Electric Power Systems Research 103 (2013) 61–69

Contents lists available at SciVerse ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Microgrid reliability modeling and battery scheduling using stochastic linear programming

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ARTICLE INFO

Article history:
Received 16 January 2013
Received in revised form 12 April 2013
Accepted 6 May 2013
Available online 5 June 2013

Keywords:
Batteries
Optimal scheduling
Smart grids
Stochastic systems
Uncertainty
Microgrids

ABSTRACT

This paper describes the introduction of stochastic linear programming into Operations DER-CAM, a tool used to obtain optimal operating schedules for a given microgrid under local economic and environmental conditions. This application follows previous work on optimal scheduling of a lithium-iron-phosphate battery given the output uncertainty of a 1 MW molten carbonate fuel cell. Both are in the Santa Rita Jail microgrid, located in Dublin, California. This fuel cell has proven unreliable, partially justifying the consideration of storage options. Several stochastic DER-CAM runs are executed to compare different scenarios to values obtained by a deterministic approach. Results indicate that using a stochastic approach provides a conservative yet more lucrative battery schedule. Lower expected energy bills result, given fuel cell outages, in potential savings exceeding 6%.

1. Introduction

The microgrid concept has recently gained significant attention from academia, equipment vendors, and energy companies alike. A microgrid can be defined as a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid, and can connect and disconnect from the grid, enabling it to operate in both grid-connected and islanded-modes [1]. Microgrids can contribute to ensure reliable, low cost, and environmentally friendly energy by taking advantage of distributed energy resources (DER) (including renewable sources), small-scale yet efficient fossil-fired combined heat and power technology (CHP), and both mobile and stationary storage technologies [2–4]. Furthermore, microgrids can provide locally high power quality and reliability (PQR) to sensitive loads and/or critical infrastructure [5]. By increasing the number of supply sources, microgrids are prone to a high degree of operational complexity, particularly when storage technologies are used under time dependent energy tariffs and peak pricing [6,7]. Because loads are inevitably quite variable in small systems, it is crucial to tightly control sources so that loads are reliably served, particularly under uncertainty and if islanded operation is a goal.

The microgrid planning and scheduling problem has been previously addressed using different approaches. Most models found in the literature use linear or mixed integer linear programming [8–11], while a few adopt nonlinear programming [12,13]. However, little work has been published considering uncertainty [14,15], suggesting a need for the contributions introduced with this work.

This paper follows on previous work on the problem of optimal scheduling of a reconfigurable (4 MWh–1 MW or 2 MWh–2 MW) lithium-iron-phosphate (LFP) battery, considered for use at the Santa Rita Jail (SRJ), given the output uncertainty of a legacy fuel cell [16].

This almost 3 MW peak facility is located in Dublin, California, and houses up to 4500 inmates. During the past decade, it has installed a series of efficiency and DER technologies to reduce its energy consumption, including a 1.2 MW rooftop photovoltaic (PV) system and a 1 MW molten carbonate fuel cell (MCFC) operating as a CHP unit [16]. The fuel cell has proven unreliable and is

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http://dx.doi.org/10.1016/j.epsr.2013.05.005

frequently out of service. These assumed random outages combined with time variable tariffs for both energy and power demand incurs significant potential financial penalties [16]. Fuel cell outages result in increased utility electricity purchases, significantly higher peak power demand charges, and losses of heat supply replaced by natural gas purchase. Please note that heat loads are not explicitly addressed in this work, so all natural gas purchases are tied to MCFC generation and not to replace its foregone waste heat. In part to mitigate this unreliability problem, the Jail has added local electrical storage in the form of an LFP battery.

This paper adds to previous work by expanding on the Operations version of the Distributed Energy Resources – Customer Adoption Model (Operations DER-CAM) by introducing stochastic linear programming and introducing uncertainty in MCFC availability, which determines an adjusted battery schedule.

DER-CAM [17], is a mixed integer linear programming algorithm (MILP) developed at the Lawrence Berkeley National Laboratory (LBNL) written and implemented in GAMS. It has two main versions that may be used to size and/or schedule the optimal DER capacity for a given site: (1) I + P-DER-CAM (Investment and Planning) picks optimal microgrid equipment combinations and the corresponding dispatch, based on 36 or 84 typical days representing a year of hourly energy loads and technology costs and performance, fuel prices, existing weather data, and the utility tariff; (2) Operations DER-CAM as applied in this study is used for the optimization of the detailed dispatch in a microgrid for a given period, typically a week ahead, with a time resolution of 5 min, 15 min, or 1 h, assuming the installed capacity is known, and using weather forecasts from the web to forecast requirements.

2. Modeling

2.1. Stochastic programming

To date, only deterministic methods have been applied within DER-CAM, i.e., assuming all loads and operational parameters are known. In this work, the uncertainty in MCFC availability is added to Operations DER-CAM, which requires a stochastic approach to the problem. Unlike the I + P version, Operations DER-CAM is used in situations where the microgrid configuration is known and the algorithm is used to optimize dispatch, typically on a week-ahead basis, using the time step most relevant to the economics, typically 15 min.

The enhancements now introduced are accomplished by using a stochastic linear programming method, with the problem modeled as having general recourse [18,19]. This is a standard approach wherein variables are split into different stages, referring to different moments of decision. In this particular case, two stages are considered and the distinction is made depending on whether or not their values must be known before any scenario occurs. Variables that do not depend on scenarios are first stage variables, and the ones that do are second stage variables that reflect the uncertainty in the problem.

Stochastic linear programming is a well-known approach for scheduling problems, with a wide range of applications. In [20], two-stage stochastic programming is used to deal with scheduling problems of chemical batch processes, while in [21] a stochastic programming approach with disruption scenarios is used for vehicle scheduling in public transport. Applications to energy systems can also be found, e.g. in [22], where two-stage stochastic programming is used to develop offering strategies for wind power production while considering the uncertainty in wind power and market prices. In [23], two-stage stochastic mixed-integer linear programming is used to design time-of-use (TOU) rates to deal with demand response options.

Battery scheduling problems can also be found in the literature, namely in [24], where a deterministic MILP program is developed to schedule battery charging by a set of PV arrays on a space station. In [25], the collective discharge scheduling problem is addressed using a decision-making algorithm, while in [26] charge and discharge strategies are used to study the sensitivity of electric vehicle battery economics.

In the application presented here, a schedule for the LFP battery is needed on a week-ahead basis, without knowing MCFC availability. This means that charging or discharging the battery must be planned before knowing whether the MCFC will be generating, and these will be the first stage variables of the problem. Other variables, such as electricity purchases, will depend on whether or not the MCFC is running, and will therefore take different values in different scenarios, making them second stage variables.

The virtue of using this stochastic approach is that all scenarios are explicitly considered in the model, meaning the first stage variables will be determined minimizing the expected losses of all scenarios against the solution found.

This approach allows the LFP battery scheduling to be calculated accounting for the uncertainty in the future MCFC output, and thereby balancing the potential outcomes that may occur; that is, if the MCFC availability is uncertain, an LFP battery schedule is required that minimizes the expected energy cost regardless of the MCFC availability that actually transpires. Under this stochastic approach, the problem can be described as:

$$\min c_1^{\perp} x_1 + E[f(x_1, \tilde{\omega})] \tag{1}$$

$$s.t. \quad x_1 \geq 0 \tag{2}$$

where x_1 represents all first stage decision variables, determined prior to the realization of any uncertain scenario. In the stochastic formulation of Operations DER-CAM now adopted, such variables include battery input and output decisions (charging and discharging over time). This subset of x_1 describing the LFP charging and discharging decisions in each of the 672 timesteps (15 min resolution over 7 days), and how it differs from the second stage equivalents are the key point of interest in this work. All other variables assumed scenario-independent are also included. In this case, the electricity production from the PV array is treated as known. Many sources of uncertainty may exist, and PV output is clearly one of them. They are not addressed here because fuel cell uncertainty has a stronger influence on costs at this reliable solar site. Further, while the existing PV array is rated at 1.2 MW, in practice its peak output is far short of this level, making the MCFC a more critical resource (see Fig. 1). In this formulation, c_1 represents the cost coefficient vector of first stage variables, and $E[f(x_1, \tilde{\omega})]$ is the expected value of the second stage problem, where second stage variables are calculated for each specific data scenario ω. Here, $\tilde{\omega}$ is a discrete random variable defined over probability space (Ω, P), with $p_\omega = P\{\tilde{\omega} = \omega\}$ for each scenario $\omega \in \Omega$.

The generic formulation of the second stage problem, also known as the recourse sub problem, is written as:

$$f(x_1, \omega) = \min c_2^{\perp} x_{2,\omega} \tag{3}$$

$$s.t. \quad A_1 x_1 \leq b_1 \tag{4}$$

$$A_{2,\omega} x_{2,\omega} + B_1 x_1 \leq b_{2,\omega}, \quad a_\omega \in b_{2,\omega} \tag{5}$$

$$x_{2,\omega} \geq 0 \tag{6}$$

where $x_{2,\omega}$ represents all second stage decision variables in each scenario ω, including the subset of uncertain fuel cell operation variables, electric utility purchases and sales, CO_2 emissions, among all other variables that depend on the scenario outcome. Here, c_2 represents the cost coefficient vector of second stage variables.