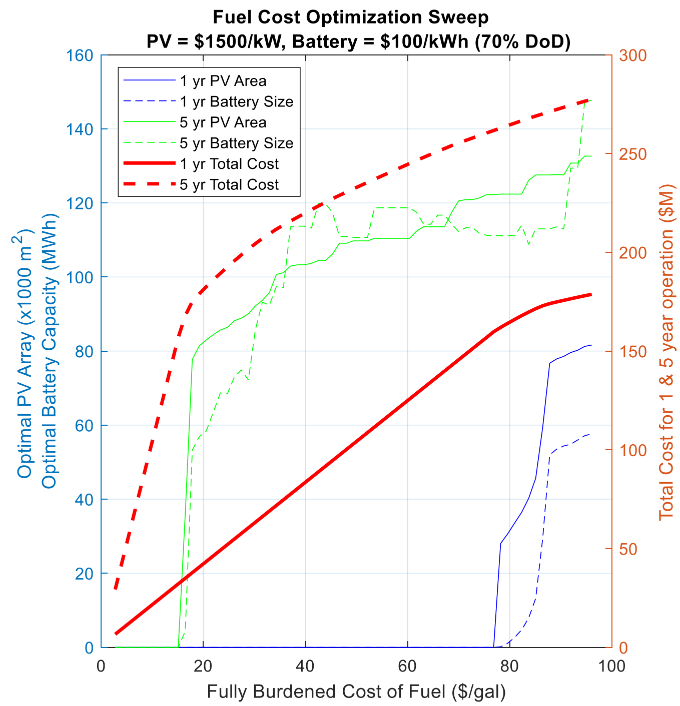

Fig. 9. 1 year and 5 year FBCF sweep using lead-acid batteries.

Figure 10 shows there is still a global minimum cost, and that the erratic variations of the five year PV and battery parameters are due to the relative insensitivity of optimal cost to a change in battery size. When the algorithm determines the optimal combination of PV and battery, we believe that this insensitivity allows the model to over-fit the complex energy requirement and solar resource datasets that are shown in Fig. 1 and Fig. 2. For this surface the optimal 5 year cost is $225M for a 105,000 m^2 PV array and 112 MWh battery.

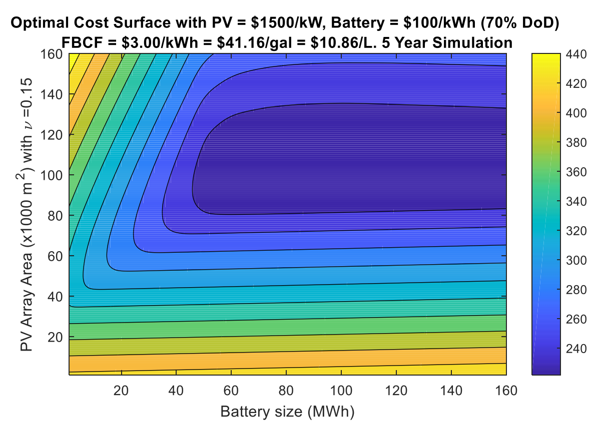

Fig. 10. Total cost surface for variations in PV array size and battery size, using $3 /kWh fuel and lead-acid battery parameters.

VI. Conclusions

In this work, we have shown that the decreasing cost and increasing performance of PV and battery storage can make these technologies cost effective in non-permanent defense, humanitarian, disaster recovery and construction applications. Cost effectiveness is the most sensitive to FBCF, followed by the cost of PV panels and the unit cost of batteries.

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