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Coordinating microgrid procurement decisions with a dispatch strategy featuring a concentration gradient

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HIGHLIGHTS

- We combine a year-long hourly procurement strategy with minute-level dispatch.
- We linearize our model to increase tractability.
- We use a battery model derived from electrochemical principles.
- We include temperature and voltage transient effects via concentration gradients.
- Solutions from the minute-level model closely match load.

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ABSTRACT

A mathematical model designs and operates a hybrid power system consisting of diesel generators, photovoltaic cells and battery storage to minimize fuel use at remote sites subject to meeting variable demand profiles, given the following constraints: power generated must meet demand in every time period; power generated by any technology cannot exceed its maximum rating; and best practices should be enforced to prolong the life of the technologies. We solve this optimization model in two phases: (i) we obtain the design and dispatch strategy for an hourly load profile, and (ii) we use the design strategy, derived in (i), as input to produce the optimal dispatch strategy at the minute level. Our contributions consist of: combining a year-long hourly optimization procurement strategy with a minute-level dispatch strategy, and using a high-fidelity battery model at the minute-level derived from electrochemical engineering principles that incorporate temperature and voltage transient effects. We solve both phases of the optimization problem to within 5% of optimality and demonstrate that solutions from the minute-level model more closely match the load, more closely capture battery and generator behavior, and provide fuel savings from a few percent to 30% over that provided by the hour-level model for the tested scenarios.

1. Introduction

A Forward Operating Base (FOB) is a secured military facility used to support tactical operations in foreign areas for several months to a few years. Scioletti et al. [1] propose an optimization model at a one-hour time fidelity over an annual horizon to determine the mix of equipment and the corresponding dispatch strategy at FOBs to reduce costs and fossil fuel consumption. By contrast, we present a two-phase model: Phase I, which we term ($\mathcal{H}$), and base off the work of Scioletti et al. [1], takes as input hourly energy demand, solar irradiance, temperature data and fuel cost and determines a design strategy, i.e., how many and what size generators, batteries, and photovoltaic (PV) cells to purchase to reliably power an off-grid site. The objective of our Phase I model minimizes diesel generator fuel consumption; constraints prevent over-cycling, enforce power limitations, and ensure that demand is met in each time period. Primarily, we use the hourly dispatch to inform procurement decisions; however, we cannot dispatch at the hourly level nor forecast demand for a year. Therefore, we construct a minute-level model to allow for near-real time dispatch.

Phase II, which we term ($\mathcal{M}$), uses the design strategy from ($\mathcal{H}$),

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minute-level energy demand, and temperature data to provide a minute-level dispatch strategy, i.e., how those technologies are operated, in each time period, to optimally meet the load for a 24-h horizon, i.e., 1440 time periods. The objective is largely the same as that used in the Phase I model with the exception of the procurement decisions that constitute a sunk cost, and the photovoltaic system that supplies as much power as the product of the anticipated solar panel output and the number of panels [2]. Other contrasting aspects follow: The battery system must start and end the day with an 80% state-of-charge while adhering to its limitations and inefficiencies. The generators may supply nameplate power rating conditional on restrictions regarding ramping times and minimum down times. The corresponding dispatch strategy schedules equipment usage and helps a microcontroller-based power management system make real-time dispatch decisions.

The remainder of the paper is organized as follows: Section 2 provides a review of relevant literature. Section 3 details first our hour-time-fidelity model, followed by our minute-time-fidelity model; regarding the latter, we explain the relevant detailed battery chemistry. Section 4 provides the mathematical formulation and its linearization of the optimization model at the minute-time-fidelity level; we provide a citation for the hour-level equivalent. We then give numerical results in Section 5 consisting of a description of the data, the benefits of using the minute-time-fidelity model over its hour-fidelity counterpart, and a parametric analysis based on varying some of the input values. Section 6 concludes.

2. Literature review

The literature on microgrid optimization is vast, and we provide a brief overview here. Many researchers investigate optimizing hybrid systems, both those that are grid-connected and those that are off-grid [3–8]; however, these authors do not employ mixed integer linear programs (MILPs), which produce a provably (near-)optimal solution. The following research all involves using heuristic, rather than exact, approaches to determine a solution: Abido [9] solves a multi-objective optimization model by a Pareto evolutionary algorithm based on fuzzy logic to develop a dispatch strategy. This approach shows promise in providing good, but not optimal, results to energy dispatch problems. Moghaddam [10] solves a multi-objective optimization model by minimizing fuel cost and emissions while adhering to power balance, generation, and transmission constraints with an adaptive modified particle swarm technique. Ashari [11] develops a dispatch strategy for a photovoltaic, diesel generator, and battery hybrid system for which a heuristic determines the time periods in which it is more advantageous to draw power from a battery than to run a generator at low power output, i.e., low efficiency. Park [12] uses tabu search, simulated annealing, and particle swarm optimization to solve non-smooth economic dispatch problems.

Research by [13–17] use MILPs to optimize distributed generation systems using exact approaches; however, none of these considers a minute-level time step, nor do even more computationally complex nonlinear models that restrict the time horizon to 24 hours [18,19].

Batteries in hybrid systems are usually treated simplistically [16], whereas stand-alone battery systems are modeled in more detail. Barley [20] develops battery charging and discharging techniques for stand-alone power systems using a diesel generator, wind and/or solar photovoltaic, and battery systems. Achaibou [21] shows how to model voltage levels. Dufo-López [22] more accurately models the aging of a battery system in a solar photovoltaic and lead-acid battery system. Gao [23] models the complete behavior of a lithium-ion battery with thermal effects and response to transient power demand.

We present two different optimization models that contain batteries, varying in their level of detail. The first model, ($\mathcal{H}$), employs an hourly-fidelity, linearized model presented in [1], which expresses voltage of the battery as a linear function of the state-of-charge and employs a linear version of Peukert's law [24]. Such models have been extensively used in the literature [25]. The battery model used the second optimization model, ($\mathcal{M}$), captures minute-level battery operations in which the voltage transients along with temperature effects become critical. Here, we simplify the model based on an electrochemical principle presented by Guo et al. [26] by employing a polynomial approximation, as presented by Subramanian et al. [27]. The final form of the model can also be found in work by Ramachandran et al. [28].

Once a dispatch strategy has been established, a project management system controls the equipment in real time. Tazvinga [29] shows how a model-predictive controller yields better performance than an open-loop controller for a diesel generator, wind, solar photovoltaic, and battery system. McLarty [30] optimizes the dispatch of a multi-chiller cooling plant with cold-water thermal storage using a project management system for the UC Irvine microgrid. We construct an optimization model for a hybrid system whose solutions are usable in near-real time.

Our contributions in this paper include: (i) a mixed integer programing approach to developing an energy dispatch strategy for a microgrid using minute-level time fidelity with a concentration gradient for the battery and ramping effects for the generators; and (ii) the integration of this minute-level model with the decisions from an hourly model, and associated analysis between the compatibility of the two models.

3. Background

Our two models, ($\mathcal{H}$) and ($\mathcal{M}$), work in tandem to determine a procurement strategy given a coarse dispatch strategy and then subsequently refine the dispatch strategy given the procurement strategy. We detail these models in this section, including the more precise characterization of the generator and battery behavior in the latter model. We give a flow chart of our methodology in Fig. 1.

3.1. Hour-level battery model

Phase I of our hybrid optimization model ($\mathcal{H}$) is a linearized model and considers parameters such as fuel cost, procurement costs of the power-producing technologies (i.e., generators, batteries, and photovoltaic cells), lifecycle cost of batteries and generators, and the electric efficiencies of power flow into and out of these technologies. In addition, the model incorporates energy demand, solar irradiance, and temperature effects at the site for each (hourly) time period during the 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 also provides 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 hourly time period. This model is modified from that in Scioletti et al. [1] to include the effects of temperature on the performance of generators and batteries.

Specifically, the hourly battery model presented by Scioletti et al. [1] treats internal resistance (r_b^{int}) and the rate capacity parameters (c_b^-) as being independent of temperature. In this paper, we extend that model to include temperature effects in these parameters. By using Arrhenius-type temperature dependence (due to the fact that solid phase diffusion and reaction rate coefficients conform [31]), the parameters θ_{bt}^c and θ_{bt}^r, expressed in Eqs. (1) and (2), are multiplied by internal resistance (r_b^{int}) and rate capacity (c_b^-) to give rise to temperature-dependent parameters (r_{bt}^{int}, c_{bt}^-). The battery temperature is assumed to be the same as the ambient temperature and, therefore, known a priori, allowing us to treat the temperature dependence as a parameter, rather than a variable. While internal resistance changes the voltage of the battery up and down during charging and discharging, respectively, the rate capacity parameter places an upper bound on allowable current in a given time period. Table 1 provides a contrast between the