Electrical Power and Energy Systems 80 (2016) 396–406

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

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

Central versus localized optimization-based approaches to power management in distribution networks with residential battery storage

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ARTICLE INFO

Article history:
Received 29 January 2015
Received in revised form 29 December 2015
Accepted 27 January 2016
Available online 27 February 2016

Keywords:
Demand-response
Battery scheduling
Peak-load reduction
Photovoltaics
Reverse power flow

ABSTRACT

In this paper we propose two optimization-based algorithms for coordinating residential battery storage when solar photovoltaic (PV) generation in excess of load is compensated via net metering. Our objective is to balance increases in daily operational savings that accrue to customers with the management of reverse power flows and/or peak loads approaching a network capacity. To achieve this objective we present a central quadratic program (QP)-based algorithm, where residential customers implement a distributor-specified day-ahead battery schedule. We also present a local QP-based algorithm, where each residential customer implements a day-ahead battery schedule subject to three distributor-specified weights. To complete our assessment of the distributor benefit, both QP-based scheduling algorithms are applied to measured load and generation data from 145 residential customers located in an Australian distribution network. The results of this case study confirm both QP-based scheduling algorithms manage reverse power flow and peak loads within a distribution network. In the context of net metering, all customers exhibit the same operational savings when implementing the central QP-based algorithm, while the local QP-based algorithm disproportionately penalizes some customers.

Introduction

Recently, there has been a rapid uptake of grid-connected solar photovoltaics (PV) in many countries [1]. Drivers include the ever-decreasing cost of PV panels [2,3], concerns regarding climate change, and government incentives such as feed-in tariffs and net metering offered directly to residents investing in on-site renewable generation [4–6].

Consequently, many electrical distributors are now faced with managing bi-directional power flows in distribution networks previously designed for one-way power flow [7,8]. Of particular concern to distributors are power flows approaching a network capacity and reverse power flows inducing voltage rise, especially when either situation leads to substantial network investment [9–12].

Demand-side approaches to managing distribution power flows potentially defer (or possibly avoid) significant costs associated with distribution reinforcement [13–28]. The demand-side approach in [13] curbs PV production when such production induces significant voltage rise, creating a need for grid reinforcement [14]. To further improve distribution supply voltages the demand-side approach in [15] considers a sophisticated controller in the PV inverter that adjusts the real and reactive power supplied to, or absorbed by, the distribution grid. For the purpose of improving supply voltages in a distribution network the approach in [16] is to charge residential battery storage co-located with solar PV when a predetermined threshold for PV generation is exceeded. Other demand-side approaches that potentially manage distribution supply voltages and/or peak demand include direct load control [17–22], and price-responsive load control [23–25]. For example, distributor-specified time-of-use electricity prices are included in the category of price-responsive load control [25]. A customer implementing a distributor's request to switch a thermal load on or off is an example of direct load control [22].

However, without careful coordination, the potential benefits of demand-side approaches to managing bi-directional power flows in a distribution network might not be realized [19,29–31,26,32]. For example, a second load peak in the distribution grid may arise when autonomous, time-based electric vehicle charging schedules are implemented [19], potentially leading to a need for costly distribution reinforcement. Furthermore, increases in reverse power flows (or peak loads) potentially arise when a battery connected to a distribution grid is discharged (or charged) in response to time-varying electricity prices [31,33], which may also necessitate

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http://dx.doi.org/10.1016/j.ijepes.2016.01.048
0142-0615/

network investment. Moreover, PV storage systems designed to increase self consumption may not explicitly assist distributors in avoiding PV-related voltage rise [26,32].

Several authors have investigated coordinated approaches to scheduling demand-side battery storage with the objective of alleviating the need for grid reinforcement by managing bi-directional power flows in a distribution network [31,34,35,26,14]. For example, a linear program (LP) is employed in [31] to reduce peak power flows (potentially in the reverse direction) through a distribution substation. Furthermore, [31] proposes direct control of a customer's battery schedule by the distributor when the LP-based power flow reductions are required. To support PV self-consumption in addition to minimizing significant voltage rise in a distribution grid, different control strategies are proposed in [26], which are benchmarked and evaluated in terms of economic viability. The optimization problem in [34] includes penalties for large power fluctuations to and from an interconnection point that connects a smart grid to an upstream electricity network. To reduce power fluctuations within a distribution grid, [34] proposes direct control of demand-side battery schedules by a distributor. In contrast, a central energy management system (EMS) in [35] coordinates supply and demand within a microgrid in a number of ways. For example, a central EMS in [35] either dispatches power flow references to customers connected to a microgrid, or directly controls battery charge and discharge schedules of each microgrid customer. That is, each microgrid customer in [35] has a local EMS that manages residential battery schedules subject to central EMS references or directives.

In the recent literature most approaches to scheduling residential battery storage focus on the (potentially infrequent) need for managing bi-directional power flows in a distribution grid [14,35,26,34] or look to reduce electricity bills for the customer [36,37]. In contrast, our recent work looks to balance these two objectives, namely increasing the operational savings that accrue to residential customers with PV storage systems against the management of distribution power flows to alleviating voltage and or load conditions that necessitate grid reinforcement [33,38]. In this paper we propose two approaches that more directly balance these two objectives, thereby extending our previous work in [33,38]. Further, we apply the forecasting methodology proposed in [39] to assess the effectiveness of each algorithm when there exists uncertainty in day-ahead load and generation forecasts.

More specifically, in this paper we present two coordinated demand-side approaches to managing bi-directional power flows within a distribution grid, when excess generation is compensated via net metering. The first approach is referred to as central quadratic program (QP) energy-shifting, where selected customers implement a distributor-specified day-ahead battery schedule. The second approach is referred to as local QP energy-shifting, where three distributor-specified weights are incorporated into the QP-based algorithm of selected customers to obtain a day-ahead battery charge and discharge schedule. In both QP-based approaches our objective is to balance an increase in operational savings that accrue to customers scheduling battery storage, with reductions in reverse power flows and/or load peaks within a distribution grid. We apply each QP-based approach to measured load and generation data from 145 Australian residential customers and investigate customer and distributor benefits of coordinated residential battery scheduling.

To implement central QP energy-shifting a distributor does the following: (1) identifies a region in the distribution grid to implement a coordinated approach to residential battery scheduling; (2) forecasts the day-ahead power flows along an interconnection point to the distribution region; (3) runs optimization-based algorithms daily; and (4) broadcasts a day-ahead battery charge and discharge schedule to each regional customer. Furthermore, each regional customer requires an energy management system that: (1) coordinates with Advanced Metering Infrastructure (AMI) to advise the distributor of existing battery parameters including the current state of charge; (2) coordinates with the AMI to receive a day-ahead battery charge and discharge schedule from the distributor; and (3) schedules battery storage in the day-ahead.

To implement local QP energy-shifting a distributor does the following: (1) identifies a region in the distribution grid to implement a coordinated approach to residential battery scheduling; and (2) broadcasts three day-ahead weights to each regional customer. Furthermore, each regional customer requires an energy management system that: (1) coordinates with AMI to receive day-ahead prices for energy delivered to and from the grid; (2) coordinates with AMI to receive the three distributor-specified weights to be applied in the day-ahead; (3) forecasts the day-ahead residential load and PV generation; (4) runs optimization-based algorithms daily; and (5) schedules battery storage in the day-ahead.

This paper is organized as follows. In Section "Preliminaries" we introduce a distribution region with graph notation and define a residential system. In Section "Problem formulation" we represent a distribution network with a directed graph, and introduce a methodology for distributor-based and customer-based forecasts. In Section "Two algorithms for battery scheduling" we present two QP-based algorithms to coordinate residential battery charge and discharge schedules within a distribution region. In Section " Assessing the benefits" the two QP-based algorithms are implemented and evaluated given real-world data from an Australian electricity distributor.

Notation

Let $\mathbb{R}^s$ denote s-dimensional vectors of real numbers and $\mathbb{R}^s_{\geqslant 0}$ s-dimensional vectors with all non-negative components where, as usual, $\mathbb{R}^1 = \mathbb{R}$. $\mathbf{I}$ denotes the s-by-s identity matrix and $\mathbb{1} \in \mathbb{R}^s_{\geqslant 0}$ denotes the all-1s column vector of length s. $\mathbf{0}$ denotes an all-zero matrix, or an all-zero column vector, where the context will make clear the dimension intended, and $\mathbf{T} = [t_{ij}]$ denotes the s-by-s matrix satisfying $t_{ij} = 1$ for $i \geqslant j$ and $t_{ij} = 0$ elsewhere.

Preliminaries

In what follows each residential customer connected to a distribution network may deliver power to, or receive power from, a distributor. Fig. 1 represents the residential system of each customer connected to a distribution network. To manage bi-directional power flows in a distribution network we consider coordinated approaches to charging and discharging residential battery storage.

In more detail, we consider a *region* in the distribution network. We identify residential customers in the specified region, and consider ways to coordinate their day-ahead battery schedules. We envision our coordinated approach to scheduling residential battery storage will assist distributors seeking to reduce peak demand and/or manage reverse power flows approaching a regional capacity. To define a region in the distribution grid we employ a graph notation similar to that in [40].

Directed graphs

A directed graph $\mathcal{G}$ consists of a set of M vertices $\mathcal{V} = \{1, \ldots, M\}$ and a set of directed edges $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$. Each directed edge from vertex i to vertex j is represented by $(i, j) \in \mathcal{E}$. The *transitive closure* of $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ that defines the set of all directed paths is denoted by the matrix $\mathcal{M}^{\mathcal{G}}$. The entries of $\mathcal{M}^{\mathcal{G}}$, where vertices $i, j \in \mathcal{V}$, are $\mathcal{M}^{\mathcal{G}}_{ji} = 1$ if there exists a directed path from vertex i to vertex j, or $i = j$, otherwise $\mathcal{M}^{\mathcal{G}}_{ji} = 0$.