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Characterizing solutions in optimal microgrid procurement and dispatch strategies

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HIGHLIGHTS

- We study a hybrid power system.
- An optimization model uses simulated and observed load data.
- We clean and impute the observed data.
- We compare the design and dispatch from the simulated and observed data.
- We investigate the characteristics of load that influence the model's behavior.

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ABSTRACT

As part of an energy-reduction study at remote sites, we explore a power system comprised of hybrid renewable energy technologies, specifically, photovoltaic cells, battery storage, and diesel generators. An optimization model determines the design and dispatch strategy of the power system to meet load off grid, such as at a military forward operating base. The model alternately uses two types of load data from government agencies, simulated and observed, to assess the effects of these inputs. Because the latter data set contains errors and is incomplete, we detail the process of cleaning and imputing it to provide a year's worth in hourly increments for two forward operating bases in Afghanistan. We then construct an approximation of a realistic 600-soldier camp load from the full year of observed data. We compare the design and dispatch output from the optimization model using the simulated and constructed (observed) data sets and demonstrate that the results can differ. We investigate the characteristics of load that influence the optimization model's behavior regarding the design and dispatch strategy and show that mean load has a more pronounced effect than its shape. In addition, the photovoltaic cells are often used to help the generators run more efficiently, especially under load variability.

1. Introduction and literature review

Hybrid power systems integrate energy-producing technologies and energy-storage media to provide power to off-grid locations. Applications of hybrid power systems include, but are not limited to, military forward operating bases (FOBs), disaster recovery sites, and remote and rural locations with no access to a power grid. In our study, we consider a hybrid power system that uses diesel generators, photovoltaic cells, and batteries in a microgrid to power military FOBs; we specifically consider these technologies due to their cost and feasibility of transport to a remote site, as well as their low profile, which makes them less susceptible to attack and destruction. Most papers addressing distributed generation systems in off-grid applications use observed or simulated data for short time horizons, e.g., between one day and one week, whereas we use a full year of simulated and observed load data to take into account the effects of seasonality and changes in mission activity.

The power demand at a site depends on several factors including the population at the site, types of building construction, climate, and microgrid configuration. In order to determine which technologies to purchase to power the loads, energy demand needs to be estimated; this is often done using simulated and/or real data from comparable sites. Simulated load data is generated by software such as National Renewable Laboratory's EnergyPlus, a physics-based, building performance program that determines

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energy demand through a set of detailed inputs such as building materials, plug loads, lighting and Environmental Control Unit specifications, and Typical Meteorological Year (TMY) climate data [1].

If the electrical loads at a site are known, optimization models can be used to make procurement and dispatch decisions. An optimization model for a hybrid power system considers parameters such as fuel cost, the procurement costs of the power-producing technologies (generators, batteries, and photovoltaic cells), the lifecycle costs of batteries and generators, and the electric efficiencies of power flow into and out of these technologies. In addition, the model incorporates energy demand and solar irradiance at the site for each time period during a horizon. The number and type of technologies to be procured, as well as the amount of fuel used, are variables within the optimization model. In addition to procurement decisions, the model may also provide the dispatch of the hybrid system, which includes when each technology is turned on or off, for how long, and how much power it should produce within each time period.

If the load inputs to an optimization model are unrealistic, the model's procurement strategy may be infeasible and/or costly because it over- or under-estimates the number and/or type of technologies to purchase. The purpose of this paper is to examine how the load inputs, observed or simulated, affect procurement and power system design decisions, namely, how many and what sizes of generators, batteries, and photovoltaic (PV) cells should be purchased to reliably power an off-grid site, and how those technologies are operated to optimally meet the loads. The optimization model, henceforth referred to as $(\mathcal{U})$ [2], is fully detailed in Appendix A.

There are advantages and disadvantages to using simulated versus observed loads. The former can be generated within minutes, whereas observed loads have to be metered and collected over the length of a proposed time horizon. In addition, simulated load data is clean, i.e., there are no missing and/or errant values, and once the simulation model has been created, it can be run multiple times with varied inputs to reflect different geographic locations and load sizes. However, simulation models can be difficult and time consuming to build; in addition, they may be lacking necessary information, such as mission activity or the changing number of camp inhabitants, leading to inaccurate load predictions. Conversely, observed data exactly records energy demand, taking into account additional realistic variability such as mission activities, weather, and inefficiencies in the way people consume energy. Disadvantages of using observed data include the time and cost of collection and metering, and the presence of errors as a result of human or machine miscollection. Both input types are useful, and observed data should be used to validate simulated loads.

The objective function of $(\mathcal{U})$ minimizes the cost of procuring the technologies and fuel, and the lifecycle costs of the technologies. To obtain meaningful variable values for the hybrid power system, we impose the following operational constraints: (i) power generated must meet demand in every time period unless a shortfall penalty is incurred; (ii) power generated by any of the technologies cannot exceed its maximum rating; and (iii) best practices should be enforced to prolong the life of the technologies. These include limiting the depth of discharge of the batteries and setting a limit on the minimum power that is provided by a generator to avoid the inefficient energy use experienced at lower power demands.

Our contributions in this paper include:

(i) Cleaning and imputing sets of observed FOB load data to provide the hourly energy demand for at least a year of 8760 consecutive hours. We detail the methods that we use to clean and impute a data set with hundreds of missing values. To date, little empirical work concerning cleaning real load data for use in an optimization model addressing military logistics has appeared; in this sense, we provide a guide that practitioners can use when handling real-world data.

(ii) Constructing an observed camp load based on observed, building-level, energy demand data from (i) that matches the size of a simulated camp to facilitate a comparison of the loads. At the time of this writing, no concerted efforts have been documented that try to "match" observed data with their simulated counterpart. Our coordination of these two types of data allows for a comparison of the output from an optimization model based on real and synthetic data; see (iii).

(iii) Investigating the impact of providing $(\mathcal{U})$ with simulated versus constructed data on the output. We compare the results from using the simulated and constructed loads based on (a) the objective function value, (b) the procurement strategy, and (c) the way in which generators are used. To the best of our knowledge, such a comparison has not been made; however, researchers typically use simulated and empirical data interchangeably, which may not constitute good practice.

(iv) Assessing the impact of the load's shape, mean, variance, and maximum on the optimization model output. Givler et al. [3], which constitutes the closest work to ours in this particular aspect, mention possible effects of building sizes and functions on load shape but do not investigate the effects of load shape on their optimization model's output.

(v) Presenting a formula for estimating the objective function value based on the mean value of the load. To our knowledge, no papers in the open literature quantify this relationship.

A vast body of literature exists that relates energy systems to demand profiles in so far as the authors are concerned with shifting peak loads to mitigate extreme demands. For example, [4] examines a real-time operational strategy for an islanded microgrid to reduce costs, while [5] extends this work to create an energy management system to optimally operate distributed generation resources, including storage systems. Marzband et al. [6] addresses real-time operation under uncertainty through the use of neural networks and Markov-chain analysis and provides numerical results. While these and other authors attempt to change consumer behavior to lower investment costs and mitigate wear and tear on an energy system, the purpose of our study is to determine the effects of a given demand pattern on a microgrid procurement strategy and the corresponding costs. We do this by generating loads under a variety of statistical conditions and examining the output from an optimization model that produces procurement strategies.

Several authors note the importance of the load input to a hybrid power optimization model. Dufo-López and Bernal-Agustín [7] state that load profile study and determination are the first steps in the design of any electric power system. Kamel and Dahl [8] remark that accurately forecasting the load is important for an optimal system design; Shaahid and El-Amin [9] affirm that a crucial element of any power generation system is load and that it has a pronounced effect on system design. Most optimization models are built to meet load requirements [10,11,9,12,13,2,14], and there are potentially costly consequences for inaccurate load approximation. Underestimating the load can lead to a failure to procure enough energy-producing technologies, which is particularly problematic for the FOB application; in turn,